PoultryBot

a robot for poultry house applications

Bastiaan A. Vroegindeweij

Propositions

1. Mathematically optimal solutions in path planning for floor egg collection in poultry houses are not practical. (this thesis)

2. Though robots are based on deterministic logic, they behave unpredictably in real-life environments. (this thesis)

3. Humans should not be used as gold standard in Artificial Intelligence systems.

4. The impact of science is not in the mean of the results, but in the variation.

5. Explaining scientific research by means of a pictorial book says more than 55115 words, 11 equations, 12 tables and 41 figures.

6. Just like in Precision Livestock Farming, society in general should apply discrimination by default.

Propositions belonging to the thesis, entitled

'PoultryBot, a robot for poultry house applications – *Localisation, path planning, object recognition and performance evaluation*'

Bastiaan Abraham Vroegindeweij
Wageningen, 10 april 2018

PoultryBot,

a robot for poultry house applications

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Localisation,
path planning,
object recognition
and
performance evaluation

Bastiaan A. Vroegindeweij

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Table of contents

Chapter 1

General introduction

1.1 Historical developments in poultry production

Although keeping poultry as a farming activity already existed for ages, during the 20th century it became a real profession. In the course of that century, poultry farming underwent several major revolutions in which the production system was drastically changed.

In the beginning of the 20^{th} century, hens were kept in small-sized flocks in the back yard of farms where hens had the freedom to exert their natural behaviour (Ketelaars 1992). A first intensification of production and specialisation of farming was possible when dedicated small poultry houses were introduced, surrounded by pasture. These so-called loose housing systems allowed for a higher number of hens per farm with increased flock density. As hens foraged in the pasture and on a litter floor in the houses, this led to problems with parasites and diseases transmitted through the faeces on the floor (Hilbrich 1985). To prevent the hens from accessing their faeces, housing systems with slatted or wired floors were introduced. The use of these systems, however, led to other problems like hysteria, cannibalism and feather pecking (Prip 1976).

The next major development was the introduction of battery cage systems, with the first commercial cages appearing in the 1930's in the USA (Arndt 1931). From the 1960's onwards they became also common practice in Western Europe (Ketelaars 1992, Bell 1995), and contributed to a further increase in flock size per farm. Improved control over animal behaviour, animal health and environmental conditions as well as more intensive use of space resulted in more efficient and economic production. Compared to the earlier loose housing systems, the labour conditions improved and labour requirements decreased due to mechanised egg collection. This yielded more clean eggs and alleviated the mandatory and physically demanding gathering of eggs that hens used to lay on the floor of the loose housing systems. Also, the introduction of chain- and belt systems for frequently occurring tasks like feeding and manure removal contributed to a further savings on human labour (Hoenson 1983, Muenchmeyer 1984, Rietveld - Piepers 1987, Ketelaars 1992, Sandilands and Hocking 2012). At the end of the 20^{th} century 99% of the hens in the developed countries (such as the EU, the USA, and Australia) were kept at large scale farms, with buildings housing tens of thousands of birds in cages. Clearly, compared to earlier systems, in these battery cage systems the freedom of behaviour of the hens had been largely reduced.

Concerns with respect to animal welfare in these caged production systems emerged in time, becoming explicit with the publication of Ruth Harrison's book Animal Machines (Harrison 1964) and the Brambell report (Brambell 1965). This led to European legislation safeguarding animal welfare (European Commission 1976) by stipulating specific requirements on the housing system. In response, improvements of traditional loose housing systems (single floor systems with partly slats and partly litter) were evaluated (Scholtyssek 1987, Froehlich and Oester 2001), and welfare-enhancing modifications of the battery cage system were proposed (the so-called enriched cages) (Elson 1976, Elson 1981). As these modified systems could not directly meet the demands of poultry practice, research came up with a new type of loose housing system with a multi-story interior: the multi-tier aviary (Instituut voor Pluimveeonderzoek "Het Spelderholt" 1988). The combination of more behavioural freedom for the hens with higher stocking densities and increased mechanisation was the strong point of this system, thus making it both more animal welfare friendly as well as economically viable. Still, a substantial amount of research and development on both design and managing practices proved necessary before these systems were ready to be adopted at a large scale by poultry farmers. During the eighties of the previous century, Switzerland and Sweden were front running countries in the development and adoption of those systems (Maartensson and Lundqvist 1991, Tauson, Jansson *et al*. 1992, Abrahamsson and Tauson 1998, Gunnarsson, Keeling *et al*. 1999, Tauson, Wahlström *et al*. 1999, Froehlich and Oester 2001). Later on, also other West-European countries like the Netherlands and the UK followed (Appleby, Duncan *et al*. 1988, Tauson, Jansson *et al*. 1992, Blokhuis and Metz 1995, van Niekerk and Reuvekamp 1997, Cooper and Albentosa 2003, van Emous and Fiks-van Niekerk 2003, Tauson 2005). However, it was the EU-wide ban on conventional cages (European Union 1999) that induced the further development and large scale adoption of loose housing systems and enriched cages for laying hens in Europe. In 2013, so after the completed transition of housing systems that resulted from this ban, about 85% of the Dutch laying hens were housed in non-cage systems, whereas for the EU flock this was about 42% (Windhorst 2015). Recently, similar legislation and guidelines that aim to ban traditional cages were introduced in both Australia and the USA (Van Horne and Achterbosch 2008, California 2009, Michigan 2009, Mench, Sumner *et al*. 2011). As a result, in the coming decades traditional cages will world-wide be replaced more and more by alternatives like furnished (enriched) cages or multi-tier loose housing systems. Since the non-cage or loose housing systems already have a substantial share in Europe's laying hen housing, and are expected to be used on a larger scale in other regions as well, we will investigate these systems in more detail.

1.2 The multi-tier aviary house

The multi-tier aviary house is currently the most commonly used non-cage or loose housing system in the Netherlands. Such a system consists of multiple rows of multi-story, i.e. multi-tier, housing elements. Optionally, the house can have a covered or outdoor run with automated access control, offering hens more space to roam during the day.

A cross-section of a multi-tier aviary house is given in Figure 1.1, while Figure 1.2 contains a picture taken inside such a house. Both figures show the rows of a multi-tiered housing interior, providing living space for the animals and containing the laying nests. Both the elevated floors and laying nests are equipped with conveyor belts, to facilitate easier manure removal and egg collection, respectively. Furthermore, the housing interior contains perches for the hens on which they can roost, as well as chain feeders and automatic drinking lines to nourish the hens. The floor area is covered with a loose layer of litter to allow scratching and dustbathing. In time this litter will become mixed with droppings. Sometimes, the floor contains roughage bins or pecking blocks enriching the environment and providing the hens with additional activities.

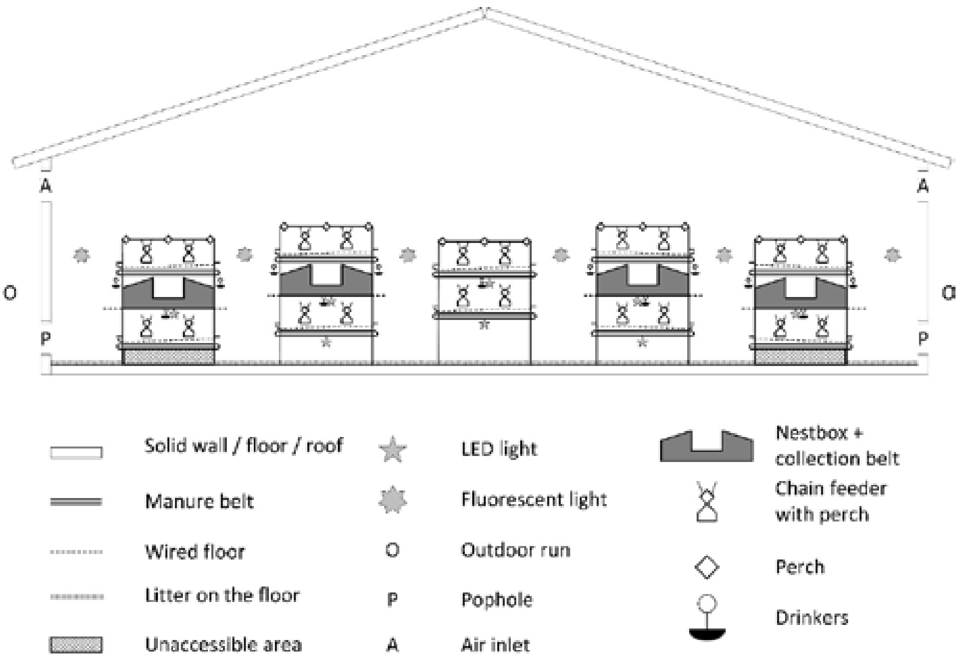

Figure 1.1: Example of the cross-section of a multi-tier aviary house. All open space is accessible to the animals, including the floor area below most housing elements. This house measures 17 meters wide and 100 meters long, and is longitudinally divided into 6 compartments.

In a multi-tier aviary, the hens will use the perches to sleep on at night and to rest on during the day. In the morning, they will visit the nest to lay their egg, while during the afternoon they are frequently found on the floor, roaming around or taking a dust bath in the litter. In between these activities, hens visit the tiers to gather their daily ration of feed and water. All in all, aviary houses are quite densely populated with animals.

The multi-tier housing elements are made of steel, and the design is to a large extend based on the dimensions and capabilities of the animal. As a result, in this system the vertical free space between and below tiers is mainly determined by the size of the hens, and can be as small as 0.5 meter. Furthermore, these housing elements can be over 2 meters wide and 2.5 meters tall, and fill more than half of the available floor space. Walking alleys between the rows with tiers are needed for inspection and management by the farmer. In the longitudinal direction, an aviary house is divided in several compartments, to separate the animals in smaller groups. Doors in the mesh wire walls provide the farmer access to neighbouring compartments.

Given the fact that the entire infrastructure is not really designed to accommodate humans, an aviary house constitutes a challenging working

Figure 1.2: Interior of a commercial aviary poultry house (different from Figure 1.1), where the hens have full freedom in their behaviour. On the left and right hand side are the interior rows, providing the animals with perches, feeders, drinkers and laying nests. On the floor, a loose layer of litter is visible which the animals use to dustbathe and scratch. The black box is a roughage bin for foraging.

environment, also because of high concentrations of dust, water vapour and ammonia in the air. These conditions also provide a challenge for existing and envisioned technical systems. With all the steel construction elements in place, the amount of obstacle-free open space in the house is limited, and to a large extend occupied with animals moving around at free will.

1.3 Daily farm work and bottlenecks

In today's aviary farming a significant part of the daily animal care is mechanised or automated, like feeding, nest egg collection, manure removal and climate control. As these tasks contain limited complexity and variation, they are fulfilled using conveyor belts and simple control logic.

But properly running an aviary house still requires good stockmanship, with intensive monitoring and awareness of animal behaviour and interactions as well as proper management and conscientiously performing of the daily tasks (van Emous and Fiks - van Niekerk 2003, Niebuhr, Zaludik *et al*. 2006). For instance, the freedom and opportunities to interact with flock mates (Blokhuis and Metz 1995, Claeys 2007) can have undesired side effects, such as laying eggs on the floor or cannibalistic pecking toward conspecifics (Gunnarsson, Keeling *et al*. 1999, Haas 2014). To make sure the hens exhibit the desired behaviour at the correct locations, such as roosting on perches at night and laying their eggs in the nest, hens can and need to be trained properly which requires considerable attention of the farmer, especially during rearing and at the start of the laying period (Appleby 1984, Tauson 2005). Still, eggs get mislaid and need to be collected at least once a day and retrieval of dead hens is a frequently recurring task as well. All these tasks are complex and challenging and on current farms they largely rely on human labour.

Tasks like inspection of animals and collection of floor eggs account for about 20 to 40% of the daily work (Blokhuis and Metz 1995, Claeys 2007). As parts of the daily tasks are closely linked to animal behaviour throughout the day, there is not much room for flexibility in the work schedule. Floor egg collection, for example, has to be done mainly in the morning. At the same time, these tasks are physically demanding with postures that lead to an increase of back problems (Drost, Meijs *et al*. 2002, Claeys 2007). Besides, the climate inside the aviary poultry house poses a clear threat to the health and wellbeing of the workers. The air quality in the house is negatively affected by animals foraging and dustbathing in the litter on the floor. This increases concentrations of airborne dust, micro-organisms and ammonia in the air. Reported values are at least several times higher compared to cage houses and were shown to exceed legal limits (Drost and van der Drift 1993, Blokhuis and Metz 1995, Claeys 2007, Winkel, Mosquera *et al*. 2009). Recent research in the USA (e.g. Shepherd, Zhao *et al*. 2015, Zhao, Shepherd *et al*. 2015a, Zhao, Shepherd *et al*. 2015b, Zhao, Zhao *et al*. 2016) on aviary, enriched cage and cage houses showed similar results, confirming these conditions still exist in current systems.

Unfavourable working conditions negatively affect the availability of labour as people are less and less interested to work in poultry farming (Zeijts, Eerdt *et al*. 2007). Unfavourable working conditions also negatively affect labour costs. In the Benelux, direct labour accounts for some 10% of the total production costs, with labour prices being 3 times higher than in countries like Brazil or India (Claeys 2007). As the costs of labour will continue to rise, this will negatively affect the competitive position of poultry farmers in North-West Europe on the world market.

But there is more. In the current poultry production systems, management is mostly applied at flock level, with limited attention for the individual animal. As the number of animals per worker is continuously increasing (Fernhout and Lei 2013), attention for the individual hens has drastically decreased. With the application of Precision Livestock Farming (Wathes, Kristensen *et al*. 2008) farmers try to counteract this development, by using automated monitoring to give more attention to the individual animal, to improve its wellbeing and health, and also the production efficiency. Although this has improved labour efficiency for monitoring, and several automated control options also exist, human labour is still frequently required to implement corrective actions in the production system.

And last but not least, nowadays consumers demand more attention of and care from the farmer for the well-being of his animals (Eurobarometer 2016). Also, recent or upcoming legislation related to animal welfare, such as the ban on electrical fences and the trimming of beak tips, will further increase the amount of labour needed for flock management.

Therefore, for poultry farming to remain a viable business in the future, changes are desired such that the labour requirements can be reduced, while at the same time more attention can be given to the health and welfare of the animals.

1.4 Possible strategies for supporting or replacing human labour

To deal with the challenges of the labour demand in aviary housings, various strategies exist. The housing system and working methods can be modified, such that animal behaviour can be managed more easily and the related labour demand decreases, while working conditions improve. Also, the farmer can be supported in his daily work, by providing him with mechanical or automated tools that assist him in or take over time-consuming or undesirable daily tasks like monitoring of the animals and floor egg collection.

Reducing labour demand resulting from managing undesirable hen behaviour, such as feather pecking and floor egg laying, can be achieved by applying design improvements to current housing systems. By fine-tuning the layout of the interior towards animal needs and capabilities the incentive for undesirable behaviour is reduced. Elements can be added to provide new activities, such as roughage bins or pecking stones. Also mechanical systems can be introduced, like a manure scraper to remove excessive litter (JPE 2015) and an air blowing system that reduces trooping of animals in corners (Schippers 2015).

A more rigorous alternative is using disruptive design methods such as "Reflexive Interactive Design" (RIO) (Bos and Groot Koerkamp 2009) to develop completely new housing concepts meeting the requirements of all stakeholders, i.e. farmer, animals and market. An example of such a design is the Roundel house (in Dutch: Rondeel). The Roundel delivers improved functionality for the farmer while undesired animal behaviour like floor laying and feather pecking is less likely to occur, thus reducing the amount of labour needed to handle the consequences of this behaviour (Wageningen UR projectteam 'Houden van Hennen' 2004, Groot Koerkamp and Bos 2008).

Assistance can be provided to the farmer, both in the execution of daily tasks and in the collection of information for management purposes. Several simple tools are already common, such as a collection stick or small rake for floor egg collection. More complex systems have been proposed, such as a mechanised rake system to remove floor eggs (Fiks-van Niekerk, Reuvekamp *et al*. 2003) or the 'Chicken Trolley' inspection system (Bijleveld and Geens 2014), but these are not yet common in practice.

Sensor systems are commonly found in livestock farming, and used for example to monitor climate conditions or animal behaviour (Quwaider, Daigle *et al*. 2010, Qi, Brookshaw *et al*. 2013, Dolecheck, Silvia *et al*. 2015). Camera systems for online monitoring the behaviour of a broiler flock are already available on the market, such as the EyeNamic system of Fancom (Fancom 2016). Using such automated sensor systems for monitoring tasks saves time and has several advantages over manual monitoring by humans. These systems can be active 24/7 offering a continuous supply of information. The quality of the collected information is potentially more constant, as these systems do not suffer from the performance limitations of human observers. They allow for simpler comparison of current data against past results and established standards, with the opportunity of faster and better detection of potential problems. Given there is sufficient information in the data and proper data processing is available, this also opens up the way for the application of methods for individual treatment of the animals. However, since sensor systems lack the ability to perform actions, human labour is still required to transform the collected information into control measures.

Autonomous robotic systems in the animal house are the next level in support or replacement of human labour. These systems can combine sensing and acting into one single system. Potential tasks include sensing of climatic properties such as temperature, humidity, and dust levels and animal status and behaviour. The actuation components of these systems offer opportunities for tasks like floor egg collection, removal of dead animals, cultivation of wet litter spots to improve floor conditions and reduce emissions, or to manage animal behaviour by dispersing trooping animals or spreading grains in the house.

Robotics is a trend in agriculture. For field applications, this started with the development of autonomous navigation systems based on vision and GPS in the 1990's (among many others: Tillett 1991, Hague, Marchant *et al*. 2000, Keicher and Seufert 2000, Ehrl, Stempfhuber *et al*. 2004) which are nowadays common technology on farm equipment and resulted in the recent introduction of a range of small-scale autonomous robots, such as Deepfield's BonïRob and Naio's Oz (Deepfield Robotics 2016, Naio Technologies 2016). In livestock applications, robotic milking was the first major application for autonomous robots, for which development started back in the 1980's. Since the 1990's, these systems are commercially available, and have seen a wide-spread usage on commercial farms since the end of that decade (John, Clark *et al*. 2016). After the introduction of autonomous milking systems, which are stationary in the barn, also mobile systems were developed for other daily tasks such as manure scraping, feeding and feed pushing, and which are now commonly found on dairy farms (Lely 2015, JOZ 2016, and many others). In more intensive livestock production systems, the use of mobile robots is still hardly seen, with only a few examples for pig feeding or house cleaning. For poultry production systems, such as aviary housings for laying hens, no autonomous robots were available at the start of this research.

1.5 Hypothesis

One of the first use-cases of mobile robots in poultry houses was presented in Vroegindeweij (2009), proposing that a mobile robot for floor egg collection offers interesting perspectives. As this task of floor egg collection still demands significant amounts of time and unhealthy physical labour from the farmer, it is considered worthwhile to further investigate this concept. Therefore, focussing on the application of mobile robots in laying hen houses, it is hypothesized that:

"Automation and robotics can have significant benefits when taking over tasks from humans in a poultry house. For a labour-intensive task like the collection of floor eggs, using an autonomous mobile robot improves the quality of floor egg collection and prevents an increase in floor laying."

To prove this hypothesis, however, a mobile robot with proper hard- and software is required that is able to perform such tasks, and it was the aim of this research to generate such a robot. The next sections review the required functionality and the suitability of available methods. Based on this analysis and review, the objective and research questions for this thesis are defined.

1.6 Required functionality

To have mobile robots perform more complex tasks in observation and control in a poultry house, as proposed in Section 1.5, they need to be flexible and autonomously adaptive to changing conditions. This limits the use of simple approaches and fixed or random paths. Instead, they require freedom in mobile robot behaviour, while not only being aware of their environment, but also able to interact with it and respond to changing conditions. Irrespective of their final application, whether it is measuring the environmental climate, collecting floor eggs or interacting with animals, all systems require some form of mobility to enable their functioning, thus indicating the need for advanced mobile robots. More specifically, these robots demand capabilities such as localisation, path planning, detection and recognition of objects in the environment. Furthermore, changing conditions should be explicitly dealt with in these elements, as well as exploiting the variation present when executing tasks. Finally, these capabilities should be brought together with actuation methods and a navigation component in a functioning proof of principle, to show their suitability under practical conditions.

As these capabilities are similar to those required for advanced robot applications in domestic environments, it is likely that research has already resulted in a number of suitable options to fulfil these functions. Therefore, first the specific requirements for localisation, path planning, object recognition and system integration are reviewed with respect to the task indicated in our hypothesis, the collection of floor eggs in a poultry house. Next, existing methods for these tasks are judged on their applicability and if necessary, indications for adaptation or improvement are given. The manipulation required for collecting floor eggs is not considered in detail in this review, as it was not considered a key component in the development of the robot. However, it was included as one of the elements for which further analysis and method selection was done in the system integration step (Section 1.6.4).

1.6.1 Localisation

First, localisation, being able to locate oneself within your surroundings, is often the only way to make the activities one is performing possible and useful (Lingemann, Nüchter *et al*. 2005). Having an answer to "Where am I?" allows relating observations and actions to a known location in the environment. Furthermore, it is an absolute necessity for advanced activities like mission control and path planning. To provide sufficient detail in the registration of floor egg locations, a localisation method should have an error of less than 1 meter for 95% of the time. To properly perform actions, a higher accuracy is desired, with an error of less than 0.1m for 95% of the time.

General localisation algorithms for wireless sensor networks and autonomous vehicles exist already for years, but have a limited indoor applicability as they mostly incorporate information from Global Navigation Satellite Systems. Other methods were developed for indoor localisation, mostly by measuring the distance between sender and receiver using light or radio communication and reaching centimetre-level accuracies (Mautz 2010). However, the dense (metal) poultry house interior limits the use of such methods. For mobile robots, also fixed beacons and dead reckoning are commonly used. Both systems might have reduced performance due to the loose litter on the floor. Placement of beacons also requires a significant installation and maintenance job.

A common alternative used in autonomous vehicles is the combination of odometry data and inertial sensing with data from laser range finders or cameras in a probabilistic framework (Thrun, Burgard *et al*. 2005, Siegwart, Nourbakhsh *et al*. 2011) This approach has several advantages for mobile robots in poultry farming:

1. It implicitly allows fusion of data from multiple sensors;
2. It explicitly deals with uncertainties present;
3. It does not rely on any additional equipment outside the robot platform.

Experiments with these probabilistic methods were already done in environments comparable to poultry houses, like museums (Burgard, Cremers *et al*. 1999, Thrun, Beetz *et al*. 2000) and airports (Triebel, Arras *et al*. 2015). However, their functioning in environments with a highly repetitive structure and few unique elements, such as orchards or an aviary house is still barely known, with Hiremath (2013) being the only known example at the start of this research. Thus, the suitability for using probabilistic localisation methods on a poultry house robot has to be investigated, including the use of various sensor data and model settings.

1.6.2 Path Planning

Second, to perform actions in a meaningful way, a certain amount of planning is required, for example to find a proper path through the house (path planning). This can be done in a heuristic-based 'at random' manner, but for more sophisticated activities, a purpose-oriented approach is desired that answers the question "Where do I go?", making planning a core component for every activity (LaValle 2006). The path planning task for floor egg collection, our example case, is a high-level task that can be done beforehand to produce a global path, and is separated from the lower-level tasks like navigation, which determines the actual movements based on its current target and the local conditions. For floor egg collection, the path to be planned should ensure full coverage of the area, to avoid eggs remaining in the house for more than 24 hours, as their locations are unknown in advance. Preferably, floor eggs are collected faster, to reduce additional floor egg laying. Reducing the number of floor eggs present in the house and the time they are present on the floor both contribute to this. Thus, multiple visits are required to locations where the probability on floor eggs is higher.

Existing path planning methods commonly use an optimisation criterion like minimum time, travelled distance or effort for a single execution of the path, and can be divided into 2 main categories. The first is finding the way from start to goal, like in car path planning or network navigation (Choset 2005, LaValle 2006). The second category aims to cover a full area, like in lawn mowing or floor cleaning (Choset 2001, Galceran and Carreras 2013).

Although floor egg collection requires the second category of path planning methods, it also requires some components from the first category, as specific locations in the area should be visited more than once in a heterogeneous manner. Therefore, a different optimisation criterion is required which is related to task performance instead of the path properties. Other problems contain similar characteristics, such as floor cleaning in buildings or security observations. However, algorithms that can provide such behaviour within a single path again and again, instead of just repeating a simple path, are only scarcely reported in literature, and most of them focus on the theoretical aspects of such problems and/or the use in multi-robot applications (for example: Ahmadi and Stone 2005, Ahmadi and Stone 2006, Elmaliach, Agmon *et al*. 2009). Since no algorithm is yet fully suited for practical application to such problems, a new algorithm is desired to plan a floor egg collection path.

1.6.3 Object recognition

To guarantee safe and proper behaviour, the mobile robot should be aware of the objects that are present in its surrounding (observation), which leads to the question "*What do I encounter on the way to my goal?*". With such awareness, the robot can properly respond to the changing conditions, thus enabling safe operation in the highly dynamical environment of a poultry house. However, the application of existing methods for sensing and perception in the agricultural environment, contains some interesting challenges as in comparison with industry the agricultural environment is unstructured and has a high degree of complexity and variability (van Henten 2006, Nof 2009, Bac, van Henten *et al*. 2014). Furthermore, the amount of background noise, the uncontrolled and adverse environmental conditions such as dust and low light levels, and the unpredictable animal behaviour complicates the use of technology to do proper observations (Frost, Schofield *et al*. 1997, Sergeant, Boyle *et al*. 1998).

In general, camera or vision systems offer opportunities to create the desired environmental awareness, even in the presence of variation and uncertainty, as they have the potential to identify a wide range of objects in varying conditions (Szeliski 2010). The downside, however, is that usually significant processing and advanced methods are required to determine image features and identify the objects present, which might limit their applicability on a mobile robot. More simple approaches rely on shape or colour features, but are also frequently limited in performance as a result of varying conditions and occlusion of objects (Kapach, Barnea *et al*. 2012). On the other hand, for the floor egg collection application, there are only four object classes considered most relevant for proper operation: eggs needing collection, hens as moving obstacles, housing as fixed obstacles and litter as it indicates free space to drive. Furthermore, if about 80% of the image pixels are classified correctly, this might already be sufficient to determine which objects are present in the vicinity of the robot.

For classification problems in agriculture that attempt to create situational awareness, such as separating leaves from cucumbers or discrimination of plant species, spectral features were used (van Henten, Hemming *et al*. 2002, Piron, Leemans *et al*. 2008, Nieuwenhuizen, Hofstee *et al*. 2010). As the spectral responses can be determined beforehand for different object categories and tend to be object-specific, their use might also be an interesting approach for the discrimination of most of the relevant objects around a mobile robot in a poultry house. Some information on the spectral response of hens and eggs was already published by Prescott and Wathes (1999) and De Ketelaere, Bamelis *et al*. (2004) and showed promising differences between object categories. Still, it is unclear which spectral features should be used, and what the performance of this method will be. Thus, a more detailed investigation is needed, both focussing on the selection of features and the assessment of performance that is possible when using this method for object recognition and discrimination in an aviary poultry house.

1.6.4 Integration

Fourth, even if the previous questions are answered and suitable methods for these functions are available, they still have to be integrated in the mobile robot to be able to answer the question "*How do I perform*". For this, first a vehicle or hardware platform is needed to integrate sensing and actuation. Next, the information on the robot's position and the desired path should be coupled with the environmental awareness and translated into movements (navigation) and actions (egg collection), all within the environment of the poultry house. Finally, a tool is required to collect the eggs, as this is the ultimate task of the robot. The robot that results from this integration step, should be able to avoid collisions with housing obstacles or hens, while collecting at least 90% of the eggs present in the house.

For each of these elements (vehicle, navigation, egg collection), already a number of methods are available. For example, a first idea for floor egg collection was already presented at the Field Robot Event in 2007 (Anonymous 2007). For navigation, a range of methods exist, such as the Dynamic Window Approach (Fox, Burgard *et al*. 1997) and the Vector Field Histogram methods (Borenstein and Koren 1991, Ulrich and Borenstein 1998, Ulrich and Borenstein 2000). However, it is unclear to what extent they match the requirements for a poultry house robot, so the available options have to be reviewed and a suitable method should be selected. This is followed by an integration step where all selected components are brought together in a single robot.

Once an integrated system is available, it is interesting and relevant to see if the proposed concept indeed functions as proposed. An experimental evaluation of the robot's performance is therefore desired, to test the concepts and to test the validity of the initial hypothesis. Furthermore, as the presence of a robot in the animal environment also influences the behaviour of the hens, their response to the robot has to be investigated to make sure there are no negative effects on animal welfare.

1.7 Objective, research questions and thesis outline

The main objective of this thesis was

"To develop an autonomous mobile robot running in a poultry house environment, capable of performing tasks such as floor egg collection, and test it in a proof of principle experiment".

In line with this objective, research questions were formulated addressing the main functional components of the robotic system: localisation, path planning, object recognition and integration. The research questions in **bold** indicate the major elements of this thesis, and are dealt with in the research chapters. The research questions were:

1. *"Where am I?"* - **How suitable and accurate are probabilistic methods for indoor localisation of a mobile robot in a poultry house?** Chapter 2 assesses the capabilities of modern probabilistic localisation methods in the context of an empty aviary poultry house. Also, the suitability of different data sources such as wheels and a motion sensor and the selection of model settings and parameters are described. In Chapter 5, an extension of this work is described to perform localisation in a poultry house with animals.
2. *"Where do I go?"* - **How can a floor egg collection path be planned, which minimizes the number of floor eggs and the time they are present on the floor?** In Chapter 3, existing knowledge on floor laying behaviour of hens is exploited in the planning of an adaptive floor egg collection path. For this, the new Non-Uniform Area Coverage (NURAC) path planning algorithm was developed, and compared to the conceptually simpler path of the farmer. The underlying sub question; "How are floor eggs in an aviary poultry house distributed?",

was analysed in a conference paper (Vroegindeweij, Van Henten *et al*. 2013).

3. *"What do I encounter on the way to my goal?"* - **How suitable and accurate are spectral features for the discrimination between various objects in a poultry house?** To answer this question, Chapter 4 investigates the spectral properties of relevant object categories a mobile robot might encounter in the poultry house environment. Based on these properties, images at a specific wavelength were acquired and pixel classification was applied. Also, the effect of varying the detection thresholds on the method's performance is described. In Chapter 5, an extension of this method is used to detect the presence of eggs on the floor.
4. *"How do I perform?"*- **What is the performance of an autonomous vehicle that integrates these methods?** For this, Chapter 5 describes the integration of these components in the PoultryBot, together with additional methods for navigation and egg collection. Several sub questions were defined to guide the selections of suitable methods for other tasks, such as for navigation and egg collection, and the evaluation of animal response on PoultryBot. Selecting a navigation method for PoultryBot and investigating the effect of PoultryBot on the hens, is described in student reports such as (Boots 2013, Schopman 2015). The development and evaluation of the egg collection device was published as conference paper in (Vroegindeweij, Kortlever *et al*. 2014). Furthermore, Chapter 5 describes the experiments done to evaluate PoultryBot's performance in a small-scale poultry house with hens. Navigation and egg collection were evaluated separately, and the results obtained are used to discuss also integrated performance.
5. *"How to continue?"* - **What is required to convert the results of this research into a reliable and economic viable product for the poultry farmer?** The General Discussion in Chapter 6 reflects on used methodologies, major findings and final achievements. It also indicates what went well in respect of the application requirements, which new requirements and functions emerged and where more attention is needed. Furthermore, Chapter 6 also addresses several components not yet considered in detail, such as vehicle design and handling animal behaviour. Although the research focussed on the technical challenges of a mobile poultry house robot, also indications are given on non-technical topics that are of relevance for successful commercialisation of this idea, such as its impact on animal welfare and its acceptance by poultry farmers and society in general.

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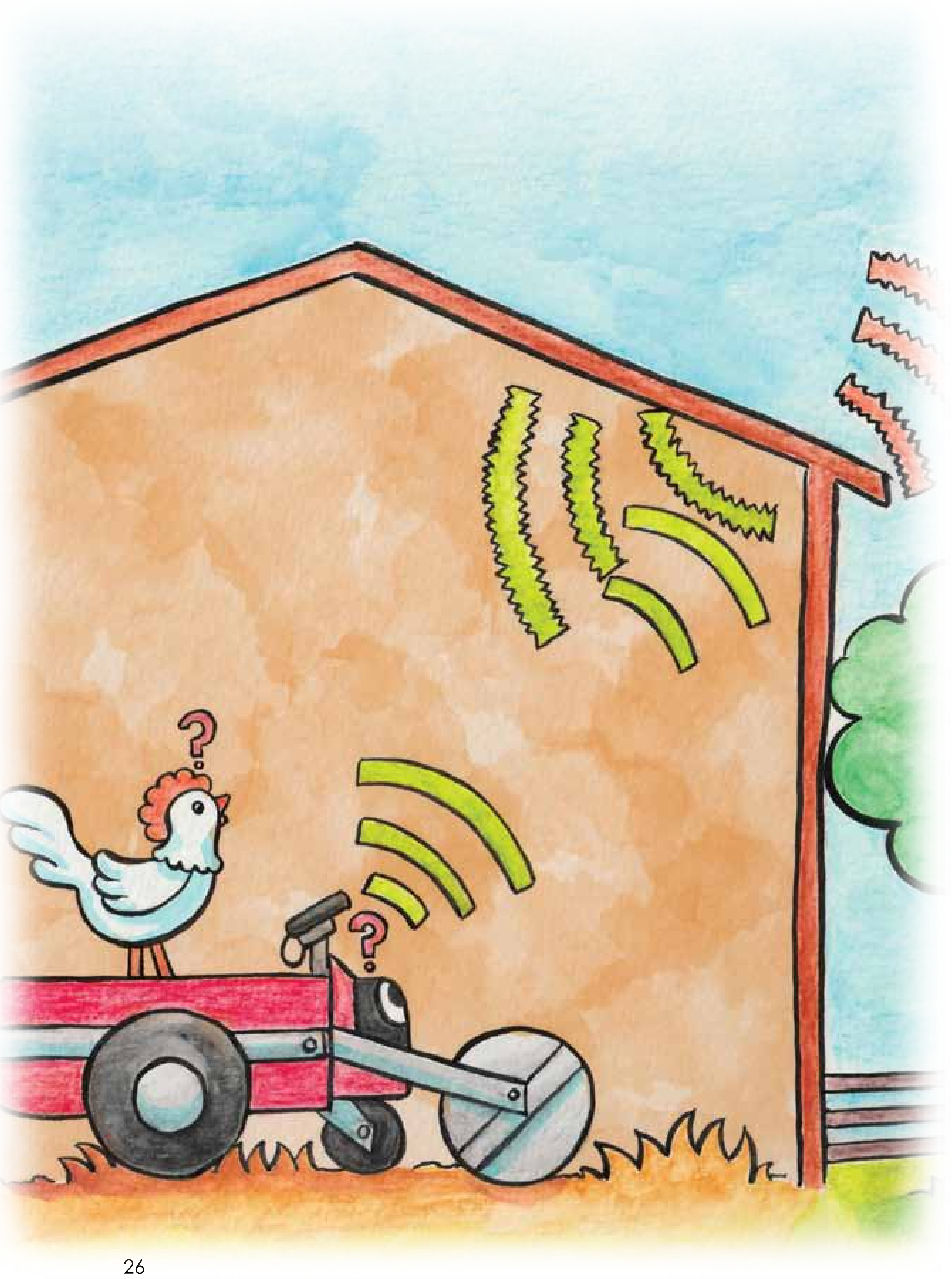

Chapter 2

Probabilistic localisation in repetitive environments: estimating a robot's position in an aviary poultry house

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Abstract

One of the problems in loose housing systems for laying hens is the laying of eggs on the floor, which need to be collected manually. In previous work, PoultryBot was presented to assist in this and other tasks. Here, probabilistic localisation with a particle filter is evaluated for use inside poultry houses. A poultry house is a challenging environment, because it is dense, with narrow static objects and many moving animals. Several methods and options were implemented and tested on data obtained with PoultryBot in a commercial poultry house. Although no animals were present, the localisation problem is still challenging here because of the repetitive nature of the poultry house interior, with its many narrow obstacles. Different parameter configurations were systematically evaluated, based on accuracy and applicability of the results. Estimated paths were quantitatively evaluated based on the Euclidian distance to a ground-truth determined with help of a total station. The presented system reached an accuracy of 0.37m for 95% of the time, with a mean error of 0.2m, making it suitable for localising PoultryBot in its future application.

2.1 Introduction

Over the last decades, poultry housing in Europe has moved from traditional cage systems to systems with more freedom for the animals, under the influence of EU directive (European Union 1999). This resulted in more manual labour, such as collecting floor eggs under unfavourable conditions (Blokhuis and Metz 1995, Claeys 2007). A poultry house robot (PoultryBot) was introduced in previous work, to assist in such tasks or take them over entirely (Vroegindeweij, van Willigenburg *et al*. 2014). The previous paper presented a path planning approach for the robotic collection of floor eggs. In order to execute the planned paths, the robot needs to localise itself in its working environment, an aviary poultry house. This is the focus of this paper.

2.1.1 Problem background

The modern aviary poultry house, as described in Blokhuis and Metz (1995) and Sandilands and Hocking (2012) and visualised in Figure 2.1, can be characterised by the following aspects that are relevant for robot localisation. First, metal construction elements provide facilities to the animals that live there. Second, the resulting structure of the house is highly repetitive, and contains very few unique elements. Third, the metal construction poles are thin and hence hard to detect. Fourth, the remaining free space is occupied by tens of thousands of animals that move around at will. Fifth, the air contains high concentrations of dust, and vapour. These five aspects all limit line of sight. Finally, the floor is covered with an uneven layer of loose litter.

Figure 2.1: PoultryBot driving among hens in a poultry house. This picture shows that the floor occupancy is high and a substantial number of construction elements are present in the environment.

2.1.2 Requirements

In order to be successful in path following, PoultryBot (shown in Figure 2.1) requires a localisation accuracy of less than 1m, for 95% of the time and preferably less than 0.1m. In terms of localisation problems, this means that at least position tracking should be achieved, i.e. estimating the robot's position while knowing from where it started, which is considered the simplest problem in mobile robot localisation (Thrun, Beetz *et al*. 2000, Thrun, Burgard *et al*. 2005). The capability of global localisation is desirable but also more complex, as the starting pose is no longer known. Other requirements on the final robot are a short installation time with a minimum adaptation to the housing and the ability to fit and work inside different types of housing.

2.1.3 Mobile robot localisation

The properties and requirements mentioned above limit the applicability and accuracy of most available localisation methods. Thus, more sophisticated methods capable of handling uncertainty and ambiguities in both sensor data, environment and position estimates are required. Probabilistic methods might be suitable for this, and are commonly used for localisation and control in mobile robotics (Thrun, Burgard *et al*. 2005, Siegwart, Nourbakhsh *et al*. 2011), especially in GNSS-denied environments. This was shown, for example, by Thrun, Fox *et al*. (2001) who used a Monte Carlo method in a museum environment. Other applications where Monte Carlo methods were successfully tested are office corridors and campus terrains (Howard and Roy 2003, Lingemann, Nüchter *et al*. 2005, Kümmerle, Triebel *et al*. 2008, González, Blanco *et al*. 2009), but also in fish tracking (Xydes, Moline *et al*. 2013) and in autonomous cars (Levinson, Askeland *et al*. 2011, Stiller, Puente León *et al*. 2011).

2.1.4 Our approach

As both museums and poultry houses have a similar static environment with dynamic obstacles and limited physical changes to the environment are allowed, it is expected that Monte Carlo methods can successfully perform robot localisation in poultry houses. Thus, we used a particle filter approach for the localisation of PoultryBot, which uses a set of particles to represent the pose estimate (position and orientation). Furthermore, this approach allows the use of raw sensor data, so no explicit handling or removal of noise in sensor measurements is required.

A processing cycle in the particle filter consists of three phases: prediction, update, and resampling. In the prediction phase, each particle's pose is moved based on a control input (e.g. odometry data) with additional noise. In the update phase, measurement data (e.g. from a laser scanner) is used to determine the particle likelihoods (e.g. by comparing the laser scanner data to a corresponding sensor model and map). In the resampling phase, likely particles are selected to be used in the next cycle more often than unlikely particles. Optionally, random new particles can be added. As input data, a map of the poultry house is used, combined with proven and simple sensors: wheel encoders, an Xsens MTi (combining a compass and an inertial measurement unit – IMU), and a laser scanner.

Still, some challenges related to the usage of these sensors remain. First, Qi, Brookshaw *et al*. (2013) indicated inaccuracies of 10% for an IMU and odometry in a poultry house alike environment. Second, compass data is known to be influenced by metal objects. Third, laser scanners might suffer from the mixed pixel problem (Ye 2008), where sensor readings are corrupted by combining reflections from object and background within one pixel. As our environment contains many small obstacles, this might have a negative impact on the quality and accuracy of the laser scanner data. Fourth, the presence of animals at the same height as the laser scanner can negatively influence the results, as they occlude static obstacles. Placing the laser scanner such that it is facing a "free zone" might solve this problem (Mastrogiovanni, Sgorbissa *et al*. 2005). Because the laser scanner height is constrained by the housing interior, looking over the animals is possible to a limited extent only.

2.1.5 Open questions and contributions

Thus, it remains unclear whether using a particle filter using information from odometry, Xsens MTi and a laser scanner is suitable for localisation in poultry housings. In this work, our approach is presented and assessed on its applicability and accuracy for localisation of Poultrybot. For each of the stages in the particle filter, various methods are presented in literature and text books (like Thrun, Burgard *et al*. 2005, Doucet and Johansen 2009, Li, Sun *et al*. 2014). However, it is unclear which methods and settings are most suitable for use on PoultryBot. Thus, several alternatives were selected for the various models and settings used in the particle filter, to assess which choices are the most suitable given our application. As detailed quantitative information on the effects of various choices is scarce in literature, the effect of our choices is also quantitatively reviewed.

Data from PoultryBot was gathered in a single experiment, separately from the location estimation. The localisation method was evaluated afterwards in a separate offline processing step. Thus, they were not limited by computation time and the effect various settings could be evaluated. The experimental data used for the evaluation was gathered in a commercial poultry house without animals, to simplify the problem. The localisation problem is still challenging here because of the repetitive nature of the poultry house interior, with its many narrow obstacles. Animals will be present in future experiments, which can be achieved by filtering the laser data or using additional sensors.

Paper outline

Section 2.2 describes the materials and methods used, consisting of the robot platform (PoultryBot), the localisation algorithm, the data collection, and the evaluation methods. The results are presented and discussed in Section 2.3, followed by a general discussion on the methods in Section 2.4. Finally, the conclusions are provided in Section 2.5.

2.2 Materials & Methods

This section described the materials and methods used in this research. First, our experimental platform PoultryBot is described (Section 2.2.1). Next, a location estimator was developed based on a particle filter, using different sensor models (Section 2.2.2). To develop and evaluate the location estimator, data and ground-truth were collected in a commercial aviary poultry house (Section 2.2.3). The evaluation procedure for the localisation estimator is given in Section 2.2.4.

2.2.1 PoultryBot

PoultryBot (Figure 2.1 & Figure 2.2) was based on the Eyesonic field robot used in the Field Robot Event of 2008 and 2009 (Wageningen University 2009). The design used three independently driven wheels to avoid slip, with an actively steered front wheel. For the experiments in this paper, PoultryBot was still remotely operated while gathering sensor data for offline processing at a later stage. The total height of the robot was limited to 0.45m by the poultry house interior.

2.2.1.1 Coordinate system

When addressing the localisation problem in the horizontal plane, the pose of the robot consists of a 3 state vector containing x, y, and θ, attached to the house coordinate frame. Orientation θ is defined as the counter-clockwise rotation with respect to the house coordinate frame's x-axis (in radians). The origin of the robot O_R is located in the centre of the rear axle. The coordinate system uses SI standard units.

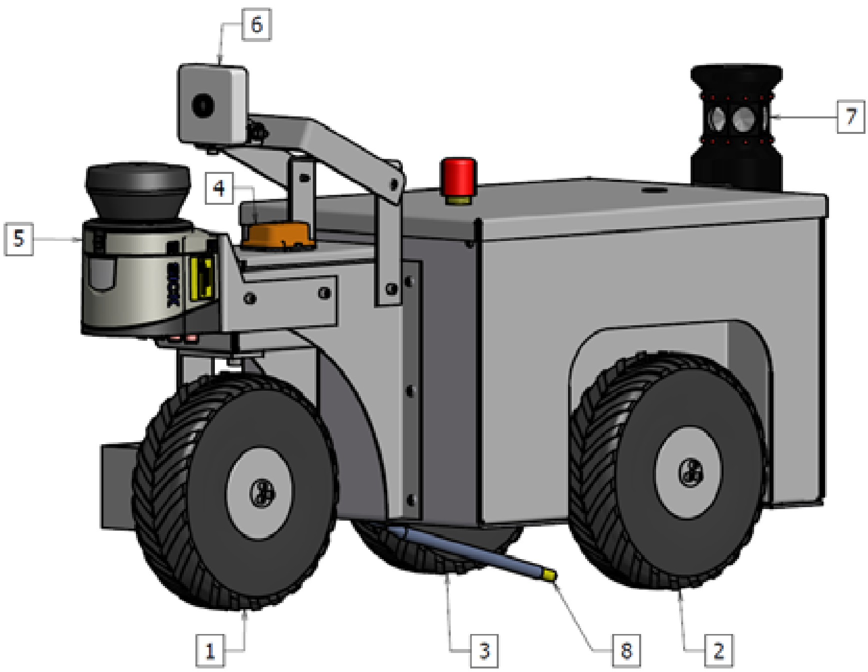


Figure 2.2: PoultryBot, in the configuration used during the experiments. Indicated are the various sensors used: 1-3) driven wheels with encoders, 4) Xsens MTi, 5) laser scanner, 6) camera, 7) prism for ground-truth measurement with the total station, 8) tracking crayon to physically register the path on the floor. The robot height was limited to 0.45m by the poultry house interior.

2.2.1.2 Sensing systems

During the experiments, several sensing systems were installed on the robot, which are indicated in Figure 2.2. All three wheels were driven by a DC motor (maxon motor RE 35) via a gearbox (maxon motor GP32C), and controlled using Roboteq AX3500 motor controllers. An optical encoder (HEDS 5540) was directly attached to the motor shaft to measure rotation and thus wheel displacement. Steering was performed by another DC motor connected to the front wheel with a belt. Direct feedback on the steering angle was obtained through a potentiometer (Vishay P11L). Deviations from the applied steering angle were immediately corrected, so the real steering angle was always close to the applied steering angle.

An Xsens MTi on top of the robot was used to register the robot's orientation θ. A Sick LMS 111 laser scanner at the front of the robot registered a 20m deep and 270° wide view, centred on the driving direction in a horizontal plane 0.37m above the ground. Finally, a Unibrain Fire-i digital camera above the robot captured images of the area in front of it. The camera was used for visualisation purposes only, and not used in the location estimation.

For data collection during the experiments, all sensors were connected to a PC with a Core i7 chipset inside the robot, running LabVIEW 2013 under Windows 7. The PC passed on the remote control signals from the operator to the motor controllers and gathered the sensor data from the sensors described above. All data was captured and logged at 10 Hz.

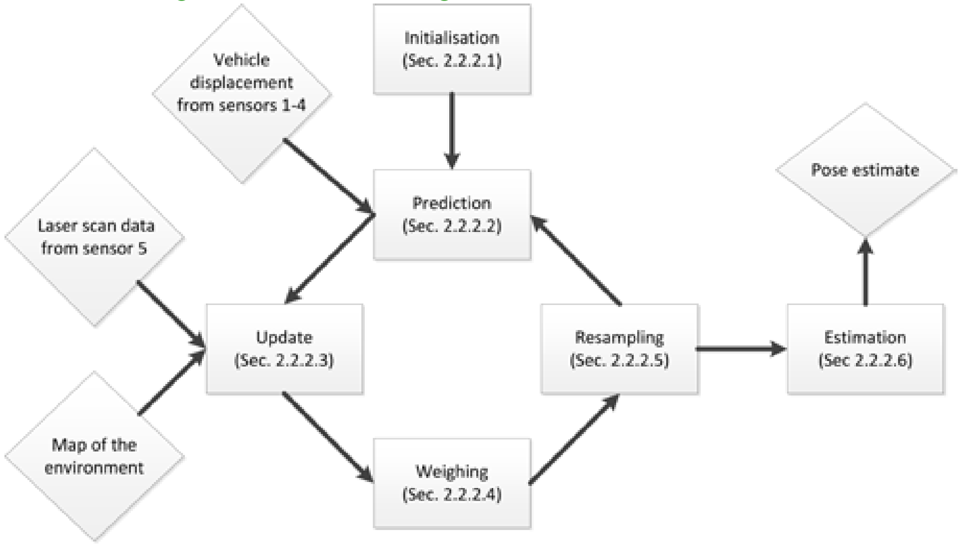
2.2.2 Location estimation algorithm

The localisation method used a particle filter, containing a distribution of N particles to represent the estimated robot pose and the variations therein. Each particle p represented a possible pose of the robot ($[x, y, \theta]$). Thus, using more particles will better represent the distribution of possible poses, but its effect on the estimation result was unclear and therefore investigated in the evaluation. Data from the sensors was off-line processed by the particle filter as visualized in Figure 2.3, with each cycle containing the steps described in Sections 2.2.2.2 through 2.2.2.6 below. All data processing steps to perform location estimation were implemented in Matlab 2012b.

2.2.2.1 Initialisation and settings

N particles were initialized by randomly assigning each particle a pose $[x \pm 0.5, y \pm 0.5, \theta \pm 0.25\ \pi]$, where x, y and θ are given by the starting pose in the ground-truth data. To evaluate whether global localisation was possible in our conditions as well, initial particle distribution can also be over a larger area and angle, with x and y distributed through the whole poultry

Figure 2.3: Process flow of the particle filter implementation. Diamonds represent data and rectangles represent process steps. Sections refer to the sections below. Sensors 1 through 5 are visualized in Figure 2.2.



house and θ in the range $[\pi, \pi]$ as the extreme case. It was expected that this works only to a certain extent, as result of repetitions in the housing interior. To avoid particle spreading when the robot is not moving, the steps for prediction, update, weighing, and resampling were only executed if the front wheel has moved more than 0.001 meter.

2.2.2.2 Prediction

A control input was applied to each particle, representing the expected robot movement δx, δy, and $\delta\theta$ estimated by the odometry data. The predicted pose $\left[\tilde{x}, \tilde{y}, \tilde{\theta}\right]$ for each particle was then generated by adding random noise (as a percentage of movement) to increase the particle spread and account for the inaccuracy of the odometry data. A filtering step was applied here to remove sensor readings with a displacement larger than 10m or a rotation larger than 2.5 radians within 100ms, thus avoiding the prediction to have impossible large displacements or rotations.

As a tricycle with limited steering angle (±45°) was used, rotation on the spot was not possible, so a simple motion model using translation and rotation was sufficient, instead of using the more complex model in Thrun, Burgard *et al*. (2005). Two types of odometry data were tested to see which one was most suitable in our conditions: 1) using the front wheel encoder (sensor 1 in Figure 2.2) and the Xsens MTi orientation data (sensor 4), and 2) using the two back wheel encoders (sensors 2 and 3). The amount of noise to be applied was varied during the evaluation. It was expected that both sets of prediction data provide similar results, and more noise would lead to less accurate results.

2.2.2.3 Update

In the update, each particle's likelihood was determined using the laser scanner data from sensor 5. This was done for each ray by matching the measured distance with the expected distance, which was derived from the particle's predicted pose $\left[\tilde{x}, \tilde{y}, \tilde{\theta}\right]$, a model of the laser scanner, and a map of the poultry house. The results of matching the individual laser rays were then combined into the particle likelihood. As a likelihood is used instead of a fixed true or false indication, this allows for implicit handling of measurement noise. In this case, measurements with noise still have a likelihood that corresponds to an object in the map, although their likelihood is lower compared to that of a noise-free measurement with an exact match to an obstacle. Two different models describing the laser scanner behaviour were implemented for this purpose: the Beam model, which is based on the behaviour of a range finder beam and described in Section 6.3 of Thrun, Burgard *et al*. (2005), and the Field model, which only uses the endpoint of a range finder beam, as described in Section 6.4 of Thrun, Burgard *et al*. (2005). Specific parameters for the Beam model and the Field model were learned from training data (which consists of raw measurement data) with a maximum likelihood estimator (given by Thrun, Burgard *et al*. (2005) in Table 6.2), thus implicitly including the effects of sensor noise and map errors. This procedure was adapted for the Field model by taking out the parameters for readings shorter than expected, as these are not included in this model.

For both models, some (dis)advantages apply given our conditions. The Beam model can be beneficial with a large number of unexpected objects (like chickens) in the surrounding, as it explicitly deals with short-range measurements. However, it is also computationally expensive due to the required raycast operation and it lacks spatial smoothness. The Field model on the other hand, is much smoother in the spatial domain, as it only considers scan endpoints by relating them to the nearest known obstacle. By pre-calculating the likelihood map based on all obstacles, it is also a fast method, but at the cost of limited handling of unexpected obstacles and treating the sensor as if it can see through walls.

Thus, both methods have their (dis)advantages, and it was unclear which one was the most suitable given our conditions, as described in Section 2.1. Furthermore, they contained several parameters that influence the likelihood determination. The initial values were learned by expectation maximisation or preliminary testing, and were expected to give the best results. However, it was unclear if and to what extend the estimation accuracy decreased if these values were changed. Using higher resolution laser data was expected to improve results, but at the cost of more calculations, so knowing the estimation accuracy using various laser data resolutions was desired. An improvement of results was also expected for including obstacles that were suspended from the housing interior, although they influenced the laser data unpredictably. These effects were all investigated in the evaluation.

2.2.2.4 Weighing

A transformation was applied to the particle likelihoods, by raising the likelihoods to a power $\alpha = 1/2$, which was indicated to work well in Liu (2001). This transformation is further discussed in Section 2.4.4. After modifying the likelihood distribution, the particle likelihoods were normalized into weights and placed in a cumulative weight vector W adding up to 1. The purpose of this step is to balance the particle likelihoods between the need for diversity (keeping different options alive) and the need for focus (eliminating samples with low likelihoods) (Liu 2001).

2.2.2.5 Resampling

Particles to be used in the next cycle were sampled according to their weights, so that heavy-weighted particles were more likely to survive and multiply, whereas light-weighted particles were more likely to disappear. During resampling, N particles were drawn with replacement from the weighted proposal distribution, to create the posterior distribution representing the pose estimate. Two methods were implemented for this step: importance sampling and low variance sampling. Importance sampling draws a random value U between 0 and 1 for each particle, and matches this to the cumulative weight vector W to obtain the index of the new particle. Low variance sampling starts with a random number V between 0 and 1/N. Then, it adds a constant offset 1/N to V for each next particle. Here too, the value of V is matched to the cumulative weight vector W to obtain the index of each new particle.

Although importance sampling is more intuitive and truly random (all samples are based on an independent random number), it is also slower. Low variance sampling is more efficient, but as its name indicates, it contains less variation, with the ultimate effect that if all particles have equal weight, the posterior distribution is the same as the proposal distribution. To see whether resampling with less variation decreases the accuracy, both methods were compared to see which one is favourable.

2.2.2.6 Estimation

The pose estimate $\left[\hat{x},\hat{y},\hat{\theta}\right]$ was determined as the mean of the sampled particles. This is straight-forward for x and y, but requires attention for the 2π wrap in θ. Thus, the sine and cosine were calculated for each value of θ, and their sums were converted back into an angle with the atan2 function.

2.2.3 Collection of experimental data

To evaluate the estimation algorithm and test the effect of various settings, data was collected in a commercial poultry house with help of PoultryBot.

2.2.3.1 Poultry house

The poultry house[1] from 'Het Anker B.V.' at Opheusden, The Netherlands, was equipped with 5 rows of the Farmer Automatic Aviary housing system (model year 2003, Farmer Automatic GmbH & Co. KG, Germany), and was longitudinally divided into six sections by mesh wire fences. For this research, only the first section of the house was used, and no hens were present at the time of the measurements, to simplify the problem. Still, the environment remained challenging and the effect of animal presence will be tested in future experiments.

A top view of the house can be found in Figure 2.4, whereas a cross-section is given in Vroegindeweij, van Willigenburg *et al.* (2014). The origin O_H was defined in the North-West corner, at the front wall of the first section, located lower-left in Figure 2.4, with the x-axis pointing right and the y-axis pointing upwards. The various types of objects present are indicated with capital letters, and further explained in the caption of Figure 2.4. Below rows A and E, the floor area was not accessible. The free height below the elevated tiers was 0.9 m for the middle row C, and 0.45 m for rows B and D. Below rows B and D, light tubes and construction bars were present, which are indicated by lines and referred by the letter L. These are special types of obstacles, hanging below the elevated tiers and are close to the laser scanner height. As result of beam divergence, they show up in the laser readings only if they are more than several meters away from the robot. This is visualized in Figure 2.5, which displays a measurement of the laser scanner on top of a map of the housing. Here, some of these Type-L obstacles are completely ignored, especially if they are close to the laser scanner. Others that are more in front of the robot and further away, do give a response, although in some cases even other objects that are below the housing interior are detected. A clear example of this is seen at

1 This house is also used/discussed in work by Vroegindeweij, Van Henten *et al.* (2013), Vroegindeweij, van Willigenburg *et al.* (2014) and Winkel, Mosquera *et al.* (2009).

coordinates [13.8, 10.6] and [18.4, 10.6] were other objects on the side of the interior row are detected. Furthermore, the clutter originating from the small poles and the difference between walls and doors (which can be open) is seen in the laser response.

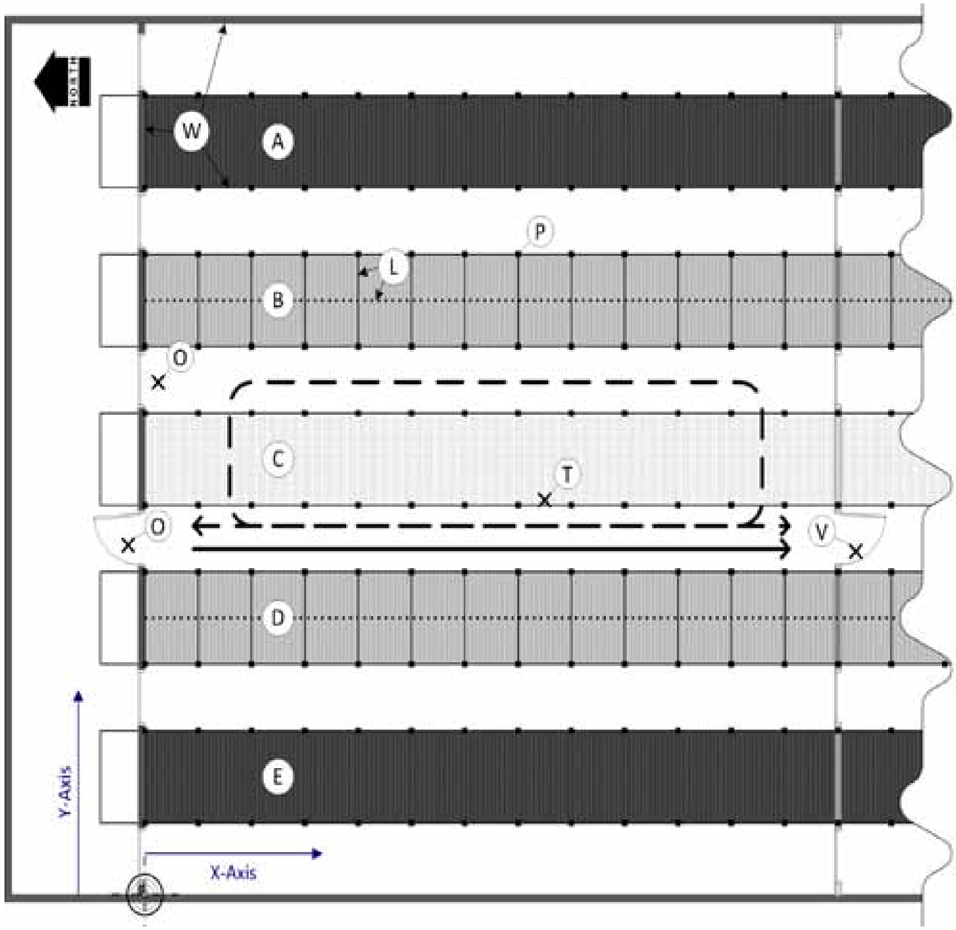


Figure 2.4: Top view of the first compartment of the poultry house. The x-axis in longitudinal direction matches with a north-south orientation, whereas the y-axis can be found along the west-east orientation. The origin of these axes is placed at the lower-left point of the first compartment. Letters A to E indicate rows with elevated tiers which provide facilities for eating, drinking, laying and resting to the animals. P are poles supporting the tiers, W are walls or wall-like obstacles, O is the human observer, T is the Total Station and V the video camera. L indicate light tubes and construction bars below rows B and D. Lines around row C indicate the paths driven by PoultryBot in the experiment.

2.2.3.2 Approach

Data was collected while manually controlling the robot to follow the desired path, which was either moving down the corridor (solid straight lines between rows C and D in Figure 2.4), driving a rectangular trajectory (dashed lines around row C), or following an advanced trajectory with multiple turns in both clockwise and counter clockwise directions (not shown). At all trajectories, forward speed was manually controlled and kept as constant as possible. For straight trajectories, steering corrections were applied only if a collision with housing interior was about to occur. For rectangular trajectories, a limited number of steering commands was issued to keep the robot on the desired track. Advanced trajectories were driven by crossing below one or more interior rows in multiple directions, such that the robot passes these rows and corridors multiple times at varying locations. In case the ground-truth estimate (explained below) was lost, the robot was halted until the ground-truth measurement regained an estimate of the robot position. All sensors were logged at 10 Hz.

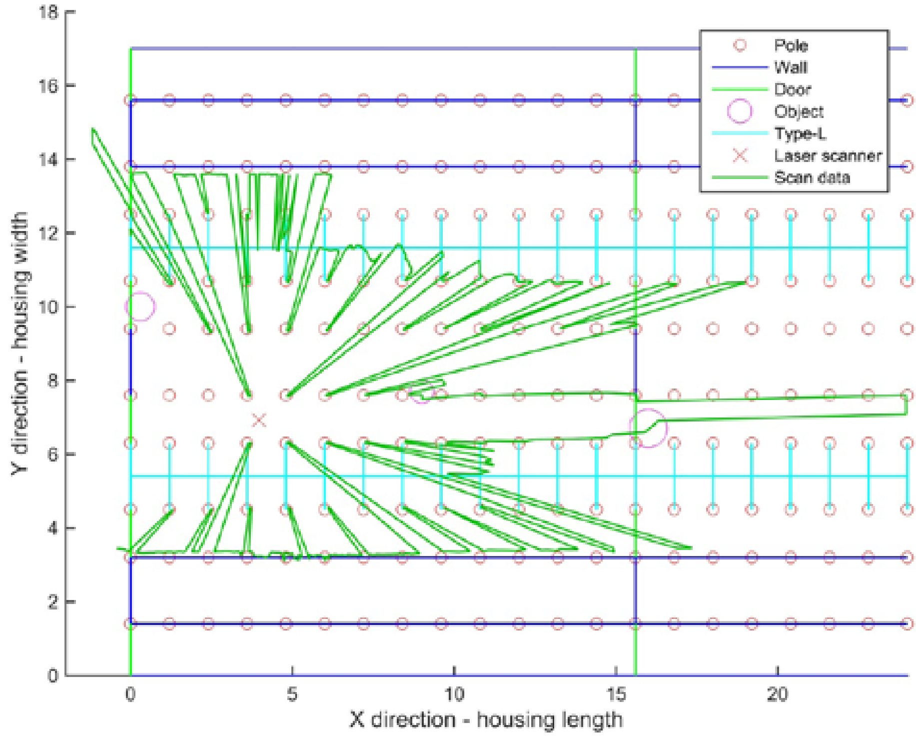


Figure 2.5: Plot of laser scanner measurement (in green) on top of the housing map. Clearly visible are the consequent responses by walls, door and poles, as well as the varying effects of Type-L obstacles.

2.2.3.3 Ground-truth measurement

Ground-truth measurements were performed with a Trimble S6 total station. When driving, an active Trimble MultiTracker prism was mounted on the robot, and the total station was set to record a position each second or every 10 cm, whichever came first. Also, a crayon was mounted below the robot centre point to physically register the path of the robot on the concrete floor. Afterwards, the driven path as drawn by the crayon was registered by walking along the line and periodically registering the location using the total station and a second prism. Furthermore, a video camera (Sony DCR-SR78) was positioned at the end of the corridor to register the behaviour of the robot and to log comments made during the experiment. Also, an observer was present to note reference information and observations made during the experiment. To make the data suitable for evaluation of the position estimator results, a rotation and translation were applied to transform the ground-truth data into the house coordinate frame.

2.2.3.4 Adding time-stamps to the ground-truth

As the ground-truth data missed time information, timestamps were added to allow quantitative evaluation of results, using the following information: 1) two recordings of the same trajectory (odometry data and ground-truth measurements); 2) one of them containing timestamps; 3) both of them contained data relating to position; 4) had exactly the same start- and endpoint; 5) with a limited amount of noise in time and position. Both recordings were matched based on the fraction of the total distance travelled, which should be the same in both recordings for any given point in time. As a result, for each matched position, a timestamp could be retrieved by a lookup operation from the recording containing timestamps. This approach scales to any situation where timestamps are missing from one of the recordings, given the required information is available (points 1 through 5 above). When all data is noise and lag free, this procedure will not decrease accuracy. However, some delay or mm-level inaccuracies might be present at both recordings, resulting in an expected maximum error of 2 cm on the matched results.

2.2.4 Evaluation of the position estimator

Based on the data collected in the experiment, various settings of the position estimation algorithm were evaluated on their performance. As processing was done off-line, real-time computation was not required. In this section the methods and settings for this evaluation are described.

2.2.4.1 Specific adaptations for our situation

Before the experimental sensor data could be used in the evaluation runs, some corrections had to be applied to the sensor data. First, as the Xsens MTi orientation measurements exhibited clear non-linear behaviour as a result of housing characteristics that influenced the compass readings, their values needed a systematic correction. Second, separate conversion factors were derived for each wheel to convert the pulse counts into displacement in meters, to correct for differences in wheel properties. Furthermore, part of the laser data was missing, and a value of -0.001m was used in those cases indicating an impossible negative sensor reading, which in turn was ignored in the position estimation. Finally, all sensor data was converted into the robot coordinate frame according to trivial coordinate transformation rules, like those given in Craig (2005).

2.2.4.2 Evaluation approach & settings

In a 3-stage evaluation procedure, different values were applied to 9 particle filter settings, to assess their influence on the applicability and accuracy of the estimator results. For each setting, an initial value and several alternatives were given based on parameter learning, preliminary experimenting or an educated choice. Various combinations of settings (called configurations) were evaluated and results were analysed with the methods described in Sections 2.2.4.3 and 2.2.4.4.

All configurations received a code referring to the choices applied. The first digit indicated the evaluation stage, the next 2 digits the chosen combination of settings and the final letter represented the use of either the Beam or the Field model in the update. Thus, configuration 205B indicates stage 2, the 5th combination of settings, and tested with the Beam model.

In each stage, trajectories with and without turns were used to include the effect of changing direction on the estimation results. Furthermore, the number of trajectories increased per stage, to enhance the (statistical) power of the evaluation as settings became established. An overview of the trajectories used per stage can be found in Table 2.1. All trajectories were used in one stage only, so in total 21 trajectories were used. After a certain configuration had been evaluated, the most promising result was used for the subsequent evaluation stages, except for the update model, where both options were always used (Beam and Field model).

Table 2.1: Distribution of available trajectory data over training and evaluation sets. All trajectories were used in one stage only, so in total 21 trajectories were used.

Trajectory / Set	Straight	Rectangular Clockwise	Rectangular Counter Clockwise	Advanced
Training	2		1	
Stage 1	1		1	
Stage 2	2	1	1	1
Stage 3	6	2	1	2

In the training stage, the parameters for the Beam and Field models were learned based on the combined data of 3 trajectories. Furthermore, this data was used to select the minimal distance type-L obstacles (like light tubes underneath the housing interior) had to be away from the robot before they were included in the raycast.

In the first evaluation stage, the settings for which a limited effect was expected or which value had to be determined in an early stage were assessed on a small dataset (see Table 2.1). The Beam and Field model were both tested, to find the most suitable one. The settings evaluated in this stage were setting 1: the resampling method, setting 2: the sensors used in the prediction step, setting 3: the laser scanner resolution, and setting 8: the inclusion of type-L obstacles in the Beam model. Setting 8 was evaluated for the Beam only, as choosing whether type-L obstacles have to be included is less relevant for the Field model. The Field model searches the closest obstacle in the map. Thus, including type-L obstacles by default results in their use when relevant, while they were ignored otherwise.

The exact configurations used are given in Table 2.2 (page 44). Due to the stochastic nature of the algorithm, each configuration was repeated 30 times per trajectory to investigate the number of repetitions required to allow statistical testing of the results. Based on the data collected in stage 1, the required sample size for doing statistical inference could be calculated (Ott and Longnecker 2001). As result, it was determined that 30 repetitions were required for the Beam model, and 15 for the Field model to have a reasonable accuracy of the estimated mean.

In the second stage, 5 trajectories (see Table 2.1) were used to evaluate 5 settings for which a larger influence was expected, again on both the Beam and Field model. These were setting 4: the number of particles used in the estimation, setting 5: the amount of noise added in the prediction step, setting 6: the update parameters, setting 7: the grid size of the Field model, and setting 8: the inclusion of type-L obstacles in the Beam model. The configurations used in this stage are given in Table 2.3 (page 45).

In the third stage, the final evaluation of both the Beam and Field update model were done based on the best-performing settings and 10 trajectories (see Table 2.1). The 11th (advanced) trajectory missed over 25% of the laser data, and was used as stress test for the estimator performance with missing data. Furthermore, the performance for setting 9: Global Localisation, was assessed. Detailed information on the configurations used is given in Table 2.4 (page 46).

2.2.4.3 Performance measure

To evaluate the results of the estimation procedure, the Euclidian distance was used. It is considered the most accurate measure indicating how far the estimate deviates from the real position at a given point in time. However, it can only be calculated if a time-stamped ground-truth measurement is available which matches the estimate. Thus, the Euclidian distance was calculated only for those estimates where a time-matched ground-truth existed. Resulting data was grouped per configuration to calculate the distribution over all replicates and locations within this configuration, and mean and median values were determined. Furthermore, the 95 percentile was calculated, to give an upper bound on the accuracy that was achieved for 95% of the time. This value also allows comparison against the required accuracy for this problem, which was set to be less than 1m for 95% of the time, and should preferably be less than 0.1m.

2.2.4.4 Statistical inference

Next, statistical testing was applied in GenStat 16 for the data of each evaluation stage, to determine whether the various configurations result in different mean accuracies. First, an initial ANOVA was applied on the Euclidian distance, with configurations as treatment. If the means of the configurations proved to be different, and clear outliers (with a mean more than twice the grand mean) could be observed, this procedure was repeated while omitting the configurations which caused these outliers. Next, if difference of means was proven at 95% confidence, a Tukey HSD test was applied to pairwise compare the means of the configurations, with a significance level of 0.05.

However, it cannot be guaranteed that the underlying assumptions for this procedure (independent identically distributed data) really hold, as the positions along a trajectory (and thus also the resulting estimates) relate to each other. Furthermore, the distribution of the results might vary between configurations, and is probably not normally distributed. Therefore, a relatively strict test was chosen for pairwise comparison, which was considered the best available at varying sample sizes and to produce confidence intervals of the results. Also, using independent random values in the estimation, a fraction of the estimates in the evaluation and the large number of data points, reduce the effect of violating these assumptions. Although caution should still be paid when interpreting the results of statistical inference, applying these methods gives deeper insight and was regarded valuable in this context. Finally, if a stable solution is found, the distribution of the Euclidian distance remains similar if trajectory lengths go to infinity, or widens if serious drift in the estimate is observed.

Table 2.2: Overview of the configurations used in evaluation stage 1. Bold numbers in brackets indicate the code of this configuration, where 100 was the default setting for this stage and the others were alternatives. All configurations were applied on both the Beam and Field model, and repeated 30 times.

Setting	Default value	Alternative values		
1) Resampling method	importance sampling **(100)**	low variance sampling **(101)**		
2) Sensors used in the prediction step	front wheel and Xsens MTi (sensors 1 and 4) **(100)**	rear wheel (sensors 2 and 3) **(102)**		
3) Laser scanner resolution	each 20th ray **(100)**	each ray **(103)**	each 5th ray **(104)**	each 10th ray **(105)**
4) Number of particles used in the estimation	300 **(100)**			
5) Amount of noise added in the prediction step	20% on displacement and 50% on rotation **(100)**			
6) Parameter values used for the update step (Table 2,5)	learned parameter values **(100)**			
7) Grid size of the Field model (Beam model n/a)	0.1m **(100)**			
8) Inclusion of type-L obstacles (Field model n/a)	no **(100)**	yes, using each 5th laser ray, for distances greater than 5.5m **(106)**	yes, using each 20th laser ray, for distances greater than 5.5m **(107)**	
9) Global localisation	no **(100)**			

Table 2.3: Overview of the configurations used in evaluation stage 2. Bold numbers in brackets indicate the code of this configuration, where 200 was the default setting for this stage and the others were alternatives. All configurations were repeated at least 30 times for the Beam model and at least 15 times for the Field model.

Setting	Default value	Alternative values		
1) Resampling method	importance sampling **(200)**			
2) Sensors used in the prediction step	front wheel and Xsens MTi (sensors 1 and 4) **(200)**			
3) Laser scanner resolution	each 5th ray for the Beam model; each 1st ray for the Field model **(200)**			
4) Number of particles used in the estimation	300 **(200)**	100 **(201)**	1000 **(202)**	
5) Amount of noise added in the prediction step	20% on displace-ment and 50% on rotation **(200)**	10% on displace-ment and 25% on rotation **(203)**	40% on displace-ment and 100% on rotation **(204)**	
6) Parameter values used for the update step (Table 2.5)	learned parameter values **(200)**	manual variation with wider distribu-tion of hits **(205)**	manual variation with narrower distribution of hits **(206)**	
7) Grid size of the Field model (Beam model n/a)	0.1m **(200)**	0.01m **(207)**	0.01m and update parameters from 205 above **(208)**	0.01m and update parameters from 206 above **(209)**
8) Inclusion of type-L obstacles (Field model n/a)	no **(200)**	yes, for distances greater than 4.8m **(210)**	yes, for distances greater than 4.8m and update parameters from 205 above **(211)**	yes, for distances greater than 4.8m and update parameters from 206 above **(212)**
		yes, included for distances greater than 6.5m **(213)**	yes, for distances greater than 6.5m and update parameters from 205 above **(214)**	yes, for distances greater than 6.5m and update parameters from 206 above **(215)**
9) Global localisation	no **(200)**			

Table 2.4: Overview of the configurations used in evaluation stage 3. Bold numbers in brackets indicate the code of this configuration, where 300 was the default setting for this stage and the others were alternatives. All configurations were repeated at least 30 times for the Beam model and at least 15 times for the Field model.

Setting	Default value	Alternative values	
1) Resampling method	importance sampling **(300)**		
2) Sensors used in the prediction step	front wheel and Xsens MTi (sensors 1 and 4) **(300)**		
3) Laser scanner resolution	each 5th ray for the Beam model; each 1st ray for the Field model **(300)**		
4) Number of particles used in the estimation	1000 for the Beam model; 300 for the Field model **(300)**		
5) Amount of noise added in the prediction step	20% on displacement and 50% on rotation **(300)**		
6) Parameter values used for the update step (Table 2.5)	narrower hit distribution for the Beam model; learned parameter values for the Field mode **(300)**		
7) Grid size of the Field model (Beam model n/a)	0.1m **(300)**		
8) Inclusion of type-L obstacles (Field model n/a)	no **(300)**		
9) Global localisation	no **(300)**	yes, in area of 6 by 4 meter around the robot and θ within 0.5 π around the starting pose **(301)**	yes, over the full compart-ment and θ in range $\pm \pi$ **(302)**

Table 2.5: Values of the parameters used in the update models, as explained in Chapter 6 of Thrun, Burgard et al. (2005). The initial values were learned on the training data (containing raw measurement data), while the values for wider and narrow hit distribution were at a manually selected offset from the learned values, to evaluate how a wider or narrower distribution of hits around an obstacle changes the results. W-values indicate weight factors for various probabilities, while σ and λ are parameters of the probability distributions.

Beam model		w_{hit}	w_{short}	w_{random}	w_{max}	σ_{hit}	λ_{short}
	Learned	0.478	0.247	0.275	0.000	0.190	0.258
205B	Wider	0.6	0.2	0.2	0	0.4	0.16
206B	Narrower	0.35	0.3	0.35	0	0.1	0.36
Field model		w_{hit}	w_{short}	w_{random}	w_{max}	σ_{hit}	λ_{short}
	Learned	0.900	n/a	0.101	0.000	0.206	n/a
205F	Wider	0.95	n/a	0.05	0	0.4	n/a
206F	Narrower	0.85	n/a	0.15	0	0.1	n/a

2.3 Results and Discussion

This section presents the results of the position estimator, and discusses them per evaluation stage, both in a qualitative and a quantitative manner.

2.3.1 Evaluation stage 1

In stage 1, settings for which a minor influence on the results was expected or which had to be determined in an early stage, were applied on a small dataset consisting of 1 straight and 1 rectangular trajectory. Evaluated here were the resampling methods (setting 1), the sensors used in the prediction step (setting 2), the laser scanner resolution (setting 3), and the inclusion of type-L obstacles in the Beam model (setting 8). See Table 2.2 for details.

2.3.1.1 Qualitative results

When looking at the estimated paths in stage 1, it seemed that the Field model showed very consistent results indicating good robustness, whereas the Beam model had more variation, with one configuration where all estimates lose track of the path. For some configurations, part of the replicates showed reasonable performance, like configuration 106B in the left part of Figure 2.6. Another part showed difficulty in tracking or even gets lost, commonly in the 2nd half or at the end of the trajectory.

Also, in several cases the particle filter reduced deviation from the ground-truth, indicating its capability of correcting errors. A clear example of such results can be observed in the right half of Figure 2.6 with configuration 105F, where an offset of 1m is completely corrected after two turns (top), which is confirmed by the evaluation results (bottom). Furthermore, it was observed that turns sometimes resulted in a deterioration of the result, but in most cases in an improvement of the accuracy. From this, it is assumed that additional information and uniqueness brought into the model by the turns is in general beneficial to the results. In general, the estimate was close to the ground-truth, and no clear offset in a particular direction could be observed.

2.3.1.2 Quantitative results

General picture

For each evaluation run in stage 1, the Euclidian distance was calculated as performance measure, and the results are summarized in Figure 2.7. Already in this stage, most configurations comply with the requirement that the Euclidian distance should be less than 1m for at least 95% of the time. This is shown by the horizontal blue bars (top ones), that are below the blue dashed line at 1m. Only the best cases, however, approximate the desired value of 0.1m (lower dashed line). For several configurations, the mean is far from the median, indicating that a large number of outliers are present here. Looking slightly further, it is observed that the Field model (all mean values below 0.21m) clearly outperformed the Beam model (all mean values at least 0.3m). Results for configuration 103B, and to a lesser extent also configurations 102B and 105B, were clearly affected by several cases where the estimator failed or had difficulty to track the path.

Evaluating the various options for the settings

Changing the resampling method (setting 1) to low variance sampling (configurations 100 and 101 in Table 2.2) showed a very small but not significant improvement, whereas changing the sensors used for prediction (setting 2) to the rear wheels clearly affected the results. Here, several replicates provided good estimates, while others performed worse. For the Beam model, 4 occasions gave a lost robot, mainly at the straight trajectory. When examining the estimated paths more closely, especially the Beam model seems not able to fully correct for errors in the prediction stage, resulting in drift of the estimate. Considering the laser scanner resolution in the likelihood determination (setting 3), a trend was observed, especially for the Field model, in that more data provided better results (see configurations 103 to 105 in Figure 2.7). Configuration 103B is the exception here, as in this case individual observations are too dependent. Combined with

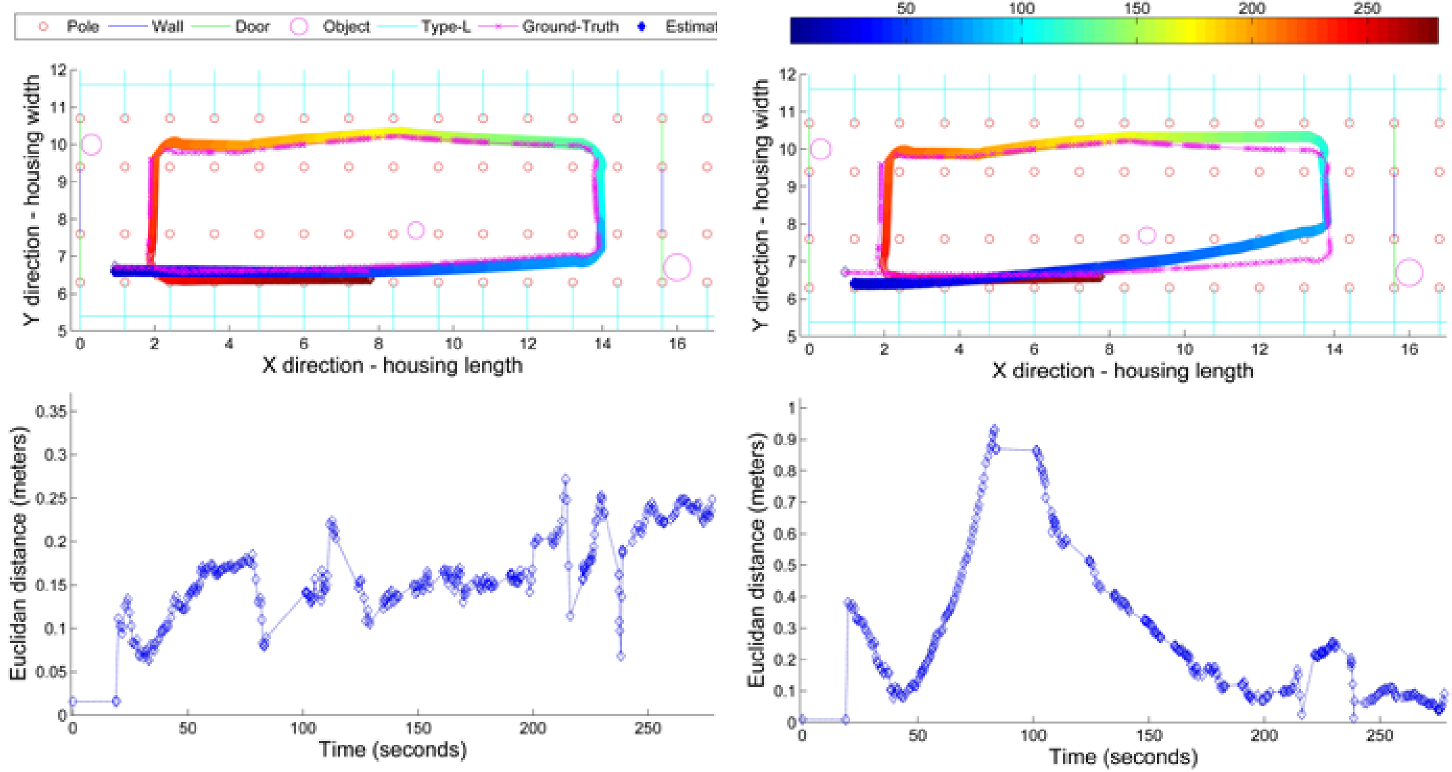


Figure 2.6: Visual representation results of several estimation runs in stage 1, with the estimation result on top and the evaluation resulton in the bottom. Coloured bar indicates time in seconds. Left: configuration 106B with very nice tracking of the trajectory. Right: configuration 105F showing a nice correction of offset in the estimation, and finally resulting in a good tracking of the trajectory.

a small rotational offset this might lead to large errors in the update. Also, results for 105B (using each 10th ray) are somewhat surprising, as it had larger errors than 100B (using each 20th ray). This might be explained by a difficulty to detect turns correctly and thus having a number of estimates lost. When considering the inclusion of type-L obstacles (setting 8), the differences in performance are not significant nor can clear improvement be seen, making it difficult to assess the effect. At each 5th ray (106B) it seems that results improved, while at each 20th ray (107B) they got worse. When observing the paths, in both cases replicates are found where the estimator gets lost, thus providing a possible explanation for these results.

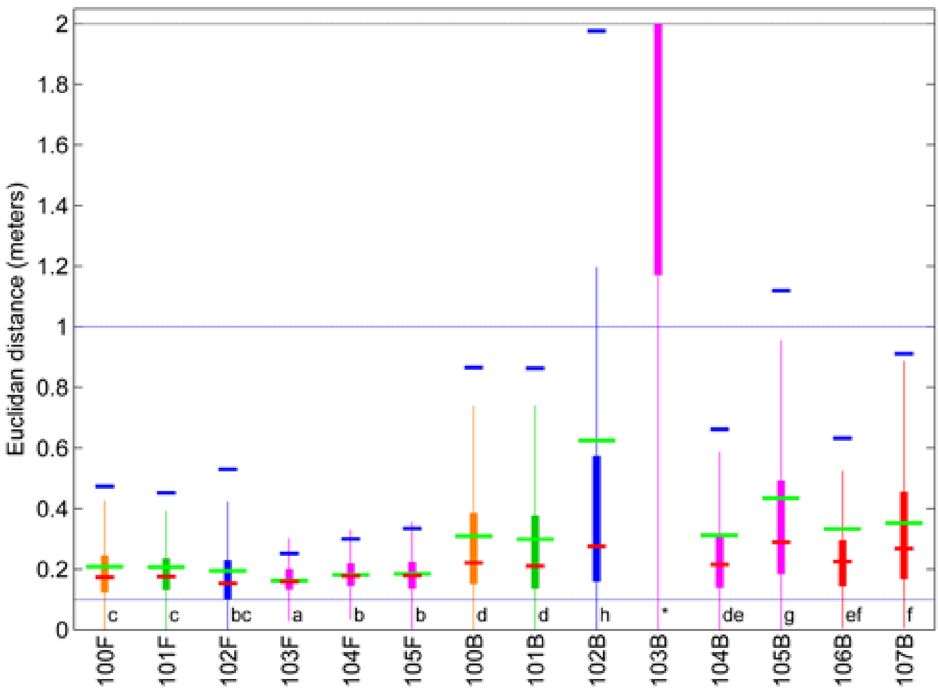


Figure 2.7: Boxplot of results of stage 1, showing the distribution of Euclidian distance per configuration, over all data available for each configuration. Also indicated are the mean (green bars), median (red bars), and 95 percentiles for each configuration. Blue horizontal lines represent the required and desired accuracy for 95% of the time. Same letters inside the graph indicate no statistical difference between configurations at p=0.05. Indices refer to the configurations, which are explained in Table 2. Configuration 100 was the default, and the others contained variations of the settings.

Choices for the next stage

As low variance sampling was considered to have some practical advantages (like more uniform resampling) over importance sampling, and no significant difference was found, it was selected to be used in the next stage. The selection of the front wheel and Xsens MTi data for prediction was based on the more constant results observed. Considering the number of laser rays used for the likelihood determination, the best-performing ones were selected, being each ray for the Field model and each 5th ray for the Beam model. The effects of using type-L obstacles (106B & 107B) were unclear, so they were not included by default in the runs of stage 2. Instead, the effect of changing the distance from which they were included was evaluated there as well.

2.3.2 Evaluation stage 2

In this stage, settings for which a larger influence was expected were applied on a dataset consisting of 2 straight, 2 rectangular, and 1 advanced trajectory. Evaluated were the number of particles used in the estimation (setting 4), the amount of noise added in the prediction step (setting 5), the parameter values used for the update step (setting 6), the grid size of the Field model (setting 7) and the inclusion of type-L obstacles at various distances (setting 8). See Table 2.3 for details.

2.3.2.1 Qualitative results

Most configurations provided good results, where in general the Field model was better than the Beam model, showing a nice match and good robustness under almost all configurations, whereas the Beam model seems more prone to changes and errors. The quality and robustness of the Field model is seen, for example, when changing the number of particles, where the Beam model needed 1000 particles (configuration 202B) to approach the results of the Field model at 100 particles (configuration 201F). The Beam model being more error-prone becomes clear at the path in Figure 2. 8D (configuration 201B), where a strong deviation is observed before the first turn, caused by deviating compass data. Using the same data in the Field model resulted in far less deviation of the real trajectory (not shown), indicating the Beam model being less capable of correcting prediction errors. As deviating compass data occurred more often, especially in longer straight parts in x-direction of the house, this seems a frequent cause of deviations from the real trajectory. Examples are shown in the top-left part of Figure 2. 8D and the top-middle part of Figure 2. 8B (configuration 205B). Thus, in future work a better calibrated compass or more accurate prediction data from fusing multiple sources is desired.

In general, on simple straight trajectories the estimation results were good and no large differences were observed, except for some wrong initial orientations. As trajectory complexity increases by including turns, shorter segments and a larger total length, differences between configurations became clearer. Here, turning often allowed the estimator either to correct errors or caused it to get lost. Thus, these paths are most interesting for both the evaluation (to discriminate between configurations) and the method itself (to discriminate between particle likelihoods). Clear examples of this are shown in Figure 2. 8A (207F) with accurate tracking and in Figure 2. 8B where an initial tracking failure is corrected nicely after 100 seconds. Thus, if configurations are robust, estimation quality remains constant with increasing complexity of trajectories, whereas less robust configurations show deterioration of the results (Figure 2. 8C), although correction remains possible (Figure 2. 8B). Furthermore, the Field model gave more constant results for a given configuration and trajectory. For both the Beam and Field model, clear differences in performance exist between trajectories.

Offsets between estimate and ground-truth generally occurred at path segments in the x-direction of the house, showing an error in the y-direction. As result of housing characteristics, dimensions in x-direction were very strict. In y-direction more variation might be present, as for example the distance between two adjacent rows was not strictly defined. Also, interior elements acting as wall (rows A and E), were not exactly straight in vertical direction. This might have caused a small mismatch in y-coordinate between reality and map, thus explaining some of the offset of the estimate. Under similar conditions, type-L obstacles were not always present in laser readings, but showed up only now and then. This might be caused by their location close to, but above, the laser scanner height. Small variations therein, combined with a non-level robot and a diverging laser beam, made it hard to predict their presence reliably and thus include them in the Beam model with clear benefits.

2.3.2.2 Quantitative results

General picture

At first sight, improvements in results between stage 1 (Figure 2.7) and stage 2 (Figure 2.9) seem small, although the latter contains more variation in trajectories. Therefore, mean Euclidian distance was also calculated per combination of input trajectory and configuration (not shown), to enable analysis in more detail. Higher mean errors per configuration were generally caused by failure of properly tracking rectangular and advanced trajectories, while low values indicate good performance also at these trajectories. About half of the time, results on the advanced trajectory slightly

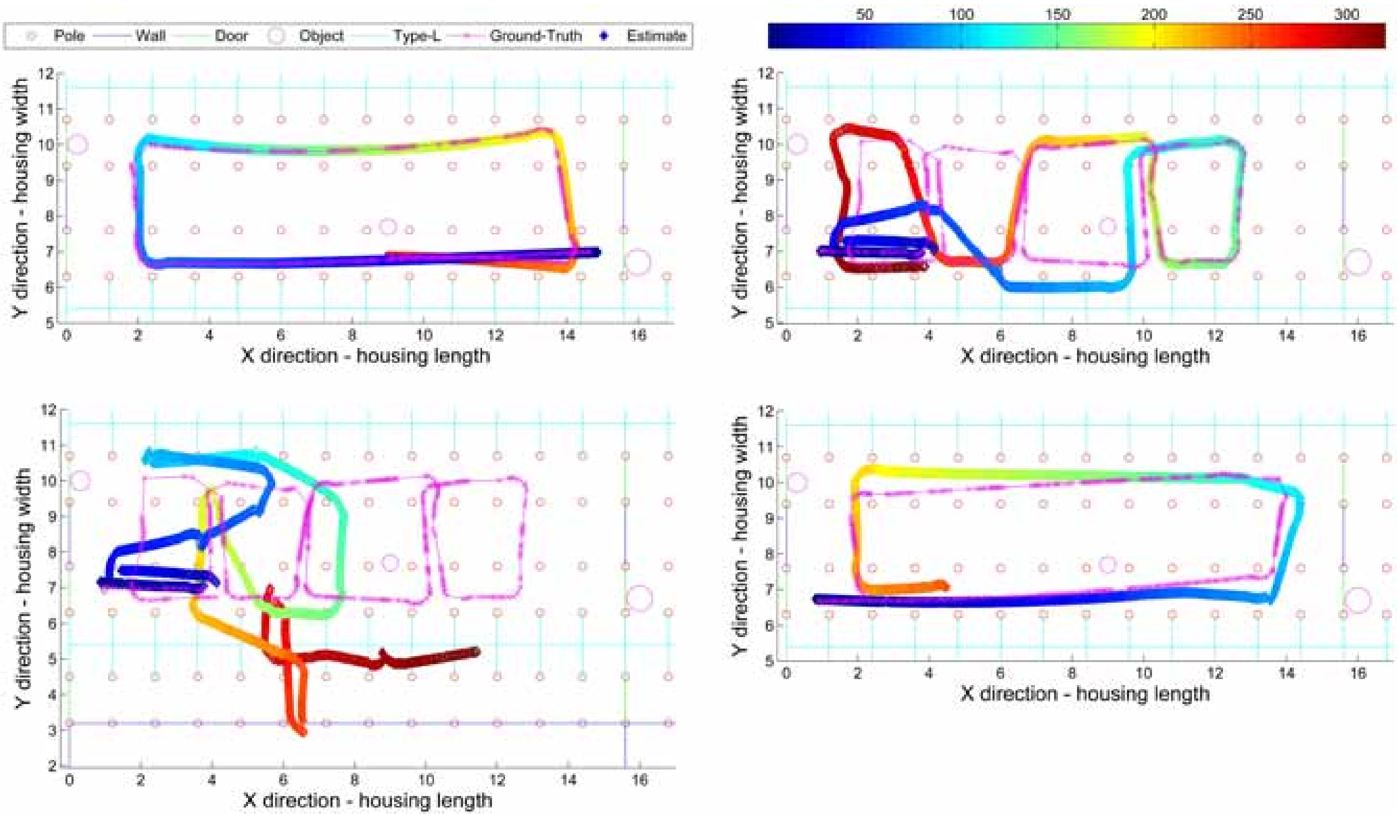


Figure 2. 8: (A-D, left-right, top-down) Visual representation of some estimation results in stage 2. Coloured bar indicates time in seconds. A) Configuration 207F showing a good estimation on a clockwise rectangular path. B) Configuration 205B showing a block pattern trajectory where the estimate quickly drifts off, captures the correct path around halfway, and keeps tracking until the end. C) Configuration 205B with a case where the estimate gets lost completely. D) Configuration 201B showing the deviations as results of compass error at the end of the straight parts in the trajectory.

outperformed those on the rectangular trajectories, like for configurations 202B, 204B and 204F. Possibly, the shorter path segments and more turns in the advanced trajectory allowed the estimator to correct more easily. The mean Euclidian distance per configuration was below 0.25m for the Field model, while the Beam model had values up to 0.5m. Estimates losing track contributed to this accuracy loss, with several Beam configurations having 10 to 30 lost estimates, versus the Field model having at most 2 lost estimates (except configuration 203F). Furthermore, this mainly happened at rectangular and advanced trajectories, containing more data points and thus having greater influence on the mean value per configuration.

Evaluating the various options for the settings

Evaluating the number of particles used (setting 4, configurations 200 through 202 in Table 2.3), showed the expected response with more particles improving the results, and clear differences between Beam and Field model (see Figure 2.9). The Field model gave reasonable results with 100 particles (configuration 201F). Using 1000 particles (202F) had no clear advantage over 300 particles (200F). The Beam model failed more often at 100 particles (201B). Using 1000 particles (202B) had a clear advantage over 300 particles (200B). Changing the amount of noise in the prediction step (setting 5), showed that less noise (configurations 203B & 203F) produced large errors in the estimation, with many replicates being lost. More noise slightly improved the results for both the Field model (204F) and the Beam model (204B), although the mean of the latter was affected by outliers from rectangular and advanced trajectories. This indicates that a certain amount of noise was required to capture the variation present in the prediction data, especially for rotation. However, too much noise made the estimate more sensitive to the repetitive nature of the environment. Furthermore, requiring these amounts of noise (20% of the displacement) raises the question whether the filtering in the update step is not too strong and a higher value of α should be used.

Deviating the parameter values for the update (setting 6) from those learned by expectation maximisation reduced accuracy as expected, except for configuration 206B and simple trajectories. Improvements observed in configuration 206B with lower values for σ_{hit} and w_{hit} (less likely to hit obstacles) might be explained from the larger share for random and short range readings, giving more room to account for unexplained data. When changing grid size of the Field model (setting 7), results did not differ significantly for the learned parameter values. With other values of the update parameters (configurations 208F & 209F) an improvement was observed with respect to the results of configuration 205F and 206F, which have a larger grid size. This might be attributed to a more accurate model representation, especially for the many small obstacles (poles) present. Including type-L obstacles at other distances (setting 8) seemed to improve the results with learned update parameters (210B & 213B), although effects were less evident at advanced trajectories. When also deviating the update parameters, results became worse, where especially the wider update option (211B & 214B) gave clear problems.

Choices for the next stage

Most changes in stage 2 did not gave a clear improvement, except for the Beam model where more particles (202B) and a narrower hit distribution in the update (206B) seemed to have an advantage. As result, only these settings were changed, whereas the others were kept the same. Including

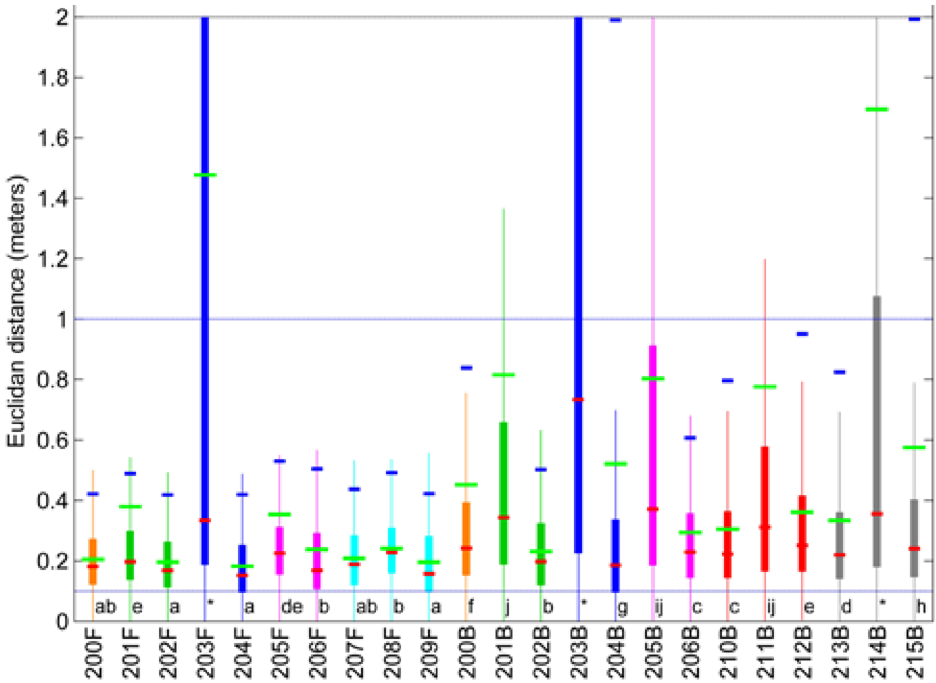


Figure 2.9: Boxplot of results of stage 2, showing the distribution of Euclidian distance per configurations, over all data available for each configuration. Figure is clipped at 2m. Also indicated are the mean (green bars), median (red bars), and 95 percentiles for each configuration. Blue horizontal lines represent the required and desired accuracy for 95% of the time. Same letters inside the graph indicate no statistical difference between configurations at p=0.05. Indices refer to the configurations, which are explained in Table 3. Configuration 200 was the default, and the others contained variations of the settings.

type-L objects tended to improve the results with initial update parameters (200B vs 210B & 214B), but not for adapted update parameters. As the latter will be used, type-L obstacles were not included in stage 3. More details on the settings used in stage 3 are given in However, it cannot be guaranteed that the underlying assumptions for this procedure (independent identically distributed data) really hold, as the positions along a trajectory (and thus also the resulting estimates) relate to each other. Furthermore, the distribution of the results might vary between configurations, and is probably not normally distributed. Therefore, a relatively strict test was chosen for pairwise comparison, which was considered the best available at varying sample sizes and to produce confidence intervals of the results. Also, using independent random values in the estimation, a fraction of the estimates in the evaluation and the large number of data points, reduce the effect of violating these assumptions. Although caution should still be paid when interpreting the results of statistical inference, applying these methods gives deeper insight and was regarded valuable in this context. Finally, if a stable solution is found, the distribution of the Euclidian distance remains similar if trajectory lengths go to infinity, or widens if serious drift in the estimate is observed..

2.3.3 Evaluation stage 3

In stage 3, the final selection of settings was evaluated on a large dataset (11 trajectories) to determine the final accuracy of both the Beam and Field model. A stress test was added to evaluate the handling of missing data. Also, the capabilities for global localisation were assessed by widening the initial particle distribution (setting 9). Details on the configurations used are given in However, it cannot be guaranteed that the underlying assumptions for this procedure (independent identically distributed data) really hold, as the positions along a trajectory (and thus also the resulting estimates) relate to each other. Furthermore, the distribution of the results might vary between configurations, and is probably not normally distributed. Therefore, a relatively strict test was chosen for pairwise comparison, which was considered the best available at varying sample sizes and to produce confidence intervals of the results. Also, using independent random values in the estimation, a fraction of the estimates in the evaluation and the large number of data points, reduce the effect of violating these assumptions. Although caution should still be paid when interpreting the results of statistical inference, applying these methods gives deeper insight and was regarded valuable in this context. Finally, if a stable solution is found, the distribution of the Euclidian distance remains similar if trajectory lengths go to infinity, or widens if serious drift in the estimate is observed.

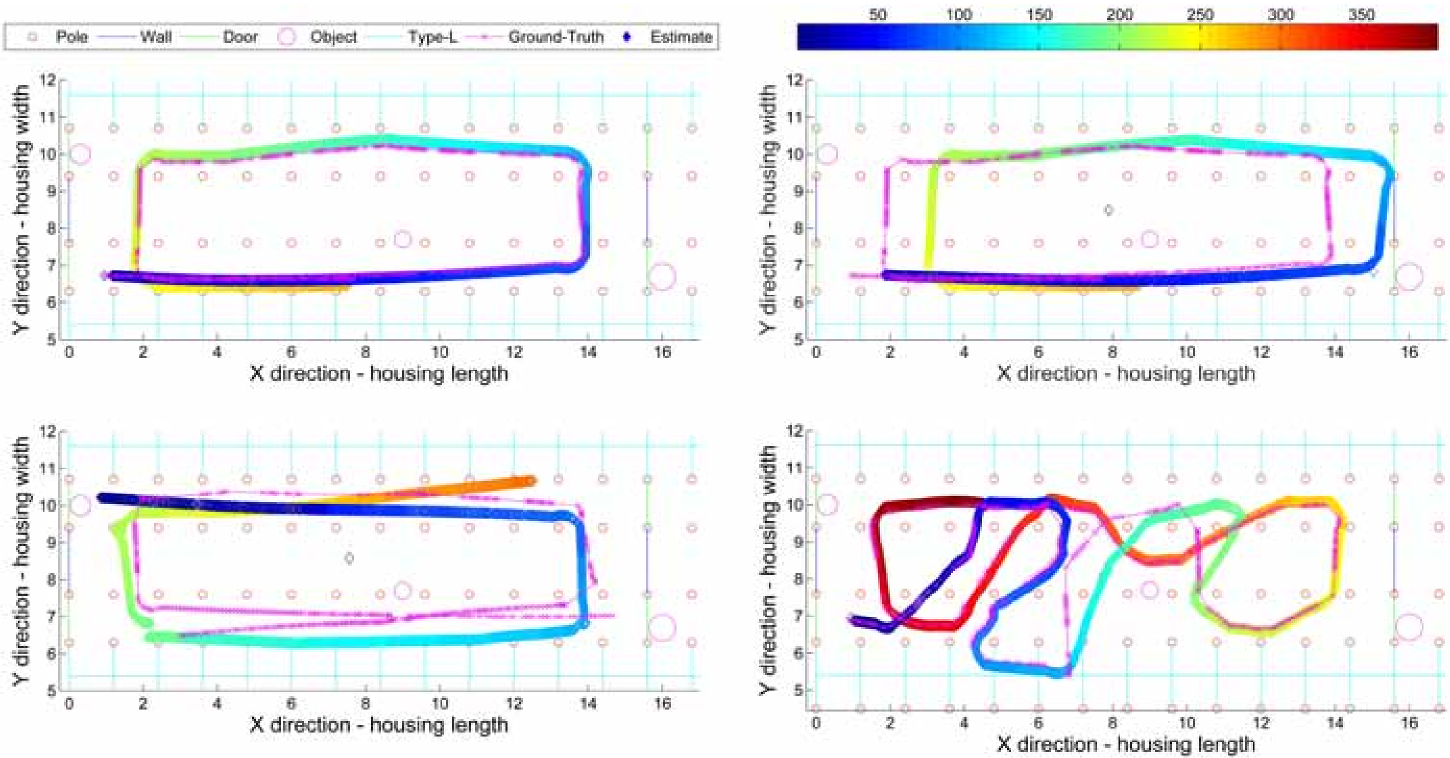


Figure 2.10: (A-D, left-right, top-down) Visual representation of some of the estimation results in stage 3. Coloured bar indicates time in seconds. A) Neat tracking of the path, with small sideward offset at part of the path (configuration 300B). B) Global localisation, with nice capturing of the path, although shifted from the real path (configuration 302B). C) Global localisation resulting in a mirrored path (configuration 302B). D) Results of stress test with more than 25% of laser data missing (configuration 300F).

2.3.3.1 Qualitative results

In general, the estimation algorithm produced good results by nicely following the ground-truth on short straight and longer rectangular and advanced trajectories. Small errors in the start pose were in general nicely captured and corrected, as well as deviations that occurred along the path, as shown in Figure 2.10A. For the stress test, with part of the laser data missing, the correct path could be captured in most cases, although larger deviations were observed, especially at locations where data was missing (Figure 2.10D, showing a good result). When performing global localisation, clear effects from the repetitive environment were seen. If the initial spread was limited (configuration 301B and 301F), the correct starting point was found or errors were corrected most of time. If particles were spread over the whole compartment (302B & 302F), the repetitive nature of the area caused problems. As result, sometimes the correct starting point and

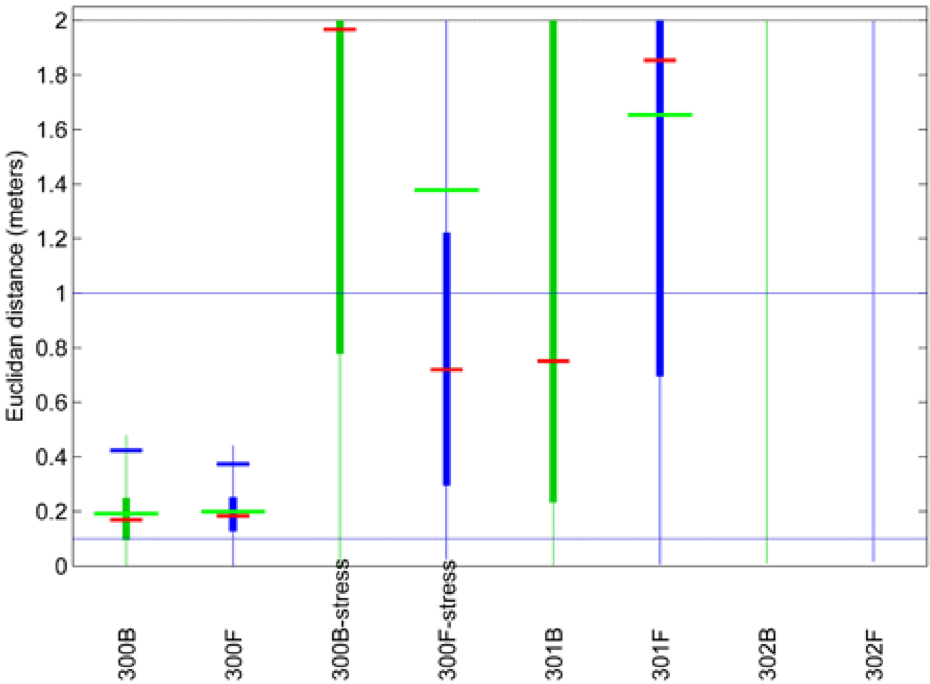


Figure 2.11: Boxplot of results of stage 3, showing the distribution of Euclidian distance per configuration. From left to right, for the Beam model (green) and the Field model (blue) the evaluation on a large dataset, the stress-test with missing data, and global localisation in a small and a large area. Indexes refer to the configurations, which are explained in table 4. Figure is clipped at 2m. Also indicated are the mean (green bars), median (red bars), and 95 percentiles (blue bars). Blue horizontal lines represent the required and desired accuracy for 95% of the time.

path structure were found, possibly in a mirrored version (like Figure 2.10C), but in most cases, the estimate failed to find or track the path. Also, the correct path structure was captured frequently, but then from a wrong starting pose.

Calculation times were about 15 to 20 seconds per frame for configuration 300B, and on average 2.5 seconds per frame for configuration 300F. Thus, for future real-time implementation a speed improvement with a factor 10 to 100 is desired. As a single-core Matlab-implementation was used, this seems possible with help of a more low-level implementation and using multi-core processing.

2.3.3.2 Quantitative results

From the results for configurations 300B and 300F in Figure 2.11, it shows that the mean Euclidian distance over 10 input trajectories was equal for both models, being 0.192m for the Beam model and 0.199m for the Field model. In the distribution of the data and the 95 percentile (0.424m and 0.374m for Beam and Field respectively), more variation can be observed. Here, the Field model had a more consistent but a slightly less accurate mean result compared to the Beam model. When examining the data in more detail (not shown), straight trajectories gave even better results (means between 0.1 and 0.15m), while the longer rectangular and advanced trajectories had means around 0.2m.

For the stress test, the Field model gave better results, but errors clearly exceed the requirement, with mean values of 2.99m for 300B-stress and 1.38m for 300F-stress, and 95% levels of 11.29m and 4.74m respectively. In part of the estimates, the error remained within several meters, especially for the Field model. In another part, the estimates got lost, leading to an unbounded error. Using less laser data in the Beam model (not shown) also seems to improve the results, probably because missing data has less impact in this case.

When performing global localisation, numerical results show a large spread. Thus, exact discussion of values is less relevant here, but under some conditions reasonable results (maximum errors within 1 or 2 meter) can be achieved.

2.4 General Discussion

2.4.1 Ground-truth

In this work, the problem of localizing a mobile robot in a commercial poultry house was addressed. A total station provided ground-truth of the robot trajectory, providing theoretical accuracies up to mm-level, even when moving (Kirschner and Stempfhuber 2008, Stempfhuber 2009). In our work, vehicle motion, the number of obstacles present and applied transformation of coordinate frames might affect this, resulting in an accuracy of 2 cm. Adding time stamps to ground-truth was based on matching the closest available point, which, in combination with small inaccuracies in time and space, might affect ground-truth accuracy. As result, a maximum error of 0.05m in ground truth is expected, which remains below the average estimation accuracy. Furthermore, having time-referenced data was considered more valuable than small improvements in ground-truth accuracy.

2.4.2 Prediction

In the final application, flooring conditions are expected to have a negative influence on the quality of the odometry and IMU data (Qi, Brookshaw *et al*. 2013), which were used as input for the prediction stage. Thus, a priori filtering on this data might be desirable, to have the estimated displacement better match the real displacement. Initial tests with a Kalman filter on combining data from multiple sensors (control input, front wheel, rear wheels and Xsens MTi) indicate that the error in the prediction data could be reduced by more than 50%. However, currently 20% noise was added in the prediction stage to have sufficient distribution of the particles, so this might have limited use.

2.4.3 Update

Under current conditions, the reliability of laser data was relatively high. With presence of animals however, about 50 to 75% of the laser readings might reflect animals' presence instead of housing objects. Not all readings represent animals, as the laser scanner is mounted such that only animal heads and tails are in view, and not their full body. Thus, identifying more likely particles can become difficult. Various approaches can be used to overcome this. Levinson, Askeland *et al*. (2011) and Burgard, Cremers *et al*. (1998) mention filtering laser data, to discriminate between relevant and irrelevant data to extract only readings which are likely to correspond to housing interior. This increases the Signal to Noise Ratio and also reduces computational load in the update step. Kootstra and de Boer (2009) indicate and evaluate a number of solutions to deal with low numbers of distinct features. Furthermore, information from other sources like cameras can be added or combined in the determination of particle likelihood.

2.4.4 Weighing and resampling

Before resampling, the particle distribution was corrected by raising the weights to the power α, set to ½. This modification was evaluated for other values of α as well, using the effective sample size (ESS) as given by (Doucet and Johansen 2009). The ESS is a measure of the likelihood distribution, with a higher ESS representing a more useful distribution.

As there was considerable variation within a trajectory, different values of α were desired for different parts of a trajectory. In several cases, however, even small values of α were not sufficient to get a high ESS. In cases with a low ESS, more particles might be required to keep enough alternative options alive. This variation in desired values of α made it difficult to select a correct value, and a lower value than ½ might be desired, especially given the amount of noise that was added in the prediction stage.

To cope with the estimate loosing track or containing high uncertainties, also random particles can be added. For this, locations within several meters around the current or last reliable estimate seem most useful, as in those cases the estimate will generally be in the neighbourhood of the real position.

2.4.5 Calculation considerations

Choosing each 5th ray for the Beam model, had a large computational effect by quadrupling the calculation times compared to the original configuration (using each 20th ray), as result of the raycast required. Although this has limited impact in the current study, which uses off-line position estimation, it might be relevant for future applications were real-time processing is required. Thus, also using each 10th ray was initially evaluated in Stage 3, showing that a mean Euclidian distance of .25m could be reached (vs 0.19m for each 5th ray) while halving the computational burden. Also reducing or adaptively changing the number of particles could provide additional benefits here, as computational time is linearly related to the number of particles, while evaluation results indicate that uncertainty is less affected.

2.4.6 Future application

Our performance is slightly worse compared to (Fox, Burgard *et al*. 1999, Thrun, Fox *et al*. 2001), which might be explained partly by less accurate input data, as well as more small obstacles that were present, which made a correct obstacle detection more difficult. Improved calibration and online updating of the map are possibilities to further improve the results. As long as the original path is tracked relatively well (deviations of less than 1 meter), the high repetitivity of the environment causes no problems. If deviations are larger, multiple options with equal likelihood arise, and the estimate can become shifted compared to the real location. Still, the algorithm's current performance is suitable for future application in a poultry house. After finishing the work for this manuscript, an online (and real-time) version of the algorithm was implemented in PoultryBot, and found to be successful in online localisation. Results obtained in this stage were considered outside the scope of the current paper.

2.5 Conclusions & Recommendations

In this work, a particle filter based localisation method was evaluated for application on PoultryBot, a mobile robot for use in poultry houses, for example to collect floor eggs. It was shown that in a poultry house without hens and after proper selection of parameters and settings, for 95% of the time an accuracy of 0.42m could be reached using the Beam model, or 0.37m using the Field model. This is well below the required accuracy of 1.0m at 95% of the time, and the achieved mean value of 0.2m approaches the desired level of 0.1m. Furthermore, the method proved capable of correcting for errors and handling missing data, and to a certain extent it is capable of performing Global localisation. It is concluded that a particle filter is indeed a suitable method for localisation of PoultryBot.

In an evaluation procedure, various settings and choices were compared, to see how these influenced the accuracy and applicability for our application. Varying the choices for the resampling method, the sensors used in the prediction step and the grid size of the Field model showed no clear differences. Increasing the laser scanner resolution and using more particles in the estimation improved the result, except when data became too dependent in the Beam model, as this is sensitive to small errors. Both changes lead to an increase of the computational load, but at some point this no longer outweighs the improvement of the results. Learned parameter values for the update step performed in general better than the alternatives. In some cases, other values allowed more room for unexplained measurements, and thus gave small improvements in the results. Relatively large amounts of prediction noise (20% of displacement) were required to handle sensor uncertainty and maintain particle spread. The effect of including type-L obstacles in the update stage on the estimation results remained unclear.

To allow application of this method in a commercial poultry house, attention should be paid to the quality and usability of the sensor data for prediction and update, and the prediction uncertainty used. More investigation is required on data filtering and the optional integration of other information sources in the update stage, to ensure correct functioning when animals block the laser scanner view.

2.5.6.1 Acknowledgements

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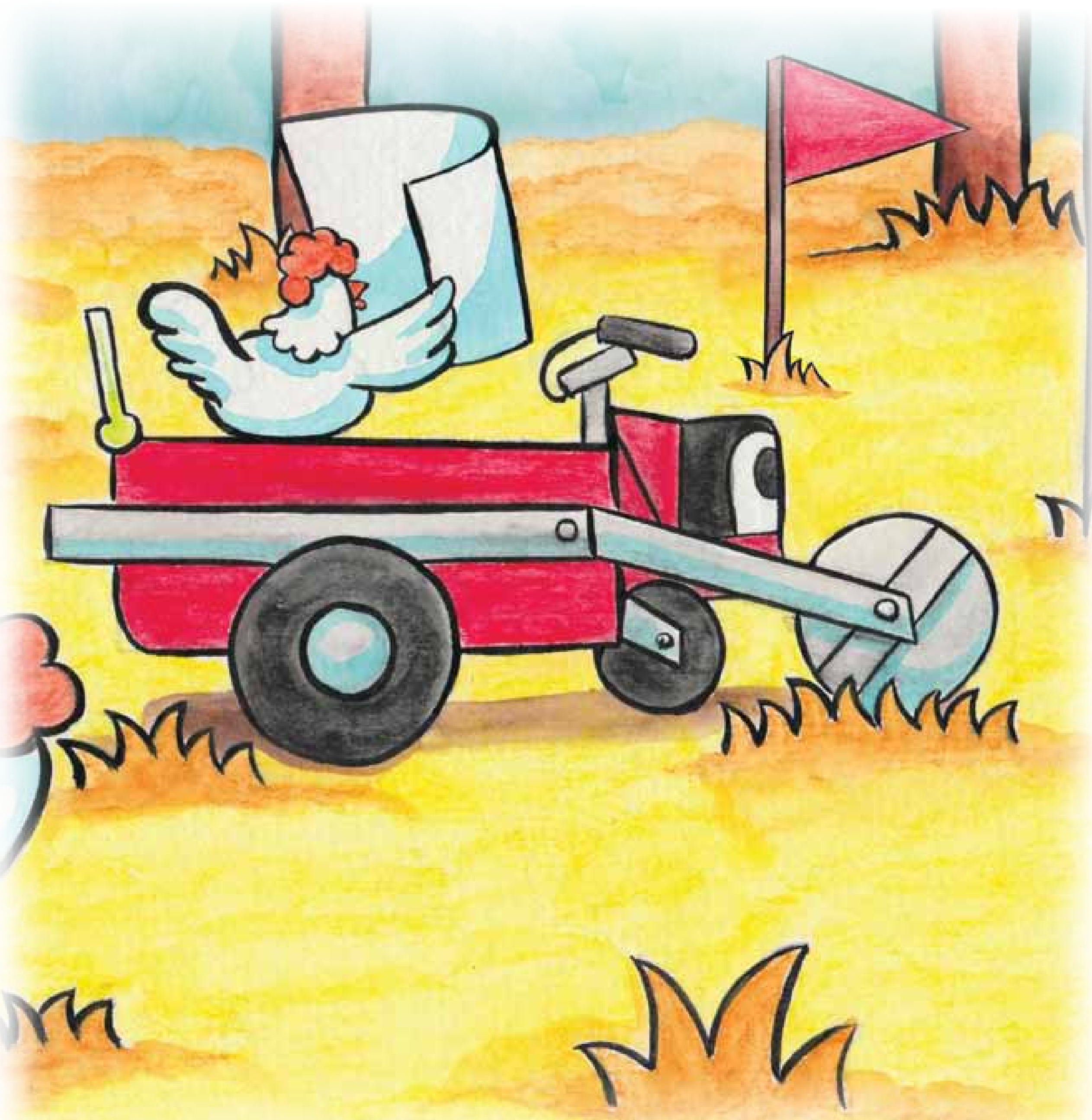

Chapter 3

Path planning for the autonomous collection of eggs on floors

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Abstract

A problem in loose housing systems for laying hens is the laying of eggs on the floor; these eggs need manual collection. This job is heavy and time-consuming and automated collection is desired. For collection using a robot, a collection path is required. A novel path planning algorithm is introduced for non-uniform repetitive area coverage (NURAC) paths and evaluated based on information about floor egg probability. Firstly, a spatial map was developed that describes the potential for floor eggs at each location in a poultry house. Next, paths for floor egg collection are planned with a dynamic programming approach that covers the house floor area and frequently revisits locations with a high potential on floor eggs. These paths are compared with the paths used for floor egg collection by a farmer and evaluated with help of a simulated set of floor eggs. With respect to the average time eggs are present on the floor, paths planned for a robot are compared to two collection rounds of a farmer. With respect to the structure of the path and the number of visits to locations with a high potential, the robot paths outperform the farmer. Although optimality of the path is not guaranteed, the presented results are promising for the use of a robot to collect floor eggs, and will result in a reduction of the demand for manual labour. Extending the floor egg model with feedback information could further improve the results.

Nomenclature

μ	Mean
a	Instance of length index
b	Instance of width index
C_k	Contribution at stage k
$c_1 - c_4$	Constants controlling the incentive function
Egg time	Time an egg is present on the floor, h
f	Factor controlling the yield increase
I	Number of cells in length of the house
i	Cell index in length direction
J	Number of cells in width of the house
j	Cell index in width direction
k	Index of cell transition or stage
L	Total set of locations
$L_{i,j}$	Location i,j, with $i=1{:}I$, $j=1{:}J$
N	Number of cell transitions
O	Optimisation criterion
$P_{i,j}$	Floor egg potential at location i,j

$P_{i(k),j(k)}$	Floor egg potential at location i,j at stage k
$R_{i,j}$	Incentive at location i,j
$R_{i(k),j(k)}$	Incentive at location i,j at stage k
T_k	State transition at stage k
t	Time, h
$t_{collection}$	Time of collection of an egg, h
t_{lay}	Time of lay of an egg, h
U	Set of possible transitions or decisions
u_k	Decision at stage k
V_k	Value function at stage k
X	Width direction of the house
x_k	State at stage k
Y	Length direction of the house
$Y_{i,j}$	Yield at location i,j
$Y_{i(k),j(k)}$	Yield at location i,j at stage k
Y_{max}	Maximum yield
σ	Variance

3.1 Introduction

3.1.1 Floor eggs

Based on the increasing concerns of the public about the welfare of production animals, the EC issued a ban on egg production in traditional battery cages by 2012 (European Union 1999). Since the 1980's, this led to a search for alternative systems, categorised as enriched cages or colony systems and loose housing systems. The basics of the latter type are centuries old but to comply with modern farming practice improvements in scale and productivity were necessary. As a result, the aviary system was developed (see Blokhuis and Metz 1995, Sandilands and Hocking 2012) which increased productivity while maintaining freedom of behaviour for the animal. In these systems hens are trained and expected to lay their eggs in the nests; However, a significant portion can be found at other places such as elevated tiers and the floor (either litter or slatted floors) and these eggs are called 'mislaid eggs'.

Laying of eggs outside the nests is induced by factors such as the inability of the hen to reach the nest, unfamiliarity with laying (especially at a younger age), conceptual mismatch between the properties of the nest and the expectation of the hen and presence of other eggs outside the nest (Appleby 1984, Zupan, Kruschwitz *et al.* 2008). Eggs laid in the litter on the floor are considered to be a problem in poultry farming. They have a lower quality due to contamination by the litter and they induce additional floor laying. Thus frequent collection of floor eggs is required (Appleby 1984, Abrahamsson and Tauson 1998, van Emous, Reuvekamp *et al*. 2001, van Emous and Fiks - van Niekerk 2003). Research has been done on measures to reduce the laying of floor eggs. This has led to specific adaptations of the housing systems and a series of management and control measures used by farmers. None of them has proven to be completely successful (Appleby 1984, Cooper and Appleby 1996b, Cooper and Appleby 1996a, Abrahamsson and Tauson 1998, Gunnarsson, Keeling *et al*. 1999, Lundberg and Keeling 1999, van Emous and Fiks - van Niekerk 2003, Tauson 2005, Zupan, Kruschwitz *et al*. 2008). One of the key control measures taken is the frequent manual collection of floor eggs. This is a physically demanding job under harsh environmental conditions and it can take up to 37% of the work time of the farmer (Drost and van der Drift 1993, van den Top, Akkermans *et al*. 1994, Blokhuis and Metz 1995).

3.1.2 Egg collection

To ease this collection task, for instance, a gripper stick, an automated collection system with a rake (Fiks-van Niekerk, Reuvekamp *et al*. 2003) and the Chicken Trolley (Anonymous 2010) have been proposed. However, despite the enormous progress already made, it is expected that the problem of floor laying will remain with current systems, as a result of variations between flocks and the specific preferences of the hens with respect to their nesting places.

Another alternative is to use an autonomous multi-functional robot platform for the collection of floor eggs. It could also be used for the monitoring of indoor climate, identifying dead hens, monitoring animal behaviour and carrying out other welfare-related tasks thereby alleviating the work of the farmer, without the need for a fixed installation in the poultry house. This idea builds on a robotic platform that was constructed for the Field Robot Event competition of 2007 (Anonymous 2007). In the freestyle task of that competition, an autonomous robot with a collection device demonstrated the collection of floor eggs (Kool, Vroegindeweij *et al*. 2007). The basic idea was well received in agricultural practice in The Netherlands (Bijleveld 2007).

As a result a research project started in 2011 at Wageningen University focusing on the development of such an autonomous multi-functional platform. To ensure safe and correct functioning of such a platform, essentially, the following functions need to be implemented (Bechar 2010), 1) mobility, steering and control, 2) sensing, 3) path planning and navigation, 4) manipulators and functional devices to deal with products, and 5) intelligence and autonomy.

3.1.3 Path planning methods

This paper addresses the path planning for such a platform focusing on floor egg collection. The path planning algorithm had to take into account that floor eggs are non-uniformly distributed with respect to space (the location in the aviary house) and time (the moment the eggs are laid). Given these characteristics, key requirements for the path planner were: 1) the time that eggs lie on the floor should be minimised to prevent loss of quality; 2) the robot should cover the whole aviary house in 24 h; 3) the robot should be able to exploit the non-uniform distribution of floor eggs in the poultry house; 4) during the ovipositioning period the robot should frequently (re-)visit locations with a higher probability on floor eggs and pay less visits to locations where the potential for floor eggs is lower.

The second requirement suggests a solution in the direction of coverage path planning (Zelinsky, Jarvis *et al*. 1993, Choset 2001). However, such algorithms commonly focus on a uniform coverage of an area and tend to limit as much as possible revisits to a location. The current problem is more related to the field of (security) sweeping. The latter, also known as patrolling, is defined by Elmaliach, Agmon *et al*. (2009) as: "travelling around an area to supervise it". With this approach, locations can be visited multiple times, but in general, this approach attempts to have a uniform visiting frequency for all locations. This can for example be done by planning a Hamiltonian cycle along all locations, and repeatedly covering this path, either by a single or multiple robots (Elmaliach, Agmon *et al*. 2009).

For a quite similar kind of problem, autonomous floor cleaning and trash collection in a large building, Ahmadi and Stone (2005) proposed a method that accounted for a non-uniform distribution and, consequently, a frequent revisit to regions of interest. Their approach relied on a world model which is based on on-line event registration and learning, followed by a greedy search algorithm for generation of the path. It is worth noting that, to the best of our knowledge, in the domain of deliberative robot path planning (LaValle 2006), the algorithm of Ahmadi and Stone (2005) is the only example of a path planning approach explicitly dealing with frequent non-uniform revisits of regions of interest. In the current paper, we follow a more or less similar approach but for floor egg collection. Main differences are that here path planning will be based on a map containing the potential for floor eggs for each location in the aviary house. Additionally, path planning will be use a dynamic programming (DP) approach so as to assure close to optimal behaviour and enable global search.

3.1.4 Objective and paper outline

Our objective is to automate the collection of floor eggs with a robot. Here, a novel path planning algorithm is presented for non-uniform repetitive area coverage (NURAC) paths. However, firstly we present the a priori knowledge for the algorithm, including a model describing the potential on floor eggs, then, we introduce the path planning algorithm. In a model case study, the path generated by the newly developed algorithm is compared with manual floor egg collection by the farmer. The paths will be evaluated in qualitative terms by looking at the structure of the path. It will also be evaluated in quantitative terms by the average time eggs spent on the floor and the number of visits to each location.

3.2 A priori knowledge as input for the path planner

In this section, the approach of the NURAC path planning system together with the information that is used as a priori knowledge for the path planner is presented. This contains a description of the reference aviary house that was used as starting point and a short description of the floor egg model with underlying literature that was used.

3.2.1 Coverage path planning for automatic floor egg collection

For coverage path planning to collect floor eggs autonomously the procedure as shown in Figure 3.1 is envisioned. Based on a priori knowledge of floor egg laying and a map with information on the housing and elevated tiers, a map is constructed which contains the location specific potential on the presence of floor eggs. This potential is related to the number of floor eggs that can be expected at each location. Next, a collection path for the robot is planned. Eggs in the aviary house are collected by following this path. During this process, information is collected about actual locations of floor eggs found. Based on this information, the floor egg potential map can be updated for the collection round on the following day, increasing the potential at locations where floor eggs were found and lowering the potential at locations where no floor eggs were found, as indicated by the feedback loop in Figure 3.1. This updated map is then available for (re-) planning of the coverage path for next day. As a result, the distribution is initially the same for all sections in the house, but distributions will start to diverge once the first eggs have been found.

In this paper, the focus is on a part of this procedure, namely the generation of a map with the potential on floor eggs as well as the

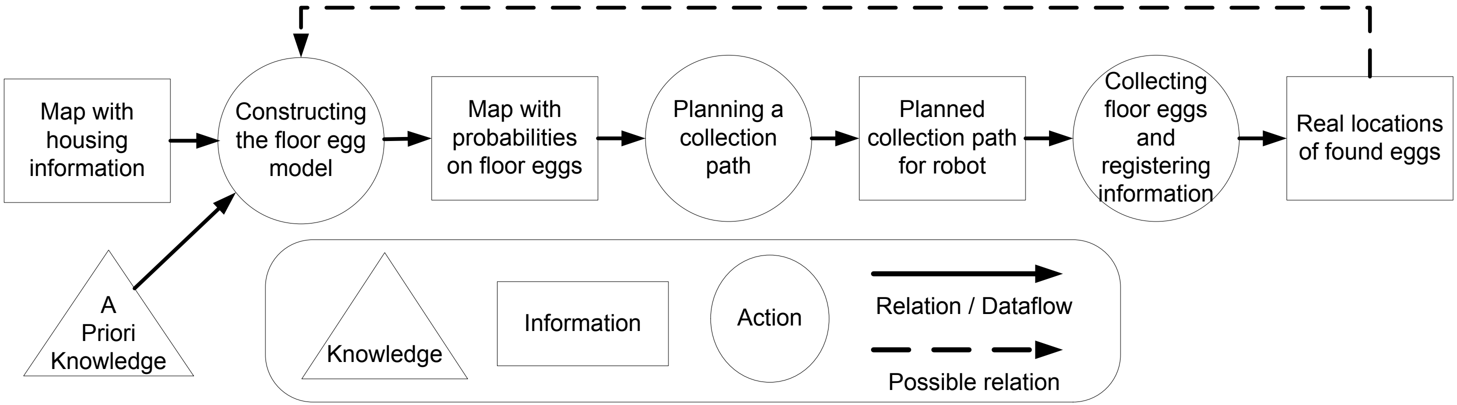

Figure 3.1: General model of the path planning approach.

generation of a collection path. The performance of the resulting path is evaluated in a simulation setting and referenced to the collection behaviour and performance of a farmer.

3.2.2 The commercial aviary house used in this case study

To have a reference situation for our model and to enable comparison of the results with practical experiences, research was based on an aviary house operated by the commercial farm 'Het Anker B.V.' at Opheusden, The Netherlands. The house accommodated 36,000 laying hens and was equipped with 5 rows of the Farmer Automatic Aviary (model year 2003, Farmer Automatic GmbH & Co. KG, Germany). A cross-section of the house is shown in Figure 3.2. On the four outer rows (A, B, D and E), Van Gent group laying nests (Van Gent International BV, The Netherlands) were provided. The front of the house was opposite to the wall where the ventilation fans were placed. The housing was longitudinally divided into six sections by mesh wire fences. The Winter Garden was not considered in this research as hens only got access to the Winter Garden after laying. The width direction (X) is defined along the cross section of the house, while length direction (Y) is defined along the aviary rows.

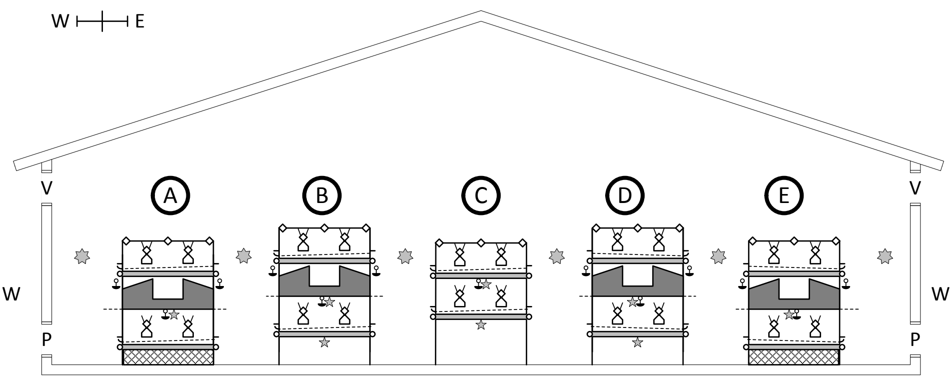

Figure 3.2: Cross-section of the reference poultry house (along X-direction). On both sides of the housing a Winter Garden (W) was present, accessible via pop holes (P). In the aviary house, rows with elevated tiers (indicated A to E) with feeding lines, drinkers, perches and laying nests were present. The whole floor was covered with litter for scratching and dust bathing, except for the rows on the outside (A and E), below which the floor area was not accessible. The free height below the elevated tiers was 0.9 m for the middle row C, and 0.45 m for rows B and D.

3.2.3 Generation of a floor egg potential map

Since experimental data on floor egg distribution were not yet available, a map was constructed containing a location specific potential on the presence of floor eggs. The resolution of this map was 0.1 by 0.1 m, and such an area was called a location. This location is expected to contain maximally 1 egg at a time. For each location on the map, a potential (P) between 0 (never a floor egg) and 1 (every day a floor egg) was calculated. The map was generated with MATLAB® 2012a. Appearance of floor eggs in space and time is generally influenced by the following aspects: 1) hens tend to have a preference for particular locations in the house when laying floor eggs, 2) egg laying and thus floor egg appearance during the day is correlated with the natural laying behaviour of hens on a diurnal basis, 3) the overall number of eggs and thus also the number of floor eggs produced during a day depends on the time in the production cycle, 4) laying behaviour depends on the particular type of hen. Hereafter, the first three aspects will be described in more detail. The effects related to a particular type of hen (originating from breed, strain and flock), will not be considered in this research.

3.2.3.1 Location specific aspects

Literature indicates that hens tend to lay eggs near the front wall and to a lesser extent near the rear wall of the house (Niekerk and Reuvekamp 1997, van Emous and Fiks - van Niekerk 2003). It is also indicated that hens prefer enclosed locations, like close to walls and corners and below and near construction elements (Appleby 1984, Lundberg and Keeling 1999). Darker locations also show a higher probability on floor eggs (Ellen, van Emous *et al*. 2007).

Floor egg potential, as a function of distance to a wall or fence, was described with an exponential decay function. For each of the four corners in a compartment these functions were combined, to form the potential map for a single compartment. A higher weight was given to the corners at the front side of the compartment. Also, a correction was made for the walkways between the aviary system and the border of the housing. It is known from practice that they contain less floor eggs, probably due to a lower animal density, draught from the pop holes to the winter garden and the fact that these areas are used by the hens as a transit from the house to the winter garden. The floor egg potential was modified in two steps. Firstly, the potential was increased depending on the height of construction elements above the floor. In case this height was zero, the potential was set to zero. Construction elements close to the floor, but accessible for the hens, led to a higher increase in potential than construction elements

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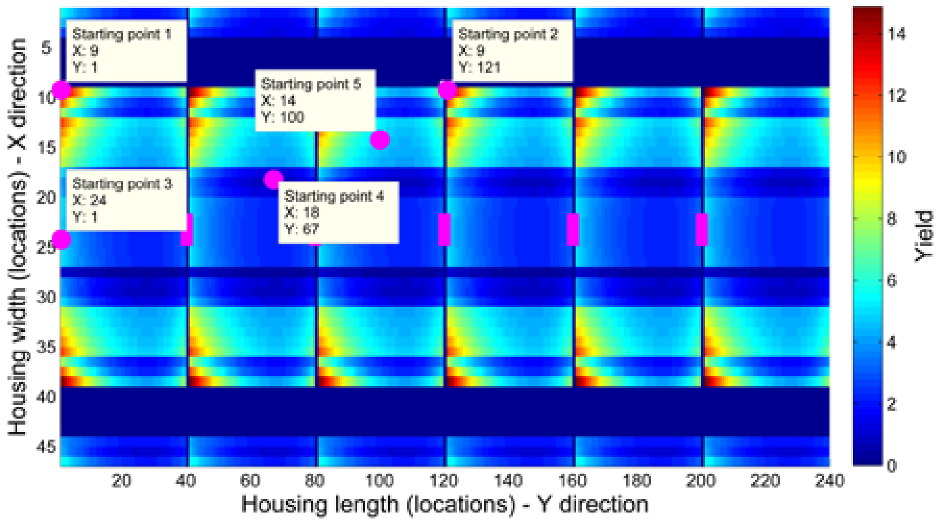

Figure 3.3: Initial yield map for the path planning which equals the summed floor egg potential. Blue indicates a low potential and dark red indicates a high potential. The horizontal dark blue lines refer to rows A and E in Figure 3.2, indicating areas that cannot be accessed by the robot or the hens. Purple dots indicate the starting points for the robot paths with their specific coordinates. The purple bars represent the robot passage ways between the sections.

more elevated over the floor. Secondly, the potential was increased for locations close to construction elements or walls, with an increase that was inversely proportional to the distance.

Figure 3.3 shows the resulting map with the location specific potential on floor eggs in the house, in which blue indicates a low potential and dark red indicates a high potential. This represents an initial situation, and can be updated based on the locations of the collected floor eggs, as stated earlier. This map was to a limited extent validated with floor egg data from practice and the results showed a qualitative agreement (Vroegindeweij, Van Henten *et al*. 2013). Also, the map was shown to two farmers and they confirmed the general trends in the location specific potential distribution of floor eggs based on their practical experience. Therefore, it was considered to be a good starting point for generation and evaluation of robot paths. For the path planning, the resolution of the map was changed from a single-resolution grid of 0.1 by 0.1 m into a multi-resolution grid of 0.4 by 0.4 m in open areas, and smaller grid sizes to accommodate the presence of interior elements. This was done by summing the potential of the single-resolution cells which were combined into one cell in the multi-resolution grid, so that the cells in the multi-resolution grid could take values between 0 and 16. The multi-resolution grid is only used to adapt the map to the presence of interior elements, in that it remains possible to preserve specific features in the potential yield map. For the path planning algorithm, this is of no relevance, as all cells are treated equally irrespective of their size.

3.2.3.2 Diurnal aspects

Joly and Alleno (2001) studied the diurnal egg laying pattern. They found that egg laying in time followed a logistic pattern that was closely correlated to the 'lights out' moment the previous day. Based on these data, a logistic function was fitted that matched the laying behaviour of the flocks at the example farm studied in this research. The resulting curve is shown in Figure 3.4.

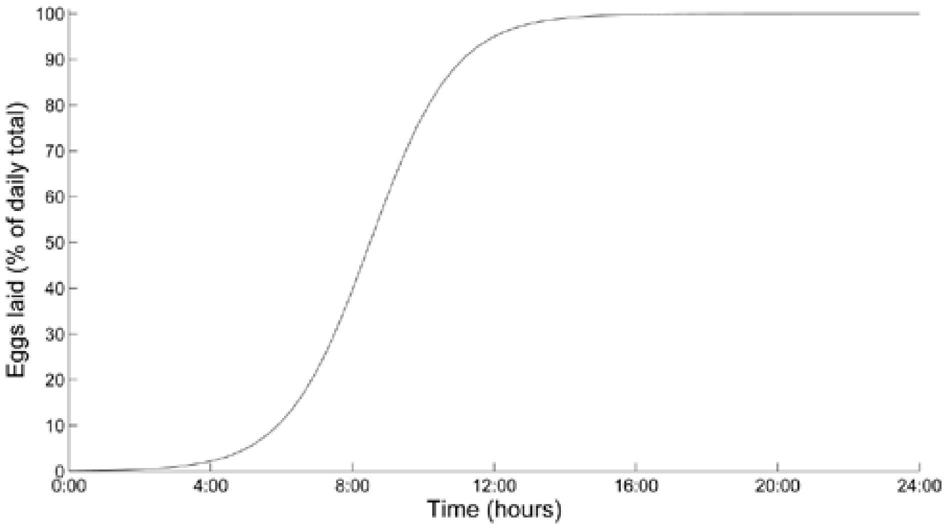

Figure 3.4: Cumulative (floor) egg production over a single day, based on the total production of eggs within a single day (Joly and Alleno 2001). Lighting was switched off around 22:00h the previous day.

3.2.3.3 Seasonal aspects

The number of floor eggs laid during a production cycle depends on: 1) the daily production level, and 2) the fraction of eggs laid on the floor. Egg production data were obtained from ISA Poultry (2008) for the breeds Isa Brown, Hisex Brown and Bovans Brown. These data were averaged on a daily basis. The fraction of eggs laid on the floor was based on data of van Emous *et al.* (2001, 2004). These fractions are also known to vary in time.

Usually, the number of eggs laid outside the nest is high in the beginning of the production cycle. Proper management and hen learning usually results in a decreasing number of eggs laid outside the nest. Additionally, during the first part of the production cycle, mislaid eggs are usually found on the 'system tiers'. Later on, more eggs are found on the floor. As there is day to day variation in the number of eggs laid by flock, a random component is added from a normal distribution with $\mu = 0$ eggs and $\sigma = 10$ eggs, based on observations in the reference poultry house. Figure 3.5 shows a realisation of a time series of the daily number of floor eggs produced by a flock of 36,000 hens during a single production cycle, as used in this research.

3.3 Coverage path planning with non-uniform frequency of revisits to hot-spots

The solution of the coverage path planning problem is based on an approximate cell decomposition of the aviary house (Choset 2001) and an algorithmic approach closely related to dynamic programming. The cell decomposition yields a set of locations L. In this example, each location $L_{i,j}$ is indicated by the indices $i = 1,2,...,I$ and $j = 1,2,...,J$ that are related to the location of the cell along the width and the length of the aviary house, given as X and Y respectively in Figure 3.3. For the path planning, the aviary house was decomposed into cells of 0.4 × 0.4 m resulting in around 11,000 cells. A robot having an assumed speed of 0.2 m.s-1 will be able to traverse such a cell in 2 s. As hens will start laying floor eggs some 7 to 10 h after lights-out, the robot will start sweeping the aviary house around 6:00 in the morning. It is assumed that approximately 13.5 h of operation will be sufficient to remove all floor eggs. Given these preliminaries, the robot has to make about 24,000 cell transitions during its operation period on a day. Then the objective of the coverage path planning is to find a path through the aviary house consisting of N=24,000 cell transitions that satisfies the following requirements:

1. It should minimise the time eggs lie on the floor,
2. It should completely cover the whole aviary house, i.e. all 11,000 cells,
3. Repeated visits are allowed, preferably to locations with a high potential on floor eggs,
4. It should stimulate visits to locations with a high potential on floor eggs in the beginning of the laying period and, vice-versa, it should stimulate visits to areas with lower potential later on the day.

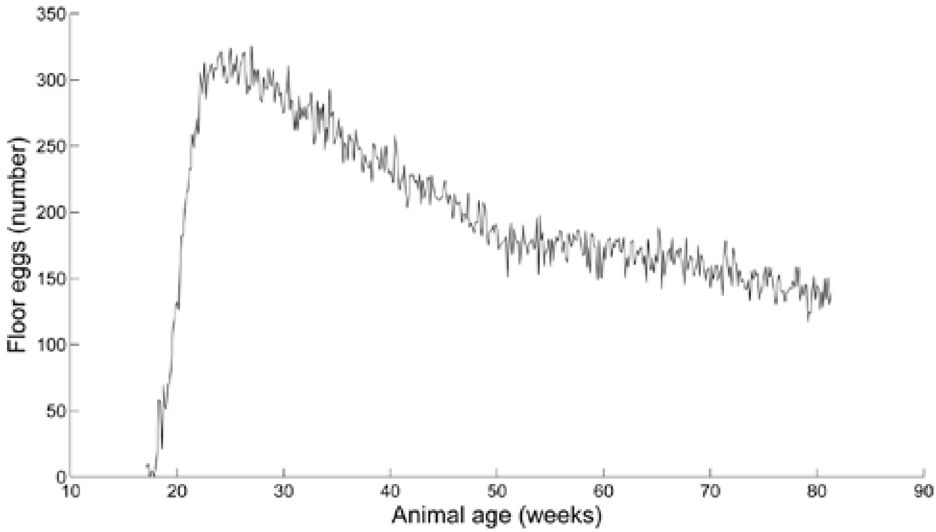

Figure 3.5: Simulated daily number of floor eggs, produced during a single production cycle by a flock of 36,000 hens.

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Objective one is hard to accommodate since it is unknown when exactly an egg has been laid and therefore, under practical conditions, the time that eggs have spent on the floor, the so-called egg time, cannot be assessed. In a simulation, this egg time can be assessed, but this is of limited use as the algorithm ultimately has to work under practical conditions as well. Therefore, it does not make sense to use this objective as objective function for the path planning procedure. As an alternative, it was decided to maximize the yield of floor eggs collected per day while traversing the aviary house. As indicated in Section 3.2.3, the distribution of floor eggs, and thus the yield per cell, is related to the potential for floor eggs in each cell, the time on the day and the day within the production cycle. Thus the objective was defined as to find a path such that this yield

$$O = \sum_{k=1}^{N} Y_{i(k),j(k)} \qquad (1)$$

is maximised. Here indices $i\ (k)$, $j\ (k)$ specify the location visited at instant k, while N is the total number of visited locations. $Y_{i,j}$ is the yield at location i, j given by:

$$Y_{i,j} = P_{i,j} \qquad (2)$$

with $P_{i,j}$ the potential on floor eggs at location $L_{i,j}$ as defined in the floor egg potential map. $P_{i,j}$ takes values in the range [0,16], which relate to a range of 0 to 16 eggs per cell. Cells containing a wall, fence or interior elements that cannot be accessed by laying hens and robots have a value of the potential $P_{i,j} = -\infty$.

It can be shown that a dynamic programming solution maximizing the objective of Eq. (1) given the yield function of Eq. (2) will result in a shortest path solution to the location with the highest potential on floor eggs reachable within the available number of cell transitions N. Then, oscillatory motions will occur between this location and the neighbour with the next highest yield. To make sure that the robot will cover the whole aviary house, including locations with lower potential on floor eggs, the yield function was modified to account for the effect of egg collection according to second requirement stated above. When the robot has visited a location, it has gathered all the eggs in this location which means that, immediately after the visit, the yield should be equal to zero. Then, after the visit, the yield to be acquired in that location was considered to grow again due to the fact that hens will continue laying eggs also at the locations already visited by the robot. For locations that have not yet been visited, the yield function of Eq. (2) was used. However, for locations visited by the robot a modified yield function was used. In that case the yield was defined as

$$Y_{i(k),j(k)} = \left(P_{i,j}\right)^2 \cdot \frac{\Delta k}{N} \cdot f \qquad (3)$$

with $P_{i,j}$ the potential on floor eggs at location $L_{i,j}$ as defined in the floor egg potential map, Δk is the number of cell transitions between the current visit and the previous visit and f is a factor. In this research a value $f = 0.1$ was used which ensured that for locations with a high potential after $0.5N$ cell transitions the yield was equal to the original yield. The modified yield function guaranteed that for locations with a high potential on floor eggs, the yield will grow faster than for locations with a lower potential on floor eggs. This represents the situation as encountered in practice, and complies with the third requirement stated above.

The fourth requirement was accommodated by introducing an incentive function that takes high values for cells with a high yield during the beginning of the search period and that gives an increasing reward for cells with a lower yield during the final stretch of the search period. For this purpose the objective function of Eq. (1) was extended to

$$O=\sum_{k=1}^{N} Y_{i(k),j(k)} \cdot \left(R_{i(k),j(k)}\right)^{2} \tag{4}$$

in which $R_{i(k),j(k)}$ is the incentive function defined as

$$R_{i(k),j(k)}=\exp\left(-1\cdot\left(\frac{\frac{N-k}{N}}{c_1}+\frac{\frac{Y_{i(k),j(k)}}{Y_{\max}}}{c_2}\right)\right)+\exp\left(-1\cdot\left(\frac{\frac{k}{N}}{c_3}+\frac{\frac{Y_{\max}-Y_{i(k),j(k)}}{Y_{\max}}}{c_4}\right)\right) \tag{5}$$

in which Y_{max} is the maximum value of $Y_{i,j} = P_{i,j}$ taken over all i and j, and c_1 to c_4 are empirically determined parameters having values $c_1 = 1.3$, $c_2 = 0.9$, $c_3 = 1.5$ and $c_4 = 1.5$. The first exponential promotes a high potential at the beginning of the path, while the second exponential promotes a lower potential towards the end of the path. Each exponential contains a component for time and one for reward.

With the objective function defined as above, the path planning problem was solved using a dynamic programming (DP) approach (Bertsekas 1995). In DP, optimisation problems are usually defined in terms of the stage k, the state x_k, a decision or control variable u_k, a state transition $T_k(x_k,u_k)$, an objective function V_k and the contribution $C_k(x_k,u_k)$ of a state transition to the objective function.

In the current problem the state of the system x_k represents the location of the robot $L_{i,j}$ in the environment at stage k. A motion of the robot, i.e. a change of the state from x_k to x_{k+1}, constitutes a transition from a cell to one of its neighbours. This transition is considered to be the decision variable $u_k \in U$. For every x_k the set of possible transitions U consists of {(1,1),(1,0),(1,-1),(0,-1),(-1,-1),(-1,0),(-1,1),(0,1)}. Then, the state transition function is $T_k(x_k,u_k) = u_k$ and the transition is $x_{k+1} = x_k + u_k$. For example if $x_k = L_{i(k),j(k)} = 5{,}2$ and $u_k = -1{,}1$ then $x_{k+1} = L_{i(k+1),j(k+1)} = 4{,}3$. The contribution to the objective function of a decision u_k yielding a transition from state x_k to x_{k+1} is $C_k = C_k(x_k,u_k) = Y_{i(k),j(k)}(R_{i(k),j(k)})^2$ with $Y_{i(k),j(k)}$ dependent on whether or not a cell has been previously visited or not as defined in Eq. 2 and 3. The value function is defined as

$$V_k = \max_{(u_k,\ldots,u_N)} \sum_{k}^{N} C_k\left(x_k, u_k\right) \tag{6}$$

It represents the optimal cost of travelling from the state x_k to the final state x_N. Then $V_0(x_0)$ indicates the optimal value of the objective function while traveling from state x_0 to state x_N. Furthermore, $V_N(x_N) = 0$, because the robot stops at instance N and therefore no additional reward is to be obtained.

When the system satisfies the so-called Markovian property (future and past states are independent when the current state is known), the principle of optimality indicates that "whatever the initial state and decision are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decision" (Bellman 1957). The Markovian property requires that current and future decisions cannot have any effect on past system behaviour (Larson and Casti 1978). Then, a recursive equation for the value function can be derived:

$$\begin{aligned} V_k\left(x_k\right) &= \max_{(u_k,\ldots,u_N)}\left[C_k\left(x_k, u_k\right) + V_{k+1}\left(x_{k+1}\right)\right] \\ &= \max_{(u_k,\ldots,u_N)}\left[C_k\left(x_k, u_k\right) + V_{k+1}\left(x_k + u_k\right)\right] \end{aligned} \tag{7}$$

This equation is usually solved in reverse order from $k = N$ to $k = 1$.

The current problem does not satisfy the Markovian property (decisions from the past do effect future costs in our problem) and therefore DP will not provide an optimal solution. The reason lies in the fact that the expected future yield $Y_{i,j} = P_{i,j}$ changes depending on past visits to $L_{i,j}$. The following example illustrates why DP does not provide an optimal solution. It also describes the way we try to remedy this problem.

DP recursively computes the solution backward in time from $k = N$ to $k = 1$. Assuming that at $k = 20$ the optimal decision is to let the robot visit location $L_{i(20),j(20)} = L_{a,b}$. Then during further computation of the solution, backward in time, it might happen that at $k = 10$ an optimal decision would also result in a visit to $L_{i(10),j(10)} = L_{a,b}$. In that case at $k = 20$ an erroneous unchanged yield value was used, as the yield $Y_{a,b}$ needs to be adapted, because as the robot will move forward in time, it will first visit $L_{a,b}$ at $k = 10$ and return to this location at $k = 20$. Then the yield associated with location $L_{a,b}$ at $k = 20$ is not determined in the correct way, and in this solution procedure it cannot be changed, yielding a potentially sub-optimal solution. Instead, the yield value associated with location $L_{a,b}$ at $k = 10$ is modified using Eq. (3).

The modified DP algorithm described above is used to calculate suboptimal solutions. The algorithm has the following structure:

k = N-1
While k > 1
  FOREACH $L_{i,j}$
    Determine all admissible u_k
    FOREACH u_k
      IF $L_{i,j}$ is visited between k and N **THEN**
        Determine Δk
        Calculate $Y_{i(k),j(k)}$ taking into account Δk
      ELSE
        Determine $Y_{i(k),j(k)}$
      ENDIF
      Determine $V_{k+1}(x_{k+1})$
      Determine $R_{i(k),j(k)}$
      Calculate $C_k(x_k, u_k)$ from $Y_{i(k),j(k)}$ and $R_{i(k),j(k)}$
      Calculate $V_k(x_k, u_k)$ from $C_k(x_k, u_k)$ and $V_{k+1}(x_{k+1})$
    END FOREACH u_k
    Select the u_k with the highest $V_k(x_k, u_k)$
    Store this u_k and $V_k(x_k)$ for this $L_{i,j}$ at this k
    Copy the list of visited x from x_{k+1} to x_k
    Add x_k to the list of visited x
  END FOREACH $L_{i,j}$
k = k-1
END WHILE

Executing this code, for a given problem situation, results in a matrix containing the best successive location for each location at each moment. Specifying a starting location and –time then automatically results in a collection path for the robot.

3

3.4 Simulation based performance evaluation of (automated) egg collection

3.4.1 Simulation of a daily production of floor eggs

In the evaluation procedure, the quality of the found strategy or path was compared with the collection method used by a farmer, based on data about location and moment of lay of the floor eggs. As this data was not available from practice, it was obtained by making a realisation of the floor egg potential map described in Section 3.2.3. To produce this realisation (resembling a daily production of floor eggs), 3 components were required: 1) the spatial distribution of floor eggs in the housing, given by the floor egg potential map in Figure 3.3; 2) the distribution of egg-laying within a day, given by Figure 3.4; 3) the number of floor eggs per day (depending on age of animals), given by Figure 3.5. Based on this information, the number of floor eggs for the current day was determined. Next, for each floor egg, a location and a moment of lay were randomly selected and stored. This procedure was run for 450 days in a row (covering an animal age between 17 and 82 weeks). For each day, it was repeated 200 times to investigate and rule out random effects, resulting in 90,000 realisations of a daily production. In each realisation, on average 198 eggs were present. In total, this resulted in a set of 17.8 million eggs, with for each egg a location and a moment of lay.

3.4.2 Assumptions and choices with respect to the collection paths

Next, robot collection paths were generated to evaluate the path planning strategy. These paths were defined by selecting a starting time and position. For $t=0$ five starting locations were selected to retrieve five collection paths. These five starting locations (and paths) were selected to investigate influences of the starting point on collection quality and were distributed over the housing area (Figure 3.3). It was assumed that the robot covered a single cell at a time and detected and collected all floor eggs present solely in this cell.

The collection path of the farmer was based on and is largely similar to the path as used in practice. As the farmer only can reach below the housing interior but not pass through or below it, he is bound to follow the pathways in the house. For reasons of simplicity, it was assumed that the collection round of the farmer is completed infinitely fast at the start time, and thus collects all floor eggs present in all cells at the same time. In the comparison, 1 to 4 collection rounds per day were used. The start times are given in Contribution at stage k.

In the evaluation, only the area between rows A and E in Figure 3.2 was taken into account, as only this area was accessible for the robot. Furthermore, it was assumed that the robot could change between compartments only through specific corridors in the middle of the house (indicated by purple bars in Figure 3.3) and that the full path was completed without stops.

Table 3.1: Start time of farmer's collection rounds

		Start time of round			
Name	Rounds	1	2	3	4
Farmer 1	1	11:00			
Farmer 2	2	10:00	14:00		
Farmer 3	3	9:00	11:00	15:00	
Farmer 4	4	7:00	9:00	11:30	15:00

3.4.3 Determination of the results

Performance of collection paths of the robot was compared with the performance of the collection paths of the farmer based on four indicators: 1) Calculation of the objective function for both situations; 2) Calculation of the time eggs are present in the housing; 3) Visit frequency on each location, in combination with the potential on this location; 4) Visual inspection of the collection path, with respect to visiting frequencies, visiting moments and coverage. For indicator 2, each path was evaluated on the complete set of production realisations, being 450 consecutive days with each 200 repetitions of, on average, 198 eggs.

The objective function in indicator 1 was the same as Eq. (4). Robot paths were planned based on this value, and farmer paths were assessed on the same indicator. Since the problem was formulated as a maximisation problem, a higher value of this indicator was regarded as beneficial.

The calculation of the (total) time eggs are present in the housing as used in indicator 2 was:

$$Egg\ time(egg) = t_{collection} - t_{lay} \tag{8}$$

where $t_{collection}$ is the moment of collection and t_{lay} the moment of lay of each individual floor egg. The total is calculated by summing the egg time for all individual eggs. This indicator is related to the original objective of the path planner: the requirement that egg should be collected as soon as possible after laying, since egg quality decreases with time on the floor. Thus, a lower value indicates a more useful collection path.

In indicator 3, the visit frequency for each location and potential was determined. More visits on a location with a higher potential on floor eggs is likely to have a higher preventive value and is thus regarded more useful.

With indicator 4 the behaviour of the collection paths was assessed in a qualitative way. In this method, the visiting behaviour was inspected on: 1) the first and last moment of visit for each location, to see which locations were visited early and which were visited only later on the day; 2) the number of visits on a specific location, as more visits will lead to a shorter egg time and decrease the chance on (additional) floor laying; 3) the visit frequency in the neighbourhood of a location, as increased visits have a preventive effect by disturbing birds in the surrounding of the location visited. Based on this information, a general practice-based opinion was formulated on the usefulness of a certain path.

To test statistical difference between the quantitative results of indicator 2, an ANOVA test was applied in Genstat 15. For this, egg times from individual eggs were used, and the percentiles (5, 25, 50, 75 and 95%) of their distribution were determined for every 14th day from day 7 to 441 (n=32) and every 10th repetition (n=20). Variation was analysed for effects of collection method.

3.5 Results

3.5.1 Inputs for the path planning strategy

The main input for the path planning strategy was the yield map containing the initial yield $Y_{i,j} = P_{i,j}$ for each location $L_{i,j}$, which is shown in Figure 3.3. In this figure, purple dots indicate the starting points of the robot with their coordinates, while the purple squares indicate the robot passage ways between sections.

3.5.2 Resulting path

The resulting path for starting point 1 is shown for part of the house in Figure 3.6. The structure of the path shown is representative for the rest of the house. An animation showing the path in more detail is given in Movie 1. It can be observed that the path was only able to access the inner part of the house (some 7,200 locations) and that it traverses this area in an unstructured way. The density of lines was highest in corners, indicating that the robot path visited these locations more often compared to the middle part of the house where line density was low. Furthermore, some locations with very low yield in the middle of the housing remained unvisited.

The path of the farmer is shown in Figure 3.7, indicated by a green line. The house interior dictated that he followed the corridors (as passing below the housing interior like the robot did, was not possible) and thus traversed the house longitudinally. As he used a gripper stick to collect the eggs, he was able to cover all locations that were lying within 1 m from the path.

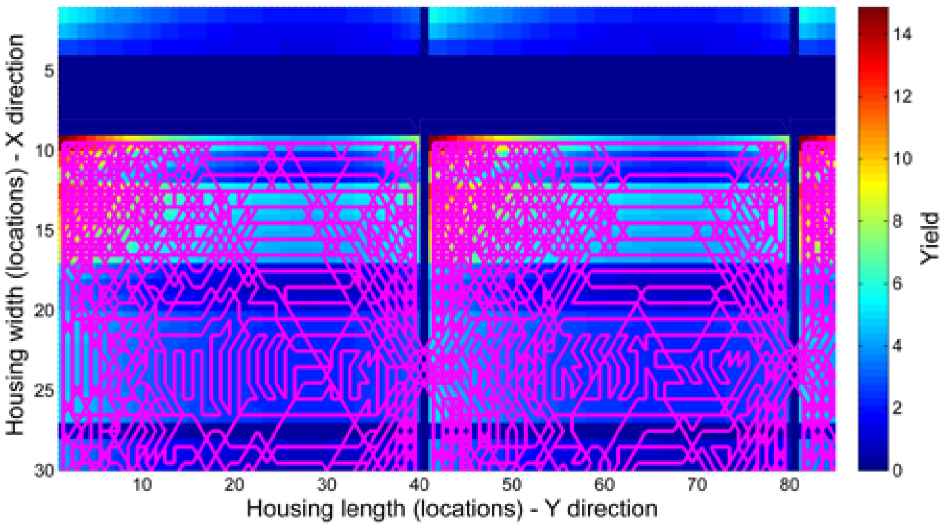

Figure 3.6: Detailed robot egg collection path 1, resulting from the path planning procedure, in part of the house and starting at starting point 1. The purple line indicates the path, which started from the top left corner. The structure of the path shown is representative for the rest of the house.

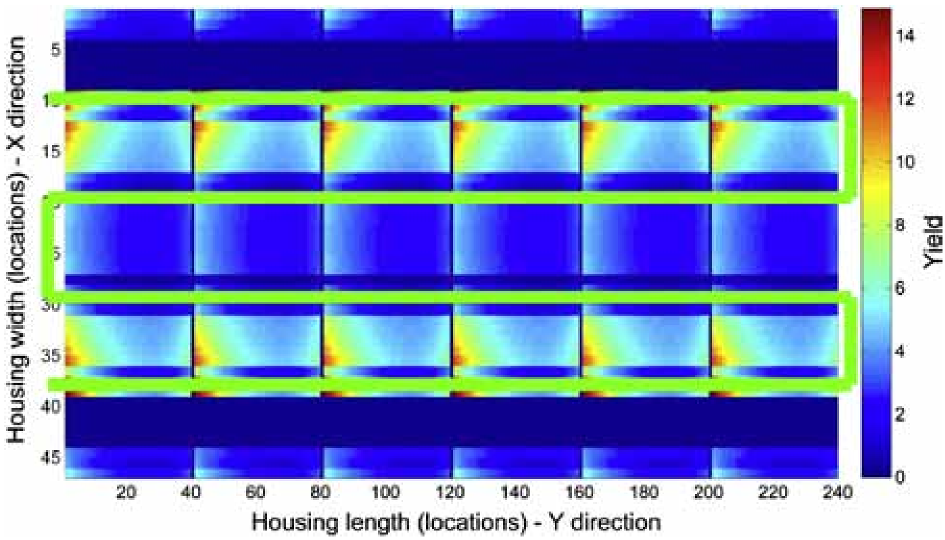

Figure 3.7: Farmer's egg collection path, indicated by the green line.

3

3.5.3 Evaluation of resulting paths

The results for indicators 1 and 2, the objective function and the egg time, are given in Table 3.2. The starting point of the robot path seemed to have no influence on the results (yields are around 37,280 for all robot paths), but repeated collection by the farmer had a clear advantage, both on the objective function (yield between 24,400 and 33,800) and the egg time (between 1.2 and 3.5 h). Variance analysis showed that egg times were similar between robot paths (around 2.4 h) and proved a difference between robot collection and farmer collection, as well as between multiple farmer visits ($P<0.001$). It can be observed that the robot path outperformed the farmer on indicator 1, the objective function, with at least a 10% difference. With respect to indicator 2, however, the robot paths were comparable to 2 collection rounds from the farmer.

The results of indicator 3, the visit frequencies, are shown in Figure 3.8. It can be seen that the farmer visited all locations with equal frequency, while the robot adapted its visit frequency to the potential. Locations with a low potential were on average visited a little over once, while locations with a high potential reached an average of 14 visits. The point of equal visits by farmer and robot was found at a potential of 5, when both visit a location 4 times. When the farmer performs less collection rounds, and thus visits location less frequently, the advantage of the robot is greater.

When assessing the paths according to indicator 4, we observed that the path first focused on areas with a high potential, which were visited within 1,800 cell transitions (1 h). Soon, the path also started to cover areas with little lower potential, and after some 10,000 cell transitions (about

Table 3.2: Results for indicators 1 and 2. Significantly different egg times ($P<0.001$) are indicated with superscript letters (a – e), and were found between the robot paths and the farmer, as well as among the egg times of the farmer.

	Indicator 1	**Indicator 2**	
	Objective function (-)	Egg time (h)	
		Mean	*Sd*
Path 1	37,282	2.39^{a}	0.32
Path 2	37,283	2.38^{a}	0.32
Path 3	37,279	2.39^{a}	0.32
Path 4	37,279	2.38^{a}	0.32
Path 5	37,277	2.38^{a}	0.32
Farmer 1	24,418	3.49^{b}	0.43
Farmer 2	28,450	2.21^{c}	0.25
Farmer 3	32,147	1.59^{d}	0.18
Farmer 4	33,768	1.20^{e}	0.14

5.5 h after the start), the path also visited areas with a low potential, like the middle of the housing. During this period, the path kept re-visiting the locations with higher potential, with a frequency depending on the potential. The path itself lacked a clear structure, and showed some random behaviour. It should be noted that areas (containing multiple locations) with a high potential will be fully covered only after several visits. By repeatedly visiting these areas, all locations were given attention and the chance on (additional) floor laying was decreased. Locations with a high potential were visited up to 17 times, while the number of visits to an area with high potential was even higher. The choice of the starting point only affected the first few hundred cell transition since the remainder of the paths were the same.

3.6 Discussion

3.6.1 Model assumptions

The map describing the distribution of floor eggs only contains an initial situation, which is the best guess given current knowledge. However, adaptability to practical conditions (including animal behaviour) is most likely improve the quality of the map. With respect to the path planning, the results under such conditions are expected to be at least as good as those presented in this paper. Furthermore, by updating the map using information about the locations of the floor eggs found during the collection round, this basic representation can be adjusted to the specific situation for the particular housing situation and flock present. This is also indicated by the feedback loop in Figure 3.1. In this way, an adaptive path planning system can be constructed that reacts actively to (changes in) animal behaviour.

DP was chosen as the method for solving the path planning problem as it was expected to outperform other graph-based methods like A* (Hart, Nilsson *et al*. 1968) on aspects such as sensitivity for local optima, relative efficient calculation with a fixed time to an (optimal) solution and the availability of feedback data. These assumptions, however, were not yet verified, and modifications required to make dynamic programming approach suitable for our application might have affected its performance with respect to the other methods. It might be interesting to compare the current approach with other methods to see whether the advantages of DP remain in our approach.

The chosen path planning approach enabled us to limit the number of calculations necessary to come up with a feasible path for the collection procedure by considering only optimal future trajectories. However, the adaptations made to the original yield function and objective function led to violation of the Markov-property. This means that optimality can no longer be guaranteed for the current implementation. A workaround to this problem is possible, by including the complete future trajectory into the formulation of the current state (Sniedovich 1986), but the required calculation effort will be larger. Furthermore, the need for an optimum can be questioned, as the underlying model as well as reality has a certain degree of uncertainty that limits the value of an optimal solution.

3.6.2 Choice of parameters

In section 3, values were given for robot speed and collection period. These numbers were estimated based on common sense and intuition and seemed realistic. As this paper contains the first description of the algorithm and its practical application, we consider the current selection to be sufficient. In future work, it might be interesting to do further analysis on this part.

The type and values of the objective function, the incentive and their parameters were chosen empirically, based on the desired behaviour of the resulting paths. These functions were not varied nor were their values optimised in any sense. Such optimisation might well give somewhat better results, but is not expected to be substantially different from the current results, as the non-optimality of the applied method also influenced the results.

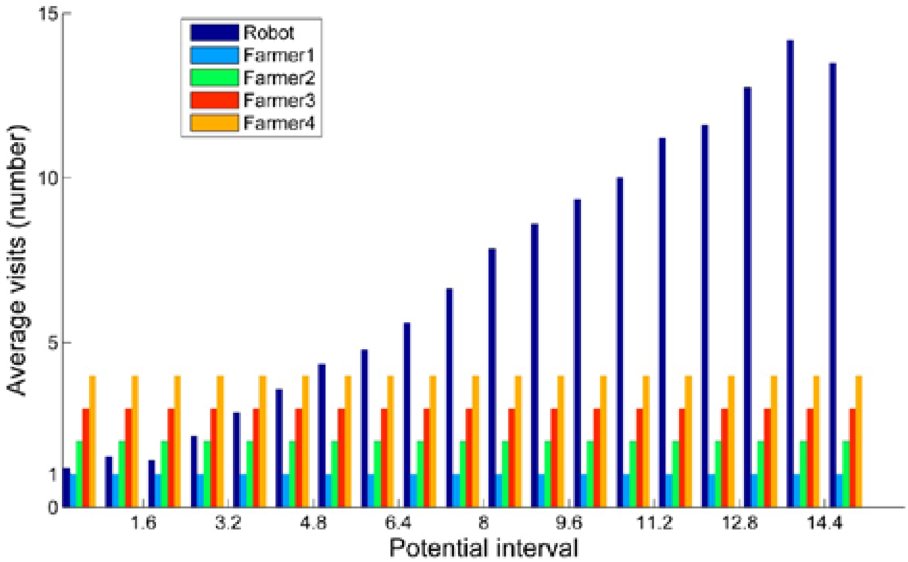

Figure 3.8: Distribution of the average number of visits to a location within a specific potential interval. Farmer visits remain equal over the potential, while the robot visits increase with potential, and can reach 14 visits for locations with a high potential.

The algorithm did not consider the effect of (sharp) turns during the path planning procedure. This resulted in a path that contains quite a number of sharp turns, of which the turning angle can be more than 135°. Such turns are physically hard to complete. Also, Choset (2001) indicates that lowering the number of turns is beneficial in both the time required to complete the path and reduction of errors. Thus, an adaptation of the cost function that results in a path with a reduced number and smaller angles of the turns might be necessary to make the calculated paths feasible for a real robot in practice.

The quantitative evaluation of the paths was based on 198 floor eggs per day, on average. This number is sensitive to variation under practical conditions. Such variation was briefly tested with the varying number of floor eggs over time and did not result in large differences in eggtime, except for some cases with very few floor eggs (less than 10 floor eggs) where missed eggs had large influence on the results.

Finally, the robot speed was currently set on a low value (0.2 $m.s^{-1}$). If a higher speeds turns out to be feasible, more locations can be visited in the same period. This will assure a faster collection of the floor eggs and probably also full coverage of the area, thereby further improving the results of the floor egg collection.

3.6.3 Results

The resulting robot paths fulfilled the third and fourth requirements (on the visiting behaviour of the path) as stated in the introduction, so the procedure can be considered as being suitable for the type of problems introduced. Prevention of floor egg laying is covered by the frequent revisiting of locations, especially those with a high potential on floor eggs. The revisiting of such locations throughout the whole day, while locations with lower potential are visited only at the end of the day, can be attributed to the incentive function, as DP alone will visit high yields in the end and lower yields in an earlier stage. If more or different control on the behaviour of the path is desired, this can be achieved by changing the incentive function or its parameters.

The currently planned paths do not reach full coverage of the area (second requirement), nor are they able to guarantee the lowest possible egg time (first requirement). This is not a major issue with respect to coverage, as the amount of unvisited locations is small (66 out of 7,200 accessible locations) and the risk for floor eggs being laid there is very low. Also, the neighbouring locations were visited at least once a day, so if eggs were present, their collection in a future situation can be assured with a good detection system, which detects and collects eggs also outside the path. In fact, the current results represent a worst-case scenario, in which the robot collects only eggs in the currently occupied cell whereas the farmer collects all eggs present in a reachable neighbourhood. Thus, an improvement in the detection and collection method to collect also eggs outside the current cell will clearly benefit the robot in the comparison with the farmer. Although the egg time results were not the lowest possible, they were still comparable with the egg time values of the farmer. Lower values are only possible if the number of visits is increased further or when the location of the eggs is more accurately known so eggs can be collected faster. For the latter, adaptation of the potential map and thus the resulting paths to current practical conditions might be a good solution. Also, an increase of the robot speed (in this research 0.2 m s^{-1}) might lower the egg time.

For the collection procedure of the farmer, full coverage was assumed. In practice, obstructions from animals and interior elements in the field of view will lower the effectiveness of the farmer. As a result, eggs will be missed in the collection, leading to a longer egg time and weakening the results for the farmer. Furthermore, as the farmer is currently considered to collect all eggs at the same time, the practical egg time for the farmer might be somewhat higher as he collects part of the eggs at a later moment. Again, such a change will benefit the robot in the comparison with the farmer.

The moment of lay for a single floor egg is currently based on a logistic curve. As this curve has a little different shape in reality with more eggs laid early on the day, this might benefit the robot by a fast collection of eggs on spots with a high potential. On the other hand, for locations with a lower potential, egg time might increase and the farmer has an advantage from his full coverage of the area during each collection round.

So, when the generated collection path is applied under practical conditions and compared with the presented data, it can be expected that the results for the farmer are somewhat overestimated. The results for the robot on the other hand will be better than presented in this work. This is still considered a fair comparison, as it takes a conservative point of view, and thus helps to clarify the benefits of using a robot for floor egg collection. Taking all these aspects into account, it can be stated that the performance of the robot paths is at least comparable with the collection performance of the farmer, and that the structure of the robot paths offers a clear advantage.

3.6.4 Opportunities

Irrespective of their performance, the generated paths are needed and useful when taking over manual activity by robots. This is especially worthwhile for the collection of floor eggs, as this is perceived as a physically demanding job under harsh environmental conditions (Blokhuis and Metz 1995). In a similar situation, the introduction of automatic milking systems, it was shown that limited technical capabilities are already sufficient to enable the introduction of automatic systems that take over manual work (Sonck 1996). As a result, this research opens up possibilities for further development of a robot for the collection of floor eggs, and to extend this concept for other tasks.

With respect to the general applicability of the presented method, it can be indicated that DP as discussed in this paper (although not in its optimal form) is a good method to solve the type of problems at hand, and provides useful results. This problem type considers all cases in which (only) some form of a priori knowledge about the occurrence of an event is available, and in which there is a need for continuous spatial coverage with non-uniform revisiting of locations. It can be strengthened by the fact that the presented method applied is not limited to a certain size, shape or formatting of the area that needs to be covered, except for the requirement that all parts should be reachable. As such, the proposed method is suitable for any kind of (poultry) housing system, from traditional floor housing up to future concepts like Rondeel, Windstreek and Eggsphere (Wageningen UR projectteam 'Houden van Hennen' 2004, Janssen, Nijkamp *et al*. 2011, Weeghel, Groot Koerkamp *et al*. 2011). Use of this method, however, is not limited to applications in poultry or agriculture but can be extended to all sorts of applications where non-uniform coverage is desired and some a priori information about the phenomena of interest is available. Examples of other applications are surveillance tasks, collection of objects or the cleaning of large buildings and the removal of trash, like indicated for Continuous Area Sweeping by Ahmadi and Stone (2005, 2006).

A next research step would be to compare the presented method against other methods or an extreme bound, to gain more insight in the capabilities of the current algorithm. When doing so the sensitivity of the assumptions on parameters like robot speed and path length can be investigated, as well as the resulting paths in terms of egg time or number of visits to a location. Such analysis was considered out of scope for the current work, but remains an interesting field for further work.

3.7 Conclusions

A novel path planning method based on DP was presented for non-uniform repetitive coverage of areas. It was applied and tested by generating robot paths for the collection of floor eggs in a non-cage poultry house. In a quantitative evaluation, the resulting paths were comparable to a standard situation from practice with 2 collection rounds of the farmer. The paths clearly outperformed the farmer with respect to revisiting specific areas and the general structure of the path, by having frequent revisits to locations with a high probability. Although optimality of the results could not be guaranteed, the method and resulting paths are still considered suitable for the type of problems described. Extending the underlying model with feedback information will create an adaptive path planner that tracks also changes over time. The presented results are very promising for the use of a robot to collect floor eggs, and will result in a reduction of the demand for manual labour.

3.8 Acknowledgements

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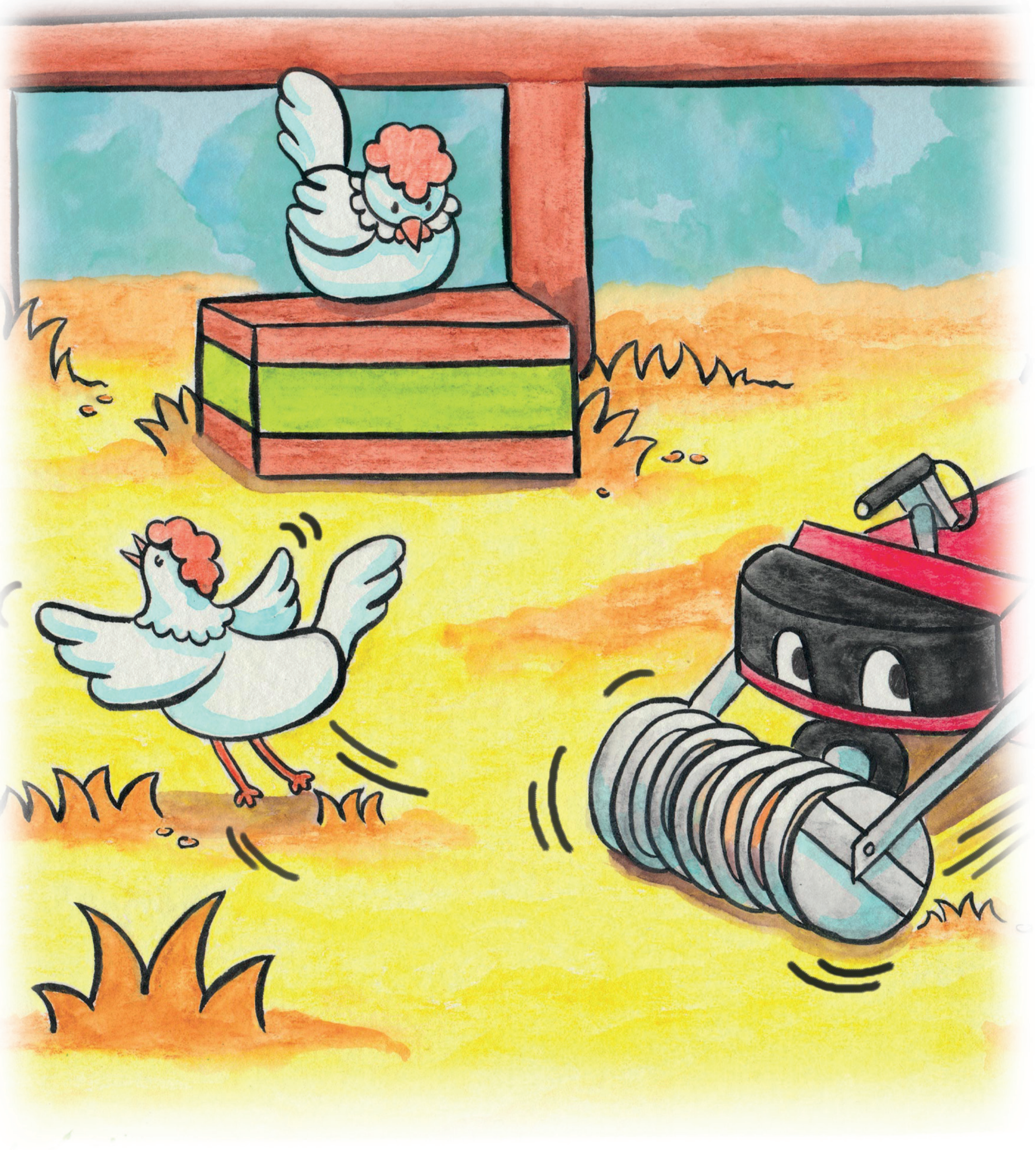

Chapter 4

Object discrimination in poultry housings using spectral reflectivity

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4

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Abstract

For handling surrounding objects, PoultryBot, our autonomous poultry house robot, needs to discriminate between various object types present in a poultry house. A simple and robust method for image pixel classification based on spectral reflectance properties is presented. Of four object categories most relevant for PoultryBot, eggs, hens, housing elements and litter, spectral reflectance distributions were measured between 400 and 1000 nm. Based on these spectral responses the wavelength band with lowest overlap between all object categories was identified, and found around 467 nm. Overlap was 16% for hens vs. eggs, 12% for housing vs. litter, and less for other combinations. Subsequently, images were captured in a commercial poultry house, using a standard monochrome camera and a band pass filter centered around 470 nm. On 87 images intensity thresholds were applied to classify each pixel into one of four categories. For eggs, the required 80% correctly classified pixels was almost reached with 79.9% of the pixels classified correctly. For hens and litter, 40 to 50% of the pixels were classified correctly, while housing elements had lower performance (15.6%). Although the imaging setup was designed to function without artificial light, its optical properties influenced image quality and resulting classification performance. To reduce these undesired effects on the images and to improve classification performance, the use of artificial lighting and additional processing steps are proposed. The presented results indicate both the simplicity and elegance of applying this method and are a suitable starting point for implementing egg detection on PoultryBot.

Nomenclature

TP	True Positive, i.e. correctly classified as object
TN	True Negative, i.e. correctly classified as non-object
FP	False Positive, i.e. incorrectly classified as object
FN	False Negative, i.e. incorrectly classified as non-object
TPR	True Positive Ratio, ratio of TP divided by $TP + FN$
FPR	False Positive Ratio, ratio of FP divided by $FP + TN$
$T1$	Threshold 1, separating litter and housing
$T2$	Threshold 2, separating housing and hens
$T3$	Threshold 3, separating hens and eggs
GT	Ground Truth

ROC	Receiver Operating Characteristic
R	Measured spectral reflectance after correction
I	Measured spectral intensity
B	Black reference, relates to sensor noise
W	White reference, relates to full exposure of sensor
FWHM	Full-Width Half Maximum, property of spectral filter
FPS	Frames per second, speed of camera shutter
F-number	Relative aperture of lens

4.1 Introduction

In current poultry production systems in Western Europe, and more and more in other parts of the world, laying hens in commercial farms have more freedom to move around in their living environment. Compared to the previously used cage housing this requires more advanced management and more human labour under unfavourable conditions, for example for the collection of floor eggs (Blokhuis and Metz 1995, Claeys 2007). In earlier work (Vroegindeweij, van Willigenburg et al. 2014), a poultry house robot (*PoultryBot*) was introduced that will assist the farmer in such tasks. For this robot, path planning and localisation methods were previously presented and evaluated (Vroegindeweij, van Willigenburg et al. 2014, Vroegindeweij, IJsselmuiden et al. 2016). Next to knowing its location and following a desired path, PoultryBot should also be aware of objects in its surroundings, especially those objects that affect its functioning, such as hens, poultry house elements and eggs. As the required response to such objects differs between object types, objects should not only be detected but also be classified into different categories. In robotics, vision-based methods are commonly applied for such detection and discrimination of objects (Ekvall, Kragic et al. 2007, Pillai and Leonard 2015, Ball, Upcroft et al. 2016, Bac, Hemming et al. 2017). Thus, the aim of this research was to investigate if vision based methods are suitable for creating environmental awareness for PoultryBot.

A poultry house constitutes a challenging environment for a robotic system with sensing based on camera vision. For details on the layout and properties of aviary poultry houses refer to e.g. Blokhuis and Metz (1995), Sandilands and Hocking (2012), and Vroegindeweij, IJsselmuiden *et al.* (2016).

Using camera vision based methods in poultry houses for laying hens is challenging as these houses are in general rather dark, with light intensities varying between 5 and 30 lux (Prescott and Wathes 1999, Ellen, van Emous *et al*. 2007). In general fluorescent or LED sources provide white light with a fairly flat spectral distribution. However, as light colour is used to control animal behaviour, light sources with different colours are used as well, and light colour can change in the poultry house within a single production cycle (Lewis and Morris 2000, Ellen, van Emous *et al*. 2007).

An additional challenge for camera vision is the fact that the aviary poultry house is densely populated with metal housing objects that offer various facilities to the animals. The remaining free space is occupied by tens of thousands of animals that move around at will. Finally, the ambient air contains high concentrations of dust and vapour. All of this reduces clear and free sight and leads to continuous variation in image content.

As a first step in the development and evaluation of a vision system for this application, detection and classification of objects at pixel level was aimed for. For the image classification and object detection, a simple method was preferred that would require limited computing power for image processing and would not require additional light to avoid undesirable effects on animal behaviour. As an initial target, pixels should be correctly classified for 80%. Correctly classifying 80% of the pixels means that all objects are at least partially classified correctly, which is expected to be sufficient for operating PoultryBot.

A relatively simple way to detect and identify objects in an agricultural scene is to exploit the differences in spectral reflection properties of the various objects present in the scene. Based on prior acquired reflection properties of the most common objects in such a scene, common and cheap monochrome cameras can be equipped with suitable filters providing an image that may require less processing for object detection and classification.

In agriculture, this method has been used for example to distinguish between various kinds of green plants (Piron, Leemans et al. 2008, Nieuwenhuizen, Hofstee *et al*. 2010) and to distinguish between fruits, leaves and stems in cucumber harvesting (van Henten, Hemming *et al*. 2002). A literature review revealed that spectral reflection properties have been investigated before in poultry farming. Prescott and Wathes (1999) have presented an extensive review of reflective properties of poultry, their housing and the light characteristics therein. They presented results of 15 hen species, of which several are closely related to current commercial hybrid species. Furthermore, they showed spectral properties of various materials present in commercial poultry houses, which turned out to be distinct from the spectral properties of hens. Spectral characteristics of hen eggs were used mainly for transmission measurements to determine the quality of shelled eggs (De Ketelaere, Bamelis et al. 2004, Mertens, Vaesen et al. 2010). Less work has been done on spectral reflectance of eggs. In Prescott and Wathes (1999), only the spectral reflectance of a brown egg was reported. Gloag, Keller et al. (2014) presented also work on other egg colours, although from a different bird, but with similar results.

This paper describes the development of a vision system for pixel based classification of objects in a laying hen house as a two-stage approach. First, the spectral features of objects that are common in poultry houses were sampled and analysed. Next, a method for imaging and pixel classification based on these spectral features is proposed. Furthermore, the performance of this method was evaluated using images taken in a commercial aviary poultry house. For this, the image pixels were classified into several object categories relevant for the operation of PoultryBot in a modern aviary poultry house, such as eggs, hens and housing.

The following section presents the approach used. Next, the laboratory stage is explained in Section 4.3, describing the preliminary analysis that was required before the proposed classification method could be applied under practical conditions. The application and verification in the practical environment of a poultry house is the topic of Section 4.4, starting with the poultry house conditions and the properties of the imaging setup. It also describes the image processing method and an analysis of performance. Section 4.5 reflects on the choices made, and indicates what changes are desired for future implementation on PoultryBot. Conclusions and indications for future work are given in Section 4.6.

4.2 A two stage development approach

The approach used to develop and test the method for pixel classification based on spectral features consists of 10 steps, separated into 2 stages, hereafter referred to as laboratory stage and application stage. The laboratory stage leads from the selection of relevant objects (**step 1**) to the selection of the most discriminating wavelength for object separation (**step 4**), all executed under lab conditions. The application stage uses the laboratory results as input for evaluation of proposed pixel classification method under practical circumstances, i.e. in a commercial poultry house. This starts with the selection of a suitable wavelength filter (**step 5**) and ends with a performance evaluation (**step 10**). Furthermore, steps 7 to 9 allow for additional image processing to improve classification, for example by filtering image noise. An overview of the individual steps in each stage is given below, while they are described in more detail in the next sections.

A. Laboratory stage

1. Define which object categories in a poultry house are relevant to create environmental awareness for PoultryBot.
2. Measure the spectral reflection for each object category at all wavelengths relevant for application in a poultry house.
3. Determine for each object category the distribution of all measured reflectance values at a given wavelength. Do this for each combination of wavelength and object.
4. Identify the wavelength with the largest discriminative power, i.e. the one with the least overlap in reflection between the object categories of interest.

B. Application stage

5. Select a suitable band pass filter for the wavelength found in step 4.
6. Acquire images in a commercial poultry house, using the selected band pass filter and a standard monochrome camera.
7. Find for each object category the distribution of pixel intensity values in these images.
8. Use this information to define threshold values for classification of pixel intensities.
9. Classify the image pixels using thresholds defined in step 8.
10. Evaluate pixel classification performance.

4.3 Laboratory stage

In the laboratory stage, the spectral reflectance of several object categories relevant for operation of PoultryBot in a commercial aviary poultry house was determined. Based on the sampled spectral reflectance, the reflectance distribution for each object category was estimated at the sampled wavelengths, and used to select the most suitable wavelength for discriminating between the object categories measured. In this section, details of the approach used in the laboratory stage are described, the results are presented, and their suitability is discussed.

4.3.1 Materials tested

In **step 1**, four main object categories were found that are relevant for the functioning of PoultryBot inside the poultry house, as they represent the majority of the objects present. These were: 1) eggs, being target objects that have to be collected, 2) hens, being moving obstacles that can be ignored while driving, because they move voluntary away from the robot, 3) housing, being static obstacles that should be avoided, like metal poles and walls, and 4) litter, covering the floor area and indicating the driveable surface. As representatives of these categories, white eggs, feathers of white hens (Dekalb White), galvanized steel, and a litter sample from a poultry house were used. In **step 2**, spectral reflection of these objects was measured using the setup described below. For each measurement, 1 or more objects were placed on a white cardboard plate, which was then put into the measurement setup. Subsequently, spectral reflectance of these objects was measured by performing a single scan over the area within the setup.

4.3.2 Spectral measurement setup

The spectral reflection data was collected using a hyperspectral line scan setup, similar to the one described in Polder and Young (2003) and Polder, Pekkeriet *et al*. (2013). The setup is shown in Figure 4.4.1, and consisted of an ImSpector V10E spectrograph (Spectral Imaging Ltd.) with a slit size of 30 μm, attached to a Photonfocus MV1_DV1320 camera and a 25 mm lens. In the ISAAC2 software that controlled the imaging setup, the acquired reflectance data was binned by 2 cells spatially and 4 cells spectrally, and outside spectral cells were removed as they contained no relevant data. Thus, each scan contained a line of 656 pixels with 192 spectral bands between 400 and 1000 nm. As light source two tungsten halogen lamps of 150 W with a fibre and a rod lens were placed below the camera. The wavelength range of these lamps was similar to those commonly found in poultry houses. The camera, spectrograph and the light source were driven by a stepper motor, moving them over the object with a fixed step size of 0.5 mm over a length of 150 mm. As result, an area with a length of 150 mm and a width of about 300 mm was measured. Camera and light source were on for at least 20 minutes before measurements to avoid start-up effects. Furthermore, the experiment was done in a dark room to avoid influence from ambient light. Also, the ISAAC2 software automatically normalized the reflectance of the object R from the measured intensity I to correct for influences from light source and background light. Reflectance was corrected for the background noise B, and expressed as fraction of the white reference W using

$$R = \frac{I - B}{W - B} \qquad (1)$$

which is based on Polder and Young (2003). Both references were acquired at the start of the measurement. The background noise B was acquired using a covered lens, while the white reference W was acquired using a 98% reflecting white plate (X-rite ColorChecker White Balance).

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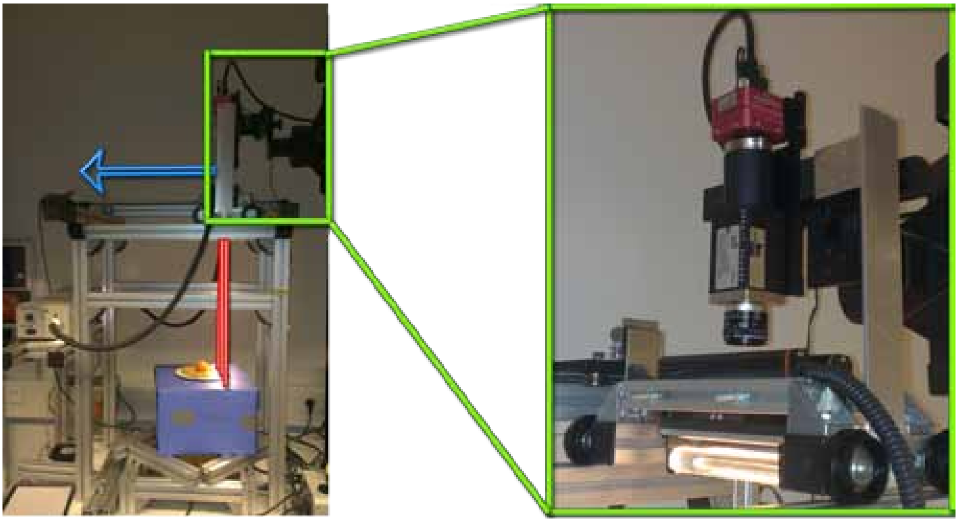


Figure 4.1: The hyperspectral imaging setup used for the experiments in step 2. On the left, the full setup is shown, with an indication of the linear motion of the camera (blue arrow) and the scan line (red triangle). The blue box is used to place the sample upon, in this case a brown egg on wood shavings. On the right, a close up of the moving construction for the camera, spectrograph and light source.

4.3.3 Processing spectral data

Processing of the acquired spectral reflectance data was performed using Matlab. For pixel selection, colour images were reconstructed from the hyperspectral data. As these were only used for visual inspection and to allow manual identification of the objects for ground truth generation, no effort was put in correct representation of the colours in these images. For each object category, between 38000 and 45000 pixels were manually selected from the acquired spectral data, by taking rectangular areas within the objects. From these samples, the reflectance distribution over all selected pixels was determined at each wavelength band (**step 3**). Next, a normal distribution was fitted to these samples, as a smoother representation of the data. In **step 4,** at each of the 192 wavelength bands the percentage of overlap was calculated per combination of object categories. For the measured distributions, this was done by applying Riemann integration on the overlapping area between the distributions of two object categories at a single wavelength band, while trapezoidal integration was used for the fitted distributions. The overlap percentage was calculated by dividing the overlapping area by the area under the distribution of the second object category. Next, the total amount of overlap per wavelength band was calculated by summing the overlap percentages of all object categories for that wavelength. Based on this, the wavelength band with the lowest sum of overlap between the four object categories was selected as the most discriminative wavelength for classification of the objects considered.

4.3.4 Results

For each of the four object categories selected in step 1, *eggs, hens, housing* and *litter,* spectral reflectance data was acquired. The hyper-spectral imaging (step 2) created for each pixel in a 2D frame a stack of 192 wavelength bands with the associated reflectance. From the hyper-spectral data, pictures like the one shown in Figure 4.2 (left) were made to visually inspect the results before further processing. Figure 4.2 shows on the left side a colour image containing the four main object categories. This image was reconstructed from the wavelength bands for display purposes only, and no effort was put in creating a correct representation of the colours. On the right hand side, the spectral responses at locations indicated in the left image are given. It shows that eggs had the highest reflectance, followed by hens and then housing and litter, although the latter two change place when it comes to the amount of reflectance above 615 nm. Furthermore, the difference between litter and both eggs and hens was large at lower wavelengths, but declined with increasing wavelengths. For housing and litter, the difference was initially small, but it increased at larger wavelengths.

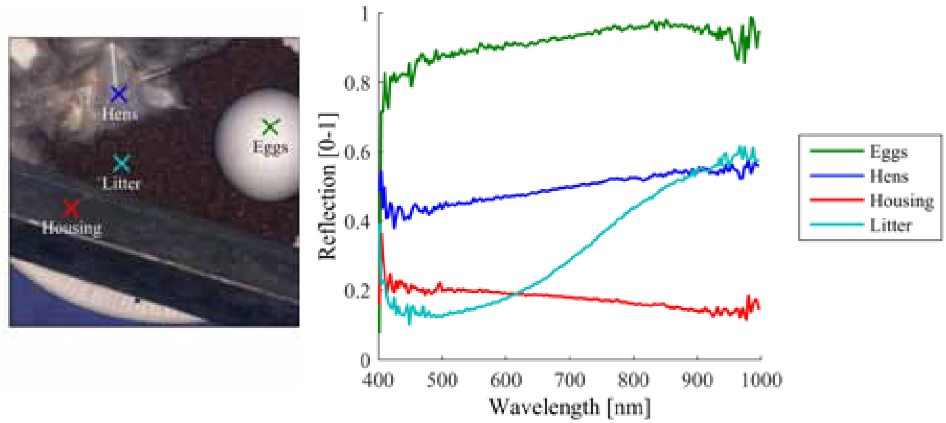
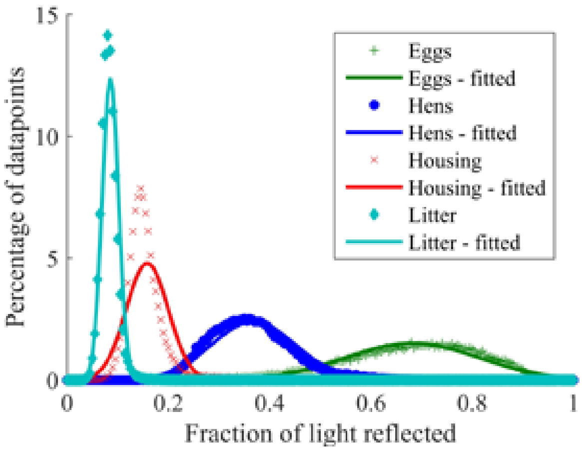


Figure 4.2: Results of hyperspectral imaging for the four object categories. On the left side a colour image is given, reconstructed from the spectral data for display purposes only, on the right side the spectra that correspond to the locations indicated on the left image.

In step 3, between 38000 and 45000 pixels for the same object category were selected to estimate the distribution of the reflectance. For the four object categories and two wavelength bands the resulting reflectance distributions are shown in Figure 4.3, together with normal distributions fitted to these data (step 3). Clear differences were found in the reflectance distributions of the various object categories. Litter and housing had narrower distributions than hens and eggs. In addition, there was some overlap between litter and housing, as well as between feathers and eggs. Furthermore, this overlap turned out to be different between the various wavelength bands.



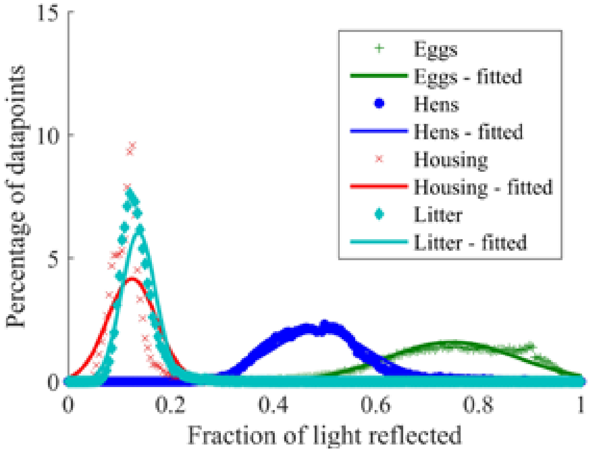


Figure 4.3: Distribution of reflectance for the 4 main object categories, at the 467 nm (top) and 663 nm (bottom) wavelength bands. Points indicate measured data, while lines represent the fitted distributions.

In step 4, overlap between all combinations of object categories was quantified for each wavelength band to identify the wavelength with the most discriminative power for the objects considered. The least overlap was found for wavelength bands between 430 and 515 nm, with the 467 nm band showing the lowest overlap. Based on the measured distributions, the percentage overlap of the measured distributions is given in Table 4.1 for the most discriminating wavelength band (467 nm, least overlap) and an arbitrary one with much more overlap, especially for housing and litter (663 nm). Data in Table 4.1 correspond to Figure 4.3. There were clear differences in overlap between both wavelength bands and the various object categories. At the 467 nm band the overlap was quite evenly distributed over the categories, with the largest overlap between eggs and hens (16.2%) and housing and litter (11.5%), and some overlap between hens and housing. At 663 nm, most overlap was found between housing and litter (78.1%), while also the overlap between eggs and hens was higher (from 16.2% to 23.0%). The combinations eggs and housing, eggs and litter and hens and litter contained hardly any overlap.

Table 4.1: Results of wavelength selection, showing the percentage of overlap between various object categories. Data is presented for the measured distributions, at the most discriminating wavelength band (467 nm) and a less suitable wavelength band (663 nm) with more overlap. Overlap percentage is calculated by dividing the overlapping area by the area under the reflection curve for the second object category.

Overlap between	**467 nm**	**663 nm**
eggs and hens	16.2%	23.0%
eggs and housing	1.7%	1.0%
eggs and litter	0.0%	0.3%
hens and housing	6.9%	2.7%
hens and litter	0.2%	0.8%
housing and litter	11.5%	78.1%

4.3.5 Discussion

In general, the measured spectral reflectance (step 2) matched the ones reported by Prescott and Wathes (1999). In the presented results, significant variation can be observed at the ends of the measured spectra. Prescott and Wathes (1999) indicate similar findings from their measurements, especially around 400 nm, which is the spectral band of UV. They did not indicate whether this originated from technical limitations of their setup or whether it was a specific feature of the sample measured. As in our experimental setup the light source emitted hardly any UV light (around

400 nm), this seems a plausible explanation for the effects seen at the lower end of the acquired spectra. Combined with limited sensitivity of the camera chip at the ends of its spectral range, this can result in reflectance values that are largely determined by sensor noise (Polder and Young 2003). As the amount of UV light available in a poultry house is limited and adding artificial UV light might have undesirable consequences for animal welfare, further investigating this spectral band seems of limited use for the application considered.

Especially for housing material, the obtained spectral reflectance was based on relatively clean materials, providing a rather constant response throughout the spectrum. In the poultry house, however, it can be expected that there is contamination with dust and poultry droppings. As housing objects are mainly made from metal with rather shiny surfaces, the angles between light source, object and imaging device influence the measured reflection. The spectral response of housing objects under practical conditions might therefore be different in shape and intensity. As the spectral response forms the basis for the discrimination between object categories, this might affect correct separation of housing elements from other object categories.

For the selection of the most discriminative wavelength band (step 4), the overlap between each combination of object types was weighted equally and the minimum in the sum of overlap percentages was used to identify the most suitable wavelength. For practical applications, however, it might also be relevant to apply different weight factors, to allow better discrimination of object categories that have higher importance. Failing to detect a housing element, for example, might have more impact on robot functioning than misclassifying litter as hens. Furthermore, more advanced statistical methods, like principal component analysis (PCA) or linear discriminant analysis (LDA) might provide better identification of the most discriminative wavelength.

Also, using multiple spectral bands simultaneously seems promising for improving the classification results. For example, by selecting separate wavelength bands for different object categories, differences in reflectance can become more distinct. When using the 437nm band for separating hens and eggs and the 940nm band for housing and litter, overlap reduces from 16.2% to 15% for hens and eggs, and from 10% to 4% for housing and litter. For brown hens and eggs (data not reported) the overlap is reduced by more than 50% when using two wavelength bands instead of one. Alternatively, the responses at different wavelengths can be combined arithmetically, for example by considering the ratio of the responses at separate wavelength bands. A disadvantage of using multi-spectral imaging, however, is that a more complex optical setup is required.

4.4 Application stage

In the application stage, the effectiveness of the chosen wavelength band for pixel classification was evaluated under the conditions found in a commercial poultry house. To this end, images were acquired with a monochrome camera using a wavelength filter around the most discriminating wavelength, and intensity-based pixel classification was performed and evaluated. This section describes the approach followed and the results obtained.

4.4.1 Experimental environment

Images were acquired in a commercial poultry house of Het Anker BV at Opheusden, the Netherlands, with animals of the same breed as used for the collection of the spectral data (Dekalb White). The house contained 6 interior rows (Big Dutchman, model year 2014) and was split into 7 compartments, each housing some 6000 hens, being 76 weeks old at time of measurement. Unfortunately, the hens were rather anxious, and thus kept clear distance from the measurement setup. Original ambient light intensities were measured using a Voltcraft MS-1300 photometer, and ranged between 5 and 15 lux at floor level. For the experiment, ambient light settings were increased from their normal value of about 30% of full intensity to 100% of full intensity for HF tube lights (Aura Light T8 Universal, Cool White) between rows and LED strips within interior rows (Big Dutchman FlexLED, Warm White colour) and to 80% of full intensity for LED strips below interior rows (Big Dutchman FlexLED). All light sources appeared white to the human eye.

4.4.2 Image acquisition

For image acquisition (**step 6**), a standard monochrome camera and a band pass filter at the selected wavelength band were used. In **step 5** a band pass filter was selected with its centre wavelength at 470 nm (MidOpt BN470, 45 nm FWHM), as being the one closest to 467 nm, which is the wavelength with the lowest amount of overlap between categories. This filter was fitted in front of a lens with 5 mm focal distance (KOWA LM5JCM10M), attached to an extra sensitive DMK 23UX174 monochrome camera. Camera settings were set to resemble application on a mobile robot, with a frame rate of 30 fps to avoid blur resulting from camera and animal movements. Furthermore, the diaphragm was fully opened (F1.8) and a fixed gain of 33.7 dB was applied at image read-out inside the camera to have sufficiently exposed images. For practical reasons, the camera was placed on a tripod at a height comparable to the mount on the robot (approximately 38 cm above floor level). The tripod was moved and rotated by hand while capturing images. Images and related camera and system settings were registered using a dedicated application in NI LabVIEW 2013. In total, 87 images were collected, covering most of the environmental variation that was present in the poultry house. In Adobe Photoshop CS6, corresponding ground-truth images were obtained by manually labelling the pixels in each image that belonged to one of the four indicated object categories: eggs, hens, housing, and litter. A fifth category 'other' contained all pixels from other objects, such as pecking blocks, or that were too dark to be reliably assigned to a category. The built-in magic-wand tool in Adobe Photoshop was used to handle groups of pixels at the same time, to allow faster annotation.

4.4.3 Image processing

Image processing in **steps 7** through **9**, but also the performance evaluation in **step 10**, was done using Matlab R2015b. The images contained clear intensity distortion, which resulted from the optical components, and was visible in the images as a vignette effect. To correct for this phenomenon, first the distortion was estimated using the method of Zheng, Yu *et al*. (2008), based on a set of 12 images of the grey concrete floor specifically obtained for this purpose in the front of the poultry house. These images were captured using similar camera settings as used during the remaining image collection. From the distortion estimated for each of these 12 images, an average correction for the vignette effect was calculated, which was subsequently applied to each image collected in the house. To set appropriate thresholds for intensity-based pixel classification, for each image collected in the poultry house, the intensity distribution within each object category was estimated based on the associated ground-truth (**step 7**). Next, these distributions were averaged over all 87 images in the set to get an average intensity distribution for each object category (eggs, hens, housing and litter). Using these average intensity distributions, a single set of thresholds was defined for intensity-based pixel classification of all 87 images (**step 8**). In fact, steps 7 and 8 repeated steps 3 and 4 in the laboratory stage, but now for placing thresholds on pixel intensities to facilitate proper object classification, instead of selecting the wavelength band that allows for the best discrimination based on object reflectance as was the case in steps 3 and 4. Here, threshold $T1$ was used to separate litter and housing, threshold $T2$ separated housing and hens, and threshold $T3$ separated hens and eggs. Ideally, the selected thresholds $T1$ through $T3$ are located between the intensity peaks for the various object categories, to minimize overlap between object categories. Thus, their position was determined by taking the intensity peaks of the object categories to be separated, and selecting the middle between these peaks as threshold value. The last step in the image processing used the selected threshold values for the pixel classification of the images into four object categories: litter, housing, hens and eggs (**step 9**).

4.4.4 Performance evaluation method

In **step 10**, the result of the classification step was compared on pixel level with the ground-truth image to determine classification performance. This resulted in a confusion matrix indicating for each ground-truth category how many pixels were classified as each of the four object categories. Various performance metrics were then calculated for each object category. First, the values for True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) were determined in a 1 vs. all approach. Based on this, the True Positive Rate (TPR) and False Positive Rate (FPR) were calculated per object category and image by

$$TPR = \frac{TP}{TP + FN} \tag{2}$$

$$FPR = \frac{FP}{FP + TN} \tag{3}$$

Furthermore, confusion matrix values were expressed as a fraction of the number of ground truth pixels for this category. To represent the quality of the classification results over the full dataset, the calculated performance metrics and confusion matrices were averaged over all images.

Finally, by varying the values used for thresholds $T1$ through $T3$, also the sensitivity of the classification performance for changes in the threshold values was evaluated. This evaluation was done in a brute force manner, by testing all possible combinations of thresholds $T1$, $T2$ and $T3$ that complied with the requirement $T3>T2>T1$. Used values ranged between 3 and 24 for $T1$, between 8 and 30 for $T2$ and between 15 and 45 in steps of 2 for $T3$. Based on these results, TPR and FPR were calculated for each combination of object category and threshold setting, and were then used to create plots showing the Receiver Operating Characteristic (ROC) to indicate the change in classification performance. As the pixels in the 'other' category had no reliable ground-truth annotation (i.e. in reality they might or might not belong to one of the first four object categories), they could not be classified correctly and therefore were ignored when varying thresholds and determining the resulting performance. Thus, with eggs as example, TP pixels are defined as pixels which have a ground-truth annotation (GT) as eggs and are also classified as eggs. FP pixels are defined as pixels with housing, hens or litter as GT, which are classified as eggs. FN pixels are defined as pixels with eggs as GT, which are classified as housing, hens or litter. TN pixels have housing, hens or litter as GT, and are also classified in one of these groups.

4.4.5 Application results

4.4.5.1 Imaging

After investigating the spectral behaviour of the relevant objects in the laboratory stage of the research, the use of this information for image classification was tested in the application stage. Image acquisition in the poultry house (step 6) using the selected wavelength filter (step 5) resulted in 87 images covering most of the variation present in the environment. One of these images is shown in Figure 4.4. In this figure the top row contains the original image, while the bottom row shows the results after vignette correction. On the left, the original brightness is used, while on the right the brightness is increased by 75% for presentation purposes only.

In Figure 4.4 it can be seen that the original image has clear differences in image intensity in the radial direction due to optical properties of the

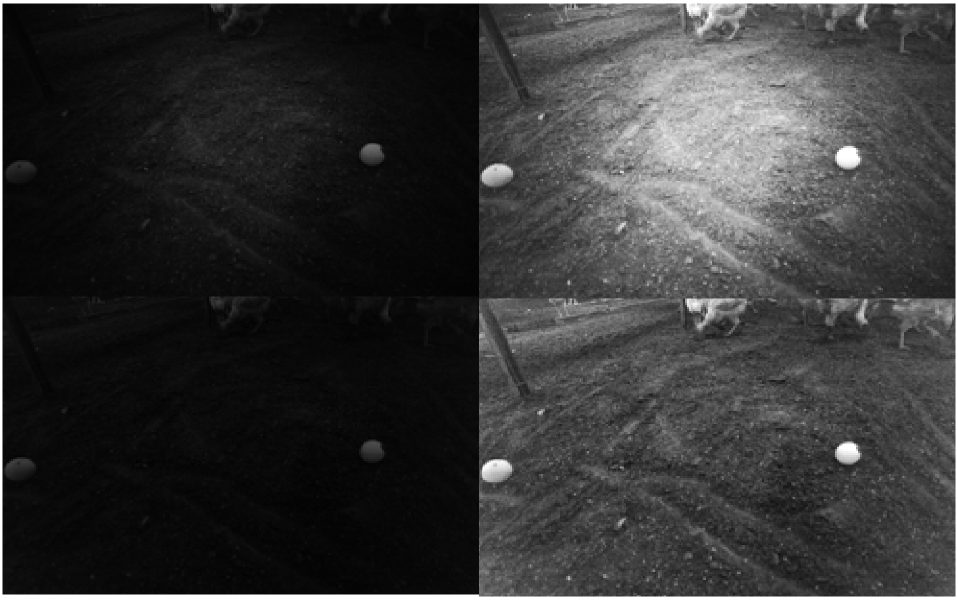


Figure 4.4: Image resulting from the application of the selected 470nm wavelength filter and a monochrome camera for imaging in a poultry house. The original image is shown top-left, while in the top-right image a correction of +75% on brightness was applied for presentation purposes. In the bottom-left image a correction was applied to compensate the vignette effect, while in the bottom-right image also the +75% brightness correction was applied for presentation purposes.

lens. Corners and image side borders did not receive light at all, as result of the optical diameter of the lens being smaller than the diagonal of the camera chip. Correcting for the vignette effect strongly reduced the radial intensity differences, as shown in the images in the bottom row, although some minor variation remained. As expected from the laboratory results at this wavelength, eggs were the brightest objects, followed by the hens. Between housing and litter no clear difference in intensity can be observed in this image. The hens being rather far away from the camera and operator might be due to the anxious behaviour of this particular flock, as this was not observed while testing among other flocks. Also, the hens in the image contain several bright spots, as a result of being close to the light sources in the poultry house, which resulted in variation in the observed intensity for this object category. On the floor level, however, the images have a rather equal distribution of ambient light.

4.4.5.2 Setting thresholds

Based on the associated ground truth, the intensity distributions for each object category could be determined for each image. In Figure 4.5 (top) the intensity distributions for each object category are shown for the image in the lower-one of Figure 4.4, and as the mean over all 87 images in the set (bottom). In theory, these distributions should be comparable to those in Figure 4.3 (top), as they describe similar objects at the same wavelength. However, as result of the intensity variation within the images, the distributions in Figure 4.5 show more overlap of the categories. This overlap is especially present for housing and litter, which limits the correct discrimination of these object categories, whereas for hens and eggs correct separation seems still possible based on these distributions. Threshold values for image classification (step 9) were placed in the middle between the peaks of the mean intensity distributions, and are indicated by the dashed vertical lines in the bottom graph of Figure 4.5. Threshold $T1$, separating the categories litter and housing, was placed at 11.5, while threshold $T2$, separating the categories housing and hens, was set to 14.5. Threshold $T3$, separating the categories hens and eggs, was set to 28.

4.4.5.3 Pixel classification

Based on these thresholds, pixel classification was applied on the collected images. Average classification results over all 87 images are given in Table 4.2, as percentage of the number of pixels in the related GT category. For each element, also the performance range is indicated by the lowest and highest values found. Furthermore, the classification results on two of the acquired images are shown in Figure 4.6, together with the original image and the associated ground truth (GT) image.

For hen pixels, on average 41.5% were classified correctly (Table 4.2), with values ranging between 25 and 55%, while on average 79.9% of the egg pixels were classified correctly, with a number of images also reaching more than 90% (not shown). Incorrectly classified hen pixels were mostly mistaken as eggs and most of the incorrectly classified egg pixels were considered to be hens, thus indicating the clear overlap between these categories as shown in Figure 4.5. This is also visible in the images in Figure 4.6 where the hens have varying brightness and part of the hen pixels are therefore incorrectly classified, mostly as eggs, but also sometimes

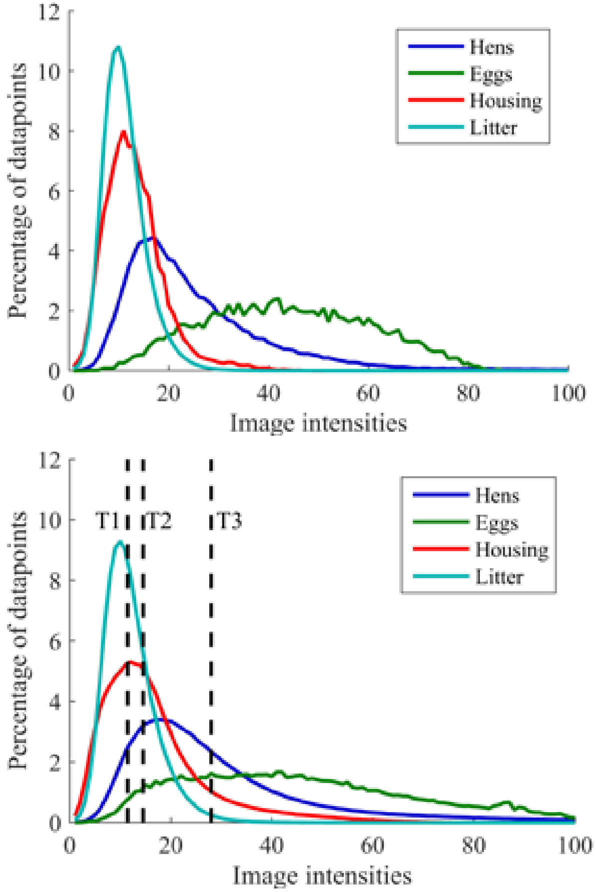


Figure 4.5: Intensity distributions per object category, after correction for the vignette effect. The top graph corresponds to the lower-left image in Figure 4.4, while the right one shows the mean distribution over all 87 images. Vertical dashed lines in the right graph indicate thresholds T1, T2 and T3 going left to right. As the images hardly contained pixels with intensities higher than 100, the x-axis omits the range between 100 and 255.

as housing or litter. Similarly, the border pixels of the eggs are somewhat darker and therefore incorrectly classified as hens. Incorrect classification of eggs as housing or litter occurred less frequently.

With respect to housing pixels, classification performance was rather poor, with on average only 15% of the pixels classified correctly and overall values did not exceed 30%. Although some pieces of the housing poles were classified correctly, many parts (up to 80%) were classified as litter, such as the pole in the right image in Figure 4.6. Misclassification as hens

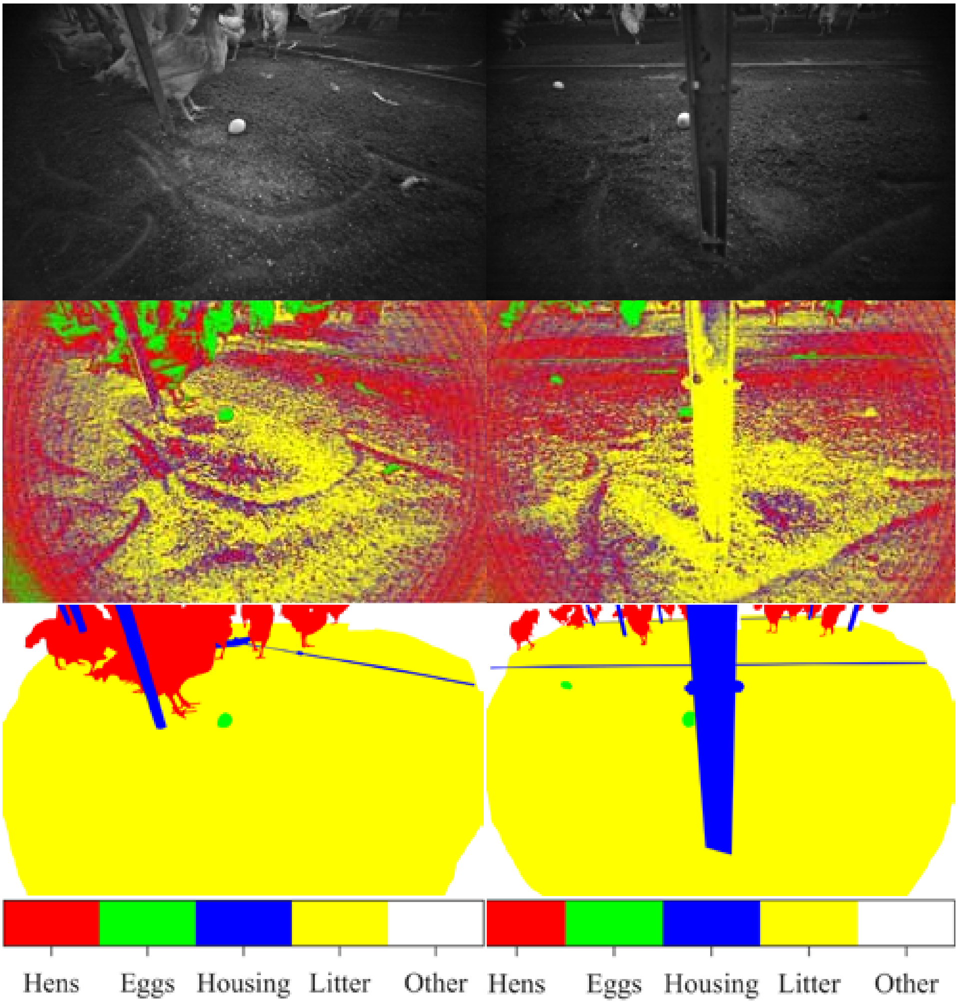


Figure 4.6: Results of pixel classification on two images. Values are set to 11.5 for T1, 14.5 for T2, and 28 for T3. The top row contains the original images (brightness increased by 75%), the middle row the classified images, while the bottom row contains the associated manually generated ground truth.

Table 4.2: Classification results averaged over all 87 images, represented as percentage of the average number of pixels in each ground-truth (GT) category. Numbers between brackets indicate the lowest and highest values found. Diagonal values indicate correct classifications or True Positives (TP). False Positives (FP) for a given category are the sum of the remaining values in the column of the corresponding TP value, while False Negatives (FN) are the sum of the remaining values in the row of the corresponding TP value. True Negatives (TN) consists of the sum of all remaining values.

	Percentage of GT classified as:				
GT category	Hens	Eggs	Housing	Litter	Number of pixels in GT
Hens	**41.5%** **(25.7% - 54.5%)**	41.3% (17.8% - 68.3%)	8.6% (4.1% - 17.2%)	8.5% (2.0% - 21.7%)	109,831 (0 - 226,168)
Eggs	16.5% (1.1% - 67.1%)	**79.9%** **(23.2% - 98.9%)**	2.2% (0.0% - 11.9%)	1.4% (00% - 17.4%)	4,817 (0 - 21,090)
Housing	31% (7.1% - 53.7%)	8.2% (0.8% - 54.8%)	**15.5%** **(4.9% - 29.1%)**	45.2% (3.8% - 80.1%)	71,569 (10,924 - 320,914)
Litter	25% (9.2% - 53.9%)	1.1% (01% - 6.7%)	21.5% (9.3% - 26%)	**52.3%** **(19.5% - 79.4%)**	1,921,486 (1,305,161 - 2,116,129)
Other	46.3% (16.3% - 58.5%)	8.6% (1,1% - 28%)	17.4% (10.4% - 21.1%)	27.6% (8.5% - 67.9%)	196,297 (55,913 - 686,343)

also occurred in up to half of the cases, mainly with objects more towards the borders of the image, like on the poles on the left image in Figure 4.6. The litter scraper, visible as the horizontal thin blue line in the GT in Figure 4.6, is partly classified as egg. Thus, the difference in spectral behaviour of housing elements under practical conditions, as indicated in Section 4.3.5, indeed seems to affect the performance here.

Litter pixels showed similar classification performance as hens, as over 50% of the litter pixels were classified correctly (Table 4.2) but also misclassification as housing or hens was observed. On average, 20 to 25% of the litter pixels were classified in each of these categories, although misclassifying up to 50% of the litter pixels as hens also occurred. From Figure 4.6, it seems that this mostly happened at locations under the housing interior (visible in the top half of the images), probably as result of higher light intensities in that area. Furthermore, the structure and uneven distribution of the litter seemed to influence the reflection of ambient light. Especially areas with visible patterns or variation in the litter structure were incorrectly classified as housing or hens, as can be seen from the middle of the left image in Figure 4.6. Similarly, hen feathers present in the litter were frequently assigned to the egg category.

During ground truth annotation, on average about 10% of the pixels remained unclassified, mainly at the image borders, and were therefore assigned to the 'other' category. The classification procedure indicated that these pixels tended to belong to hens or litter, but this could not be verified, as most of them were too dark to be reliably assigned to a category in the ground-truth annotation.

The radial rings showing up in the classified images in Figure 4.6 most likely originate from internal reflections in the optical setup used, resulting in varying intensities spanning multiple object categories. Furthermore, the bright spots from ambient light observed in Figure 4.4 are also present in the classification result, which together with the radial rings, seem at least a partial cause for the limited overall classification performance and large variation in the results. Another explanation, especially for the moderate performance seen for housing, litter and hens, might be the relatively large distance hens kept to the camera. As result, spatial variation in ambient light intensity is more likely to affect image intensity, leading to wider and potentially overlapping intensity distributions for the individual object categories in the acquired images. Close range imaging, on the other hand, is expected to yield less variation in object intensity and an improved classification performance. In the final application, i.e. with the camera mounted on PoultryBot operating in the poultry house, this is likely to happen, as hens get used to the robot rather quickly (Vroegindeweij, Boots et al. 2014), and thus also remain closer to the camera.

4.4.6 Performance evaluation results

To see how the threshold settings affect classification, values for all three thresholds were varied and classification performance was assessed. Results are presented for each threshold separately, using the True Positive Rate (TPR) and False Positive Rate (FPR), as average value over all 87 images. After that, interaction effects will be discussed shortly. As the 'other' category contained no reliable information on pixel content, i.e. pixels in reality might or might not belong to one of the four object categories, these pixels were ignored in processing and excluded from the performance results shown below.

The expected difficulty to separate between litter, housing and hens as result of overlapping intensity distributions (Figure 4.5) is confirmed by the limited performance for these objects in both ROC plots in Figure 4.7. The singular datapoints in the figures indicate performances for the object categories that are not affected by the threshold varied, and thus remain stationary. As a 4-category problem is considered, performance for random-guess classification into 4 categories (blue dotted line) was added for comparison. Since each threshold separates only 2 categories, also random-guess classification into 2 categories is shown (red dotted line), as this might be a more representative benchmark.

In the left half of Figure 4.7, a ROC curve is shown with the effect of varying threshold *T1*, which separates litter and housing, between 3 and 24, with *T2* set to 19 and *T3* to 25. The result for the lowest threshold value (*T1*=3), is indicated here by the filled diamonds. In general, performance for litter outperformed random-guess classification, whereas that for housing was at the level of random-guess classification in 2 groups. Increasing *T1* led to more litter pixels being detected correctly, while the number of false positives increased at a lower rate, showing a performance improvement for litter. At the same time, classification performance for housing pixels decreased, both for TPR and FPR, although for FPR at a faster rate. This indicates that while litter might be detected properly, for housing elements this method has limited added value.

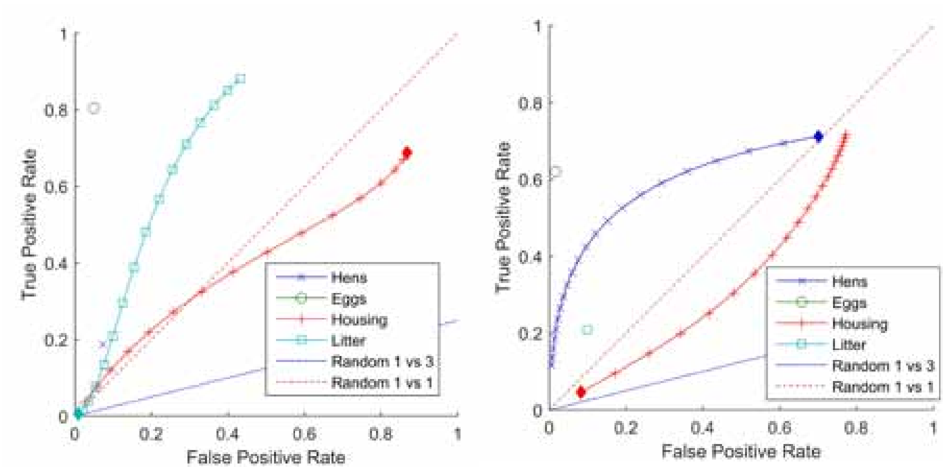


Figure 4.7: Left: Effect of changing threshold T1 between 3 and 24, which separates Litter and Housing pixels. Values for the other thresholds were set to T2 = 19 and T3 = 25; Right: Effect of changing threshold T2 between 8 and 30, which separates Hens from Housing pixels. Values for the other thresholds were set to T1 = 8 and T3 = 37. Filled diamonds (♦) indicate the result for the lowest threshold value used. As baseline, random-guess classification into 2 groups is shown by the red dashed line and random-guess classification into 4 groups by the blue dash-dot line. Singular datapoints indicate performance for the object categories not affected by this threshold.

The right half of Figure 4.7 shows the effect of varying $T2$, which separates housing and hens, between 8 (results indicated by filled diamonds) and 30, with $T1$ set to 8 and $T3$ to 37. Increasing the value for $T2$ gave higher TPR for housing, but also increased FPR, such that performance slightly increased but remained between binary and 4-class random-guess classification. As $T2$ separated housing and hens, increasing correct classification of housing pixels likely reduced correct classification of hen pixels, which is visible from the mirrored behaviour of the curves. The perceived upper limit for correct classification of hen pixels originates from the setting of $T3$, as this threshold influenced the classification performance for hens by separating hens and eggs. As result, changing $T2$ allows for proper detection of hens, while performance for housing can hardly be improved over a random-guess classification.

The separation between hens and eggs by threshold $T3$, ranging from 15 to 45 in steps of 2, with $T1$ set to 8 and $T2$ set to 15, is shown in Figure 4.8. Here, a similar trend as for $T2$ is seen, since lowering $T3$ led to better egg detection with higher TPR, at the cost of proper recognition of hens (decreasing TPR). Egg FPR remained rather constant until egg TPR approached 0.8, indicating reasonable performance for egg detection. Beyond this point, hens were also considered as egg, thus increasing the egg FPR. The position of the ROC-curve for hens on the FPR axis was determined by the setting of $T2$. This also explains the cut-off point at an FPR of 0.25, as the $T2$ setting limited the amount of False Positives at the lower end of the distribution of hen pixels. Except for the two lowest threshold values, classification for both hens and eggs clearly outperformed the random-guess alternatives. For both categories reasonable performance can be achieved, although there was a clear trade-off as result of overlap between the intensity distributions of both categories. Thus, proper classification of hens could be done, but only when missing part of the eggs. Alternatively, eggs could be detected rather well, but this also included a number of false positives on hen pixels.

Varying multiple thresholds at the same time did not affect the ROC curves given for litter and eggs, as they were dependent on $T1$ or $T3$ only and changing the settings for other thresholds did not affect the results. For hens and housing however, there was a clear effect of varying the combination of threshold settings. For hens, the line moved either left/right ($T2$, Figure 4.7 - right) or up/down ($T3$, Figure 4.8) but did not really change its shape. For Housing, similar behaviour was observed, but now with $T1$ and $T2$, while also some changes in the shape of the performance curve were visible. The low performance and overlapping distributions render further investigation of these effects of limited use.

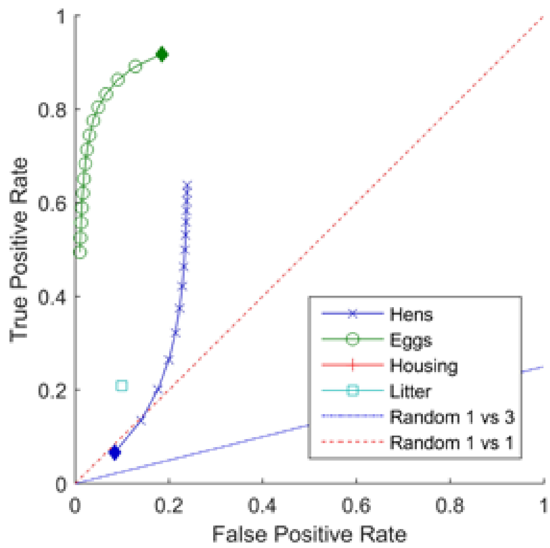


Figure 4.8: Effect of changing threshold T3, which separates pixels into Hens and Eggs, between 15 and 45 in steps of 2. Values for the other thresholds were T1 = 8 and T2 = 15. Filled diamonds (♦) indicate the result for the lowest threshold value used. Random-guess classification into 2 groups is shown by the red dashed line and into 4 groups by the blue dash-dot line. Singular datapoints indicate performance for the object categories not affected by this threshold.

4.5 Discussion

4.5.1 Effects of imaging approach

Avoiding the use of artificial light sources as part of the imaging setup in the application stage created a number of new challenges, which are discussed below. As poultry houses in general are rather dark, with a light intensity between 2 and 20 lux (Prescott, Wathes et al. 2003), an extra sensitive camera was selected to avoid the need for artificial lighting. This seemed beneficial, as artificial lighting might affect image quality through uneven light distribution and requires additional electrical power to be supplied and carried by the future robot. Lens selection was also affected by this choice. The low light conditions required a very translucent lens with a large diameter and short focal distance. For this research the best available option as indicated by the supplier was selected, with a minimum F-number of 1.8 and 5mm focal distance. Still, its diameter was not large enough to allow sufficient exposure on all areas of the camera chip, leading to unexposed areas in the corners of the image. Light intensity was further reduced by the wavelength filter. Next, the spherical shape of the lens combined with the wavelength filter led to radial distortion that is visible in the images as radial intensity fall-off and concentric rings. This is most likely caused by rays of light being reflected or refracted between the filter and the convex lens. Thus, avoiding the use of an artificial light source led to a suboptimal imaging setup, which turned out to have clear influence on the classification results. This choice may need to be reconsidered and possibly investigated in future research.

For practical application of this object discrimination method, sufficient illumination at the selected wavelength band is required. If this is not the case, there is clear influence of ambient light on the imaging results, of which an example was seen during testing in another poultry house. Here, the used wavelength of 470 nm was abundantly available from the white lights in the corridors in the rear part of the image in Figure 4.9, but hardly present below the interior rows (front part of the image) where illumination was done by orange LEDs. This leads insufficient illumination or shading in the front part of the image, as shown in Figure 4.9, with very low signal to noise ratios in the shaded areas and a need for different classification thresholds in each region. Thus, for the presented method to function

Figure 4.9: Image captured in another poultry house, showing clear shading effect as result of ambient light. In the front part of the image, the ambient light was orange-coloured and missed wavelengths around 470 nm, while in the rear part, there was white light that did include these wavelengths and thus showed higher intensities.

properly in a poultry house, it is required that the wavelengths used are sufficiently present in the ambient light and have an equal spatial distribution.

As ambient light plays a role in both problems, including ambient light conditions in the selection of the most suitable wavelength (step 5) might be a possible solution. Also, light conditions in the house could be adapted to better match the needs for image acquisition. However, as this might lead to problems with animal behaviour and can involve considerable costs, this approach seems less desirable. Alternatively, using artificial lighting as part of the imaging setup might be reconsidered, to avoid or reduce adverse effects from both the imaging setup and the housing conditions, while having only a limited influence on animal behaviour. In preliminary research (Vroegindeweij, van Hell et al. 2015), artificial lighting was already added to have sufficiently illuminated images, of which results are shown in Figure 4.10.

Compared to the images in Figure 4.4 and Figure 4.6, using an additional light source results in a more equal light distribution but also creates shading effects due to the directed beam of the light source. Such shading results in more variation in the observed reflection within object categories, leading to wider distributions. Thus, more overlap between distributions will be observed, which will complicate intensity-based classification. Proper selection of the illumination system and calibration of the setup might avoid such undesirable illumination effects, and still result in a more even distribution of light over the area. As result, the intensity distributions for the object categories are expected to be more distinct, allowing for better separation using intensity thresholds under practical conditions. As the classification results in this case are likely to improve beyond those presented in this paper, it seems worthwhile to reconsider this approach in future experiments.

4.5.2 Processing methods

In the image processing all labelled image data, i.e. all labelled pixels, were considered. Alternatively, a region of interest (ROI) can be used, to exclude pixels at specific locations in the image from the analysis. This allows image regions that were prone to adverse effects of using a suboptimal imaging setup (such as the image corners) or unequally illuminated areas (as seen in the top of the images) to be excluded from the data. Most likely, classification results will then improve, since part of the data that is difficult to classify correctly is then ignored. Preliminary investigations showed that using an ROI focussing on the centre of the image could improve performance by 2.5% for hens and 8.6% for litter. Using an ROI during classification, however, requires that only the ROI area is of relevance for robot

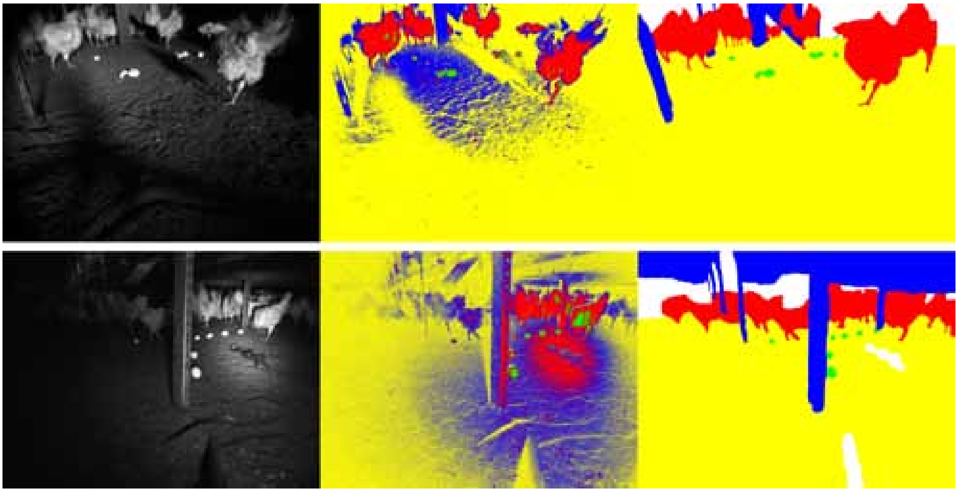


Figure 4.10: Preliminary classification results, as presented in (Vroegindeweij, van Hell et al. 2015). Top and bottom show 2 example images. From left to right: original image (brightness increased by 100% for presentation purposes), classification result, ground truth.

operation and other pieces of the image can safely be excluded because they will not affect the operation of the robot. This is the case, for example, when the excluded parts of the image will be handled at a later moment, when the robot is closer to these objects. As PoultryBot moves through the house, this seems indeed a feasible approach, and thus should be considered in continuation of this work.

Furthermore, current processing was based on a number of fixed intensity thresholds, using only information from the individual pixel in a specific spectral band. This made the method rather simple, while still offering reasonable performance. Other thresholding methods have also been evaluated such as manually varying the threshold values per image or auto-defining them using Otsu's method (Otsu 1979), but found to be harder to apply or less suitable for the current dataset. This was mainly caused by the overlapping intensity distributions of object categories and variations within the images. Using an improved imaging setup might reduce these effects. To further improve classification results, and allow for object detection using this method, other processing methods should be added to the processing pipeline, especially around steps 8 to 10 that deal with classifying the images. For example, adding filtering steps such as a median filter that can be used to reduce image noise. Also, eggs and housing elements have a specific shape that can be used in image processing and classification using morphologic image processing methods like erode, dilate and shape filtering. As such methods include specific object properties, they will potentially lead to better classification results, especially when moving from pixel to object level.

Alternatively, a completely different approach can be taken, by replacing steps 8 to 10 with a more advanced method that considers adjacent pixels or other features for the classification process. This might reduce the problems with individual intensity values, and connects better to the current state of the art in machine vision. For example, Yang, Chao et al. (2010) used fuzzy classification to classify hens in a processing facility based on measurements in specific spectral bands, achieving over 95% correct classification. Also, the use of various advanced methods, such as Conditional Random Fields, Support Vector Machines and Neural Networks are nowadays a common methods for image classification and semantic segmentation (Giacinto and Roli 2001, He, Zemel et al. 2004, Abe 2005). Then, the image is segmented into superpixels based on specific image features such as intensity or texture. Next, for each superpixel a vector containing a range of features like intensities, size, and texture is generated. After training a classifier system using a labelled dataset, this method can subsequently classify the superpixels. Although such methods can be used on the current data, they might be even more suitable for use on colour images, as they use 3 instead of 1 spectral band and might contain a wider range of features. However, these methods require extensive training using dedicated datasets, and have clear computational demands and constraints. Thus, these methods might provide more possibilities for image classification, but at the cost of more complex and demanding implementations, which in turn might limit their current applicability in mobile robotics for livestock applications. Still, as availability of computational power keeps increasing, these algorithms are an interesting option for future investigations.

4.5.3 Performance versus requirements

In this work, an approach was presented for a pixel based classification method that discriminates between various objects in a poultry house based on their spectral reflection properties. Although this approach requires a complex hyperspectral imaging setup in the laboratory stage for development, in its final application standard hardware components and simple processing methods can be used. For imaging, a monochrome camera with a wavelength filter and no additional light are sufficient, while the classification method is based on intensity thresholds only.

As the choices made in the implementation of this approach mainly depend on the properties of the objects considered, the presented method and results are largely insensitive to changes in environmental properties.

Thus, if the method is to be applied in a different environment, but with the same type of objects (white hens and eggs, regular litter and housing elements), only the setting of the thresholds in the classification step might need some fine-tuning as result of different ambient light conditions. If different object types are present, such as brown hens and eggs, or different material is used for litter or housing elements, their spectral reflectance has to be determined first. This requires re-running the laboratory stage, to see which wavelength band is in this case the most suitable one for discrimination of these objects. Initial investigations for brown eggs, for example, indicated that a different one should be selected.

When comparing the achieved performance of this approach, as shown in Section 4.4.5, against the stated performance requirements, quite reasonable results were achieved using manually defined thresholds. For eggs, the requirement of 80% correctly classified pixels was almost reached, with on average 79.9% of True Positives. For hens and litter, on average about 40 to 50% of the pixels were classified correctly, thus not yet reaching the requirement of 80% of the pixels being classified correctly. Modification of the vision setup is needed to remove undesired side effects, as well as extending the processing with other methods based on adjacent pixels or object shape. This seems a very feasible way to reach the desired level of 80% correctly classified pixels for hens and litter, and is expected to also improve the results for eggs. For housing, such adaptations are definitely required, but given the amount of overlap between the intensity distribution for housing and the intensity distributions for litter and hens, it is not sure whether the desired level can be reached at all. As alternative, image data might be combined with additional data sources such as a map or a laser scanner to properly identify housing elements.

Thus, the current method is clearly suitable for implementing egg detection on PoultryBot, and with some improvements it is also likely to be able to provide information on the presence of hens and the availability of free driving space. Even more, as long as objects can still be recognized correctly, also the performance of the current system might already be sufficient for the functioning of PoultryBot, especially when this is combined with information from other sensors to create a high level of environmental awareness. In that case, the requirement of 80% correctly classified pixels serves merely as a performance guideline, instead of being a lower limit on the acceptable performance. With these results, the desire for a universal solution using simple methods for object detection as basis for creating environmental awareness for PoultryBot is clearly met by this approach, although the use of artificial light might be reconsidered in future.

4.6 Conclusions

In this work, a simple pixel based classification method based on spectral reflectance properties was presented. This method is characterized by its simplicity in the application stage, where a wavelength filter is applied on a standard monochrome camera for image acquisition. For classifying the pixels of the acquired images into multiple object categories, the use of multiple intensity thresholds is sufficient. Based on the results presented, it can be considered as a first step in discriminating between various object categories present in an aviary poultry house, to generate environmental awareness for PoultryBot.

In the development stage, the spectral reflectance of four object categories that are relevant for PoultryBot (eggs, hens, housing and litter) was investigated in the range between 400 and 1000 nm. Clear differences could be observed in the amount of reflectance between object categories, and overlap was lowest around 467 nm, being 16% for hens and eggs, 12% for litter and housing, and lower for the other combinations.

In the application stage, 87 images were taken in a commercial poultry house, using a standard monochrome camera and a band pass filter around 470 nm. On these images, pixel classification into the four object categories was evaluated. For eggs, the requirement of 80% correctly classified pixels was almost reached (on average 79.9% True Positives). For hens and litter, 40 to 50% of the pixels were classified correctly, thus not yet matching the requirement of 80% correct classification. For housing, performance was rather low with 15.6% of the pixels classified correctly. Effects of threshold settings were evaluated using ROC curves, displaying a clear relation between the performance for the various object categories.

As the imaging setup relied on ambient light only, collected images were influenced by both the ambient light conditions and the optical properties of the setup. Thus, object intensities in the acquired images overlapped more than in lab conditions which made discrimination difficult. This influenced classification results, limiting the performance for pixel classification in this research. Still, simplicity and elegance in the application stage remain a major advantage. With about 80% of the egg pixels classified correctly, this method seems a feasible starting point for implementing egg detection on PoultryBot. A further increase in performance is expected from using additional processing of the images, or replacing the processing of the acquired images with more advanced computer vision methods.

4.7 Acknowledgments

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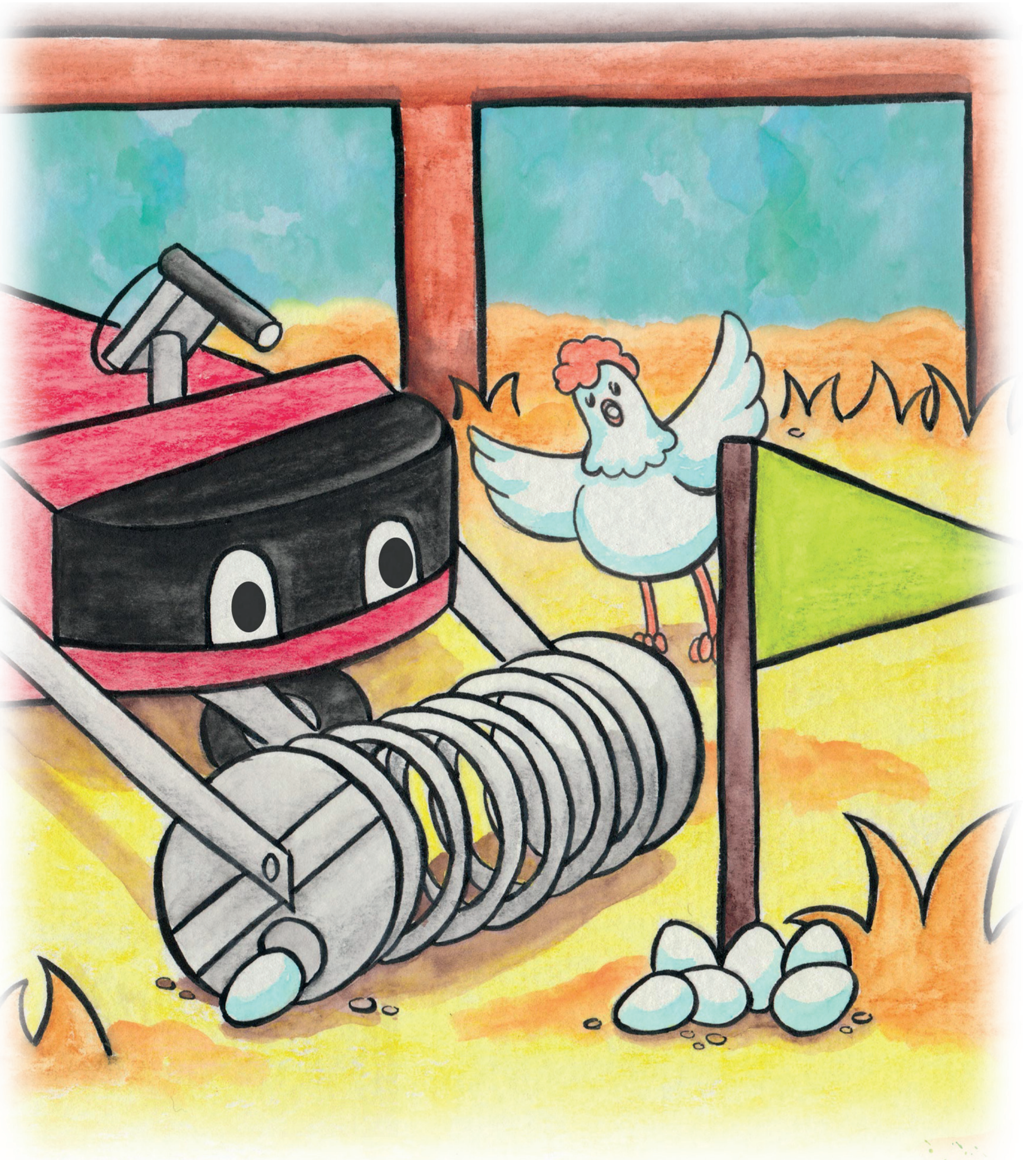

Chapter 5

Performance evaluation of PoultryBot, an autonomous mobile platform for poultry houses

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5

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Abstract

Observations of animal status, house conditions and manually collecting floor eggs are major daily tasks of poultry farmers. To assist the farmer in these tasks, PoultryBot, an autonomous mobile robot for use in poultry houses is proposed. In previous work, several components of PoultryBot were discussed in more detail. Here, component integration is described and performance of PoultryBot is evaluated under practical conditions. For navigation, different paths were used to assess PoultryBot's navigation performance for various tasks, like area sweeping and surveying close to walls. PoultryBot proved capable of navigating autonomously through the area over more than 3000m, while avoiding obstacles and dealing with the hens present. The robustness of the navigation performance was tested by confronting PoultryBot with obstacles on different positions with respect to its path and using different settings of the navigation parameters. Both factors showed clear influence on PoultryBot's driving behaviour.

For floor egg collection, performance in detection and collection of eggs was assessed on 5 predefined egg positions lateral to the robot path. Over 300 eggs were tested, of which 46% were collected successfully, 37% were not collected successfully, and 16% were missed completely. The most observed failure was the collection device being placed just next to the egg, which can be solved by improving the control algorithm. These results clearly prove the validity of the PoultryBot concept and the possibility of autonomous floor egg collection in commercial poultry houses. Furthermore, they indicate that application of smart autonomous vehicles in dense animal environments is possible.

5.1 Introduction

In an era where automation and the use of robots keep growing, opportunities arise also to take over dull or dirty tasks in livestock farming. One of the major daily tasks of every (poultry) farmer, is observing and checking the health and well-being of the animals, and making sure all housing and control systems function properly. Due to an increase of farm scale, time available per animal for observational tasks decreased. At the same time, the behavioural freedom for the animals increased. This led to an increased need for flock observation and management, as animal status now has a larger impact on the production results. Having a mobile platform that moves autonomously among the animals all day long provides the poultry farmer with more and potentially more objective information about the animals and their environment.

Besides information gathering, there is a growing interest for automation of floor egg collection in modern animal-friendly loose housing systems for laying hens. Floor eggs originate from animals that prefer to lay their eggs on some other place than the provided nest space, such as the housing floor. Based on extensive research (like Blokhuis and Metz 1995, van Niekerk and Reuvekamp 1997, Froehlich and Oester 2001, farm management improved a lot in recent decades. Combined with improved animal training, this greatly reduced the number of floor eggs.

When proper animal training and management of the farmer are applied, these floor eggs still account for 0.1 to 2 percent of the daily production. In extreme cases, the number of floor eggs can even increase to 5 or 10 percent of total egg production. In all cases, the required manual collection of these eggs puts a significant load on the daily activities of the farm's staff (Blokhuis and Metz 1995, Claeys 2007).

In the project Automation for Poultry Production at Wageningen University, PoultryBot, the first autonomous poultry house robot, was developed to aid the poultry farmer in his daily work in the modern aviary poultry house. More specifically, floor egg collection was used as an example case in the development and evaluation of PoultryBot. For floor egg collection, PoultryBot should move freely throughout the whole poultry house, while being aware of its location in the poultry house and nearby obstacles. Furthermore, the robot should be able to detect and collect floor eggs, regardless of their location in the poultry house.

Several other applications exist where robots were freely acting in a complex environment, including interaction with dynamic objects such as humans, animals or plants. For example, Rhino and Minerva acted as tour guide in musea (Burgard, Cremers *et al*. 1999, Thrun, Beetz *et al*. 2000), while Spencer guided passengers in an airport terminals (Triebel, Arras *et al*. 2015). Also in the agricultural domain, which is characterized by its complexity and limited structure (Nof 2009), significant effort was spent on autonomous robots for field work (Bakker 2009, Hiremath, Evert *et al*. 2012, Deepfield Robotics 2016) but also in orchards or greenhouses (Bac, van Henten *et al*. 2014, Bayar, Bergerman *et al*. 2015, Shalal, Low *et al*. 2015a, Shalal, Low *et al*. 2015b). Several of the methods used in these robots can also be considered useful for PoultryBot, such as the particle filter for localisation and the vision approaches used for fruit detection in horticulture (van Henten, Hemming *et al*. 2002, Bac, Hemming *et al*. 2013). Their applicability in the challenging environment of an aviary poultry house, however, still had to be proven.

With respect to livestock farming, some applications of (simple) autonomous vehicles with fixed paths are used in dairy husbandry (Lely 2015). In the domain of intensive animal production, a few research activities exist, such a student project at KU Leuven (Aertsen, Bauweleers *et al*. 2012), some preliminary investigations on a mobile monitoring robot from Australia (Qi, Brookshaw *et al*. 2013, Qi, Zhou *et al*. 2013) and a project on monitoring animal health and well-being using mobile and aerial robots at Georgia Tech. PoultryBot differentiates itself from previous examples by: 1) having more advanced systems for localisation and navigation, such that it can move freely and goal-driven throughout its environment; 2) being able to detect and interact with objects of interest; 3) a test of the whole integrated system in a real poultry house.

Previous work introduced the concept of PoultryBot, and described and evaluated several of its main features. In Vroegindeweij, IJsselmuiden *et al*. (2016), a localisation system based on the particle filter approach (Thrun, Beetz *et al*. 2000, Thrun, Burgard *et al*. 2005) that originated from museum robot Minerva, was described and evaluated in a poultry house without hens. Vroegindeweij, van Willigenburg *et al*. (2014) addressed the problem of path planning for the collection of floor eggs by presenting a new algorithm for non-uniform repetitive area coverage, as to the best of our knowledge, no such method existed at that time. Based on the use of multispectral features for fruit detection in harvesting robots from horticulture (van Henten, Hemming *et al*. 2002, Bac, Hemming *et al*. 2013), in (Vroegindeweij, van Hell *et al*. 2018), an approach was presented and tested for the discriminating between the various object types in the poultry house that are relevant for the functioning of PoultryBot. Finally, in Vroegindeweij, Kortlever *et al*. (2014), a description and evaluation of an actuator for floor egg collection is given. While individual aspects of this robotic system have been tested, to really prove that the proposed concept and methods work, they have to be tested in an integrated manner under (near) practical conditions.

The objective of the current paper is to describe the integration of the required components and to evaluate the performance of PoultryBot. As an initial performance benchmark, a number of requirements for a future implementation of PoultryBot in commercial poultry houses can be indicated. First, the robot should be able to operate autonomously, such that human intervention of the farmers are hardly required. To achieve this, it should drive collision-free through the poultry house, while being capable of handling various path types, such as traversing large areas to move from spot to spot or driving close to a wall to reduce floor laying in these areas. Furthermore, as object density in the poultry house is high and floor eggs can be found close to obstacles, PoultryBot should be able to closely approach obstacles without colliding with them. As PoultryBot's given path is task-oriented, this path should be followed as much as possible, with the freedom to avoid obstacles when required for safe navigation. Regarding its localisation result, an error of less than 0.1 meter for 95% of the time is desired to match the collected information to the correct physical location for mapping purposes. For floor egg collection, PoultryBot should detect at least 95% of the eggs present in its vicinity, with less than 5% of its detections being a false positive. Furthermore, all detected eggs within 1 meter from PoultryBot should be collected, irrespective of their location.

To determine to which degree PoultryBot could comply with these requirements, PoultryBot's capabilities were evaluated under real-life conditions (including the presence of live animals) in a test environment similar to a poultry house. Besides PoultryBot's performance, also the limitations and bottlenecks of the current approach were investigated. The remainder of this publication is organized as follows. Section 5.2 describes PoultryBot and its components. In Section 5.3 the experimental environment is detailed. In the first part of the evaluation, Section 5.4, autonomous navigation in a poultry house was tested, as core capability of PoultryBot. In the second part, Section 5.5, autonomous egg collection was evaluated as application of PoultryBot. Section 5.6 combines the observations of Sections 5.4 and 5.5 and adds a more general interpretation of the results. Section 5.7 draws conclusions and gives indications for future work.

Figure 5.1: PoultryBot among hens in the test environment

5.2 Robot configuration

This section describes the configuration of PoultryBot used during the experiments. This also includes a description of the core methods used for localisation, path planning, object detection and navigation. Finally, the resulting behaviour of PoultryBot for navigation and egg collection is described. PoultryBot itself is shown in Figure 5.1, while present in the test environment among the hens.

5.2.1 PoultryBot platform

PoultryBot (Figure 5.1) is based on the EyeSonic and SmartTrike field robots (Wageningen University 2009, Aelfers, van Esbroeck *et al*. 2015, SmartTrike 2015), and is about 1.1 m long, 0.45 m high. PoultryBot's width varies between 0.3 at the rear end and 0.55 m at the front and is not symmetrical around its length axis. For stability and to overcome uneven and loose surfaces, PoultryBot has 3 driven pneumatic wheels, of which 1 is also steered, all controlled by 2 Roboteq AX3300 motor controllers. For registering the robot's behaviour and its environment, sensors including the HEDL 5540 wheel encoders, an Xsens MTi-300 motion tracker, a DMK 23UX174 camera, and a Sick LMS 111 laser scanner were mounted on the platform. The laser scanner was placed at 0.37m above the ground. This position reduced the number of detections representing hens while at the same time the overall height of the platform remained within the height limitation of 0.45m imposed by the poultry house interior. Power was supplied by a set of batteries, with a 12 volt pack for the electronics and sensing and a 24 volt pack for the motors.

As the main task of PoultryBot is collecting floor eggs, a bended helical spring was mounted in front as collection device (see Figure 5.1). A detailed explanation and performance evaluation of this device (with over 95% of the eggs successfully collected) is given in (Vroegindeweij, Kortlever *et al*. 2014). A drive motor was added to rotate the collection device, to both improve the collection results and to facilitate unloading. To increase manoeuvrability, a lifting mechanism was included to lift the collector when no eggs had to be collected. The collection device itself was controlled using a Roboclaw 2x15A motor controller.

The on-board PC, running Windows 7 and NI LabVIEW 2013, was used to communicate with all peripherals, process incoming data and issue control commands. A distributed architecture performed all acquisition, processing and sending of information in parallel, and always made the most recent data available. Some computationally intensive operations (like the raycast in the localisation method) were performed using a C++ library. Data acquisition and processing speed was set to 10 Hz for most components, except for those having a safety-critical task which ran faster, namely at 20 Hz. Furthermore, all data from all sensors was logged at 10 Hz, together with data like the estimated location and the speed commands for the wheels.

5.2.2 Localisation method

Localization of PoultryBot was done using a particle filter (Vroegindeweij, IJsselmuiden *et al*. 2016), which was based on (Thrun, Burgard *et al*. 2005). In a particle filer, the pose of the robot is represented by a set of particles in the environment, with each particle containing a possible value for location and orientation of the robot. In each iteration of the algorithm, for each particle first a new position is predicted using information on the robot's displacement. This is followed by an update step, which evaluates for each predicted pose the correspondence between an actual measurement of the robot's environment applied to the predicted pose and a map of the robot's environment. Using the degree of correspondence as a measure of the likelihood of each particle's pose, a new set of particles is sampled from the current set of particles, which then describes the new pose estimate of the robot.

In our implementation, the prediction step used a combination of the best available information from odometry (encoder) data of all 3 wheels and the orientation data from the Xsens MTi 300. Data from all sources was checked on availability and reliability, and the most reliable source was selected. If multiple reliable sources were present, a Kalman Filter on displacement and rotation was used to fuse all reliable data into a single displacement prediction. During testing, this approach proved robust against internal communication failures and significant slip of individual wheels. The update step incorporated data from the Sick LMS 111 laser scanner. Data from the laser scanner were matched to a raycast on a pre-defined map of the poultry house containing all fixed obstacles in the environment. As this method explicitly accounted for the possibility of random and shorter-than-expected distance readings, the presence of hens in the environment did not cause any problems. For the update step, the settings for the 'beam model' from Vroegindeweij, IJsselmuiden *et al*. (2016) were used. Despite these settings were based on a situation without hens in the environment, they showed the best performance during initial testing in the experimental environment with animals, and were therefore used in this research as well.

5.2.3 Path planning

In Vroegindeweij, van Willigenburg *et al*. (2014), a method was described for coverage path planning for the collection of floor eggs. The resulting path consists of a set of waypoints. As this path planning method did not account for the kinematics of the robot, the resulting paths contained waypoints 0.4 m apart, some of them connected by sharp turns. Initial tests under practical conditions showed PoultryBot had severe difficulty in following such paths, and thus it was decided to use simpler, (manually defined) paths for the experiments in this work. These also consisted of waypoints, but now placed further apart while avoiding sharp turns. Adapting the method in (Vroegindeweij, van Willigenburg *et al*. 2014) and/or post-processing the path for this purpose is expected to produce paths the robot is capable of following and is a topic for future work. Detailed on the paths used in the experiments are given in the description of the experimental evaluation, in Sections 5.4.1.1, 5.4.2.1, and 5.5.1.

5.2.4 Object detection

Detection of objects relevant for the functioning of PoultryBot was done at multiple levels, depending on the purpose. For navigation, (large) objects surrounding the robot were registered by the laser scanner. Subsequently, their locations were fed into the navigation algorithm, and used in determining speed and steering commands, as described in section 5.2.5. For floor egg detection, a DMK 23UX174 monochrome camera with a 470 nm band pass filter attached to a lens with 5 mm focal distance was used. The image processing pipeline was based on (Vroegindeweij, van Hell *et al*. 2018). Additional filtering on object shape and size was added to improve the performance for egg detection. Using calibration images, first the vignette effect originating from the combination of lens and wavelength filter was corrected, using the method of (Zheng, Yu *et al*. 2008). Next, pixels likely to correspond to eggs were selected using a threshold, as they had the highest intensity values. Using multi-stage morphological processing on size, shape and position, blobs expected to represent eggs were segmented from the image. Finally, for each blob found its global position in the environment was determined using the pose estimate of the robot and a calibration of the camera based on the homography matrix (Wang, Hu *et al*. 2004, Dubrofsky 2009). For each detected egg, its estimated global position was used to control the egg collection, by adding special waypoints for navigation during egg collection.

5.2.5 Navigation and driving

To convert the globally planned path (consisting of waypoints) into motions while accounting for all obstacles present, the navigation method as described by Schlegel (1998), was implemented. This method allows for close approximation of obstacles as it uses the exact robot contour, instead of the commonly used circular approximation. Furthermore, it considers both forward and backward movements and allows for online adaptation of the goal position when new target locations like waypoints for egg collection emerge. Since PoultryBot is a relatively large and rectangular-shaped robot operating in a dense environment, such a method is needed for proper manoeuvring through narrow passages and collection of eggs at all possible locations (including corners and next to obstacles).

In the method of Schlegel, each combination of robot speed and steering angle that is allowed from a kinematic perspective is converted into a curvature that describes the related robot trajectory. Next, a robot-based obstacle grid is used to pre-calculate the available free space for each possible combination of obstacle location and allowable curvature. For each iteration of the navigation algorithm, the obstacle grid is filled with the current location of obstacles with respect to the robot. As the obstacle grid can be filled from any source, combining information from a map and distance sensors becomes a trivial task. For PoultryBot, the information on pre-defined map obstacles and the most recent reading of the laser scanner were used to fill the obstacle grid.

Next, from all curvatures that were allowed given the current obstacle presence, vehicle speed, and driving direction, the most suitable control option was selected using a heuristic. This heuristic weighed for each allowed control option the normalized values for free distance ahead, heading towards the goal position, the closeness to obstacles and goal position, and speed. The highest weight was for "heading towards goal" (which was thus favoured most), followed by "free space" and "avoiding obstacles", while speed and goal approximation were less important. The result was a driving behaviour that tended to steer PoultryBot quite directly towards the target position, but sometimes had difficulty to avoid obstacles, especially if the target position was further away.

5.2.6 PoultryBot's driving behaviour

Combining the elements for localisation, path planning, navigation, and object detection into PoultryBot led to a driving behaviour that can be described as follows. After switching to autonomous mode at its start position, PoultryBot drove from waypoint to waypoint, which had to be passed within a given distance and in a specified direction. While driving, PoultryBot tried to avoid the obstacles present, based on mapped locations of fixed obstacles and distance readings towards obstacles from the laser scanner. Given its current position, the next waypoint and the information on obstacles positions, Poultrybot searched for the direction towards its goal which could be followed for the longest period of time. Although obstacles should be avoided, PoultryBot was allowed to approach them closely if they were densely present in the direction of target waypoint, as long as no collisions occurred. PoultryBot stopped driving at the last waypoint if no more waypoints were available, or when manually halted. A flowchart of this behaviour is shown in the left half of Figure 5.2.

For egg collection, the same driving behaviour was used, but with additional steps for egg collection integrated into the driving behaviour, as shown in the right half of Figure 5.2. If an egg was detected at a new location, two new waypoints were inserted to the waypoint list: one before and one after the egg. When PoultryBot reached the waypoint before the egg, driving was halted and the collection device was lowered. Next, PoultryBot slowly drove towards the waypoint after the egg, while rotating the collection device and attempting to collect the egg. If the waypoint after the egg was reached, driving was halted again and the collection device was lifted. Then, navigation was continued as before, until another egg was found. If eggs were close together or new waypoints were near existing waypoints, the waypoints controlling their collection were fused to simplify driving.

This behaviour does not cover all situations in practice, such as autonomously stopping or reversing direction if a collision is about to happen. In the experiments, these situations were handled by switching to remote control (a human operator controlling the robot) in case of a collision, and retracting PoultryBot a small distance, while applying a steering correction when required. After that, control was switched back to autonomous mode, allowing PoultryBot to continue the planned path by itself. If necessary, this procedure was repeated several times until PoultryBot moved around the obstacle, or in case PoultryBot could not resolve this situation, it was moved away from the obstacle by remote control.

5.3 Experimental environment

PoultryBot's functional environment, a commercial aviary poultry house, has a number of specific characteristics relevant for correct function of a mobile robot. First, metal construction elements provide facilities to the animals that live there, and act as a densely distributed but fixed set of obstacles, with elements sometimes no more than 1.2 m apart. Second, the housing interior is designed with the size of the animal in mind. Free space below interior elements exists and is used as living area for the animals. This constrains the free height above the floor to less than 0.5 m. Third, the uneven layer of loose litter on the floor hampers smooth driving.

Fourth, enrichment objects like roughage bins or pecking blocks are obstacles scattered around. Fifth, remaining free space is cluttered by tens of thousands of animals that move around at will. All this will clearly influence PoultryBot's sensing systems and navigation behaviour. Sixth, the air contains high concentrations of dust, vapour and ammonia. All these might adversely affect the functioning of both robot hardware and

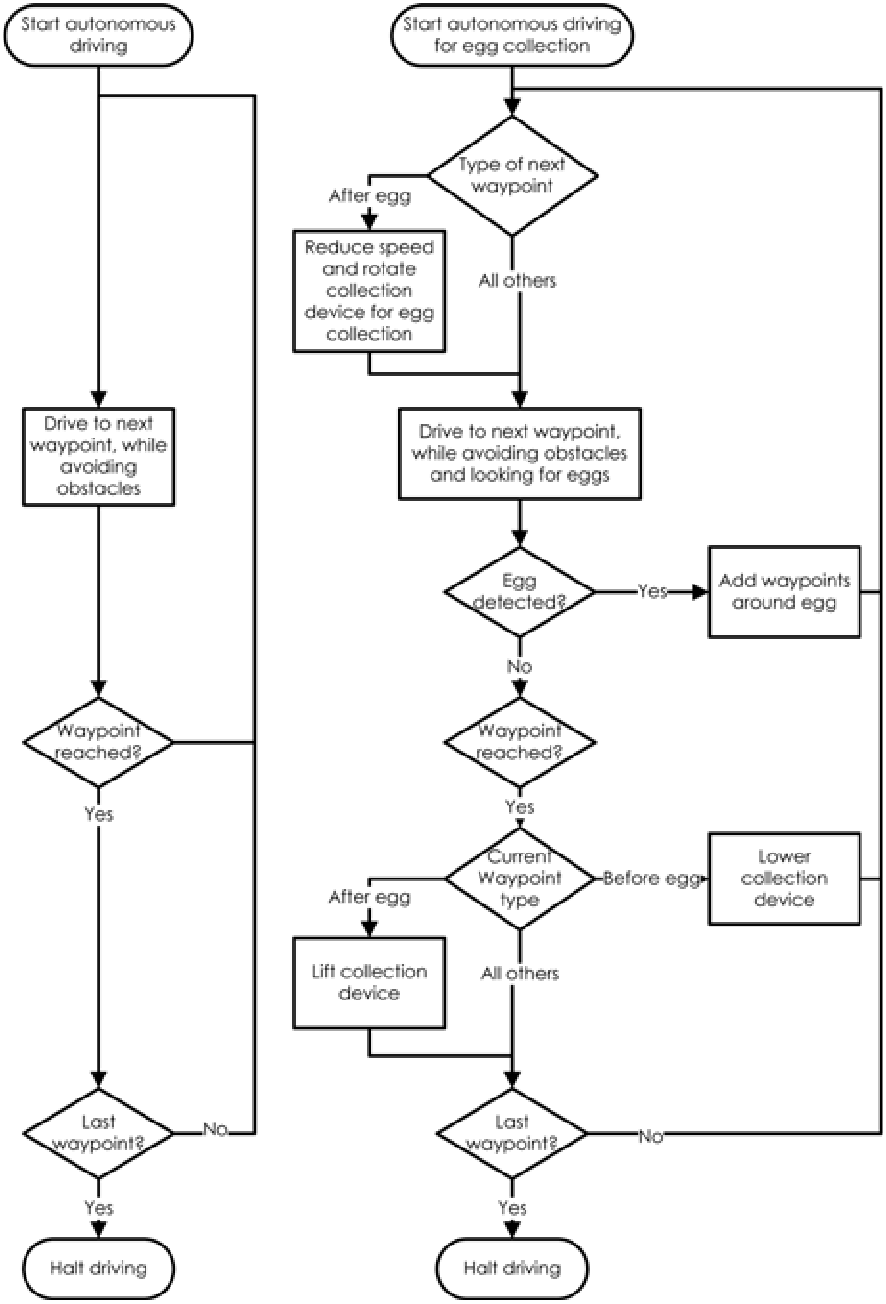

Figure 5.2: Flowchart of PoultryBot's driving behaviour. On the left, general driving behaviour is shown. On the right half, driving behaviour for egg collection is displayed.

sensing methods. The interior of a real poultry house is shown in the left part of Figure 5.3.

Although PoultryBot has to work in a commercial poultry house and several tests also were done there, it was decided to perform the final tests and evaluation described here in a smaller and more open environment. This environment simplified testing and experimental evaluation of PoultryBot's performance as settings and conditions could be varied more easily, while allowing a better view on PoultryBot's behaviour and easier assessment of error situations. In an area of 10 x 7 m, surrounded by 3 concrete walls and 1 wooden fence, 2 rows of housing interior were simulated with a wooden construction. In this area, 150 white laying hens (Dekalb White) were housed. Four feeder bins were placed, distributed over the area. Two drinker lines were placed on one of the interior rows, about 1m away from the wall. Furthermore, below one end of this row, a laying nest was constructed. A picture of this environment is given in the right half of Figure 5.3, while a schematic overview can be found in Figure 5.4. Of the six challenging characteristics mentioned above, the first five were present:

- Main housing features like construction poles and walls,
- Scattered objects like feeder bins,
- Limited free height from the floor,
- Floor conditions were similar, with a layer of straw and litter on the floor,
- Animals (freely) occlude area, but at a lower density. Still, as they were used to the robot and eager to approach it, they clearly affected PoultryBot's behaviour.

Figure 5.3: Left: Interior of a commercial poultry house. Right: model of poultry house interior uses as experimental environment for testing and evaluating PoultryBot.

As a result, the conditions in this environment were representative for a commercial poultry house, especially from a robot's point of view.

5.4 Evaluating autonomous navigation

First, autonomous driving capabilities of PoultryBot were evaluated in two experiments, to test navigation durability and navigation heuristic properties. For this, robot performance was registered by logging robot data, such as position and speed, at a frequency of 10 Hz. Furthermore, an observer noted all relevant events, conditions and observations on driving behaviour. Each event or human intervention was given a reference number and its location, a description of the event (wall collision, hit pole) and the remotely controlled corrective action applied (continued driving, retracted and steered away) were noted. A human operated video camera (Sony DCR-SR78) was used to follow and record the behaviour of the robot, and it also registered all occurring events and comments made. Both the camera and observer were located on an elevated platform to provide a better overview of the scene, while the robot operator was

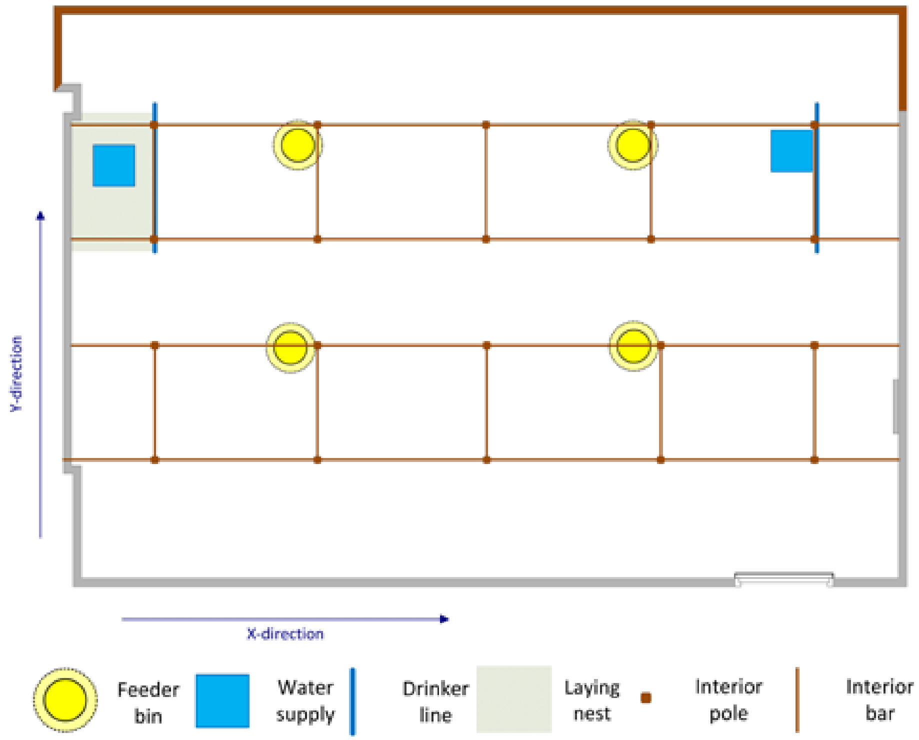

Figure 5.4: Sketch of the test environment. Yellow circles indicate feeder bins. Blue blocks + lines indicate water supply and drinker lines, while the hatched area indicates the laying nest. The brown squares and lines indicate poles and housing bars.

present in the test environment. Based on this information, performance could be evaluated in detail and causes and possible solutions for current problems or bottlenecks could be identified.

5.4.1 Experiment 1: Navigation durability

In the first experiment, the navigation capabilities of PoultryBot were tested over an extended period of time. Purpose of this experiment was to see how well the navigation performed under different conditions such as driving along a wall or traversing a large area, what kind of errors occurred, and if long-term application would lead to a change of behaviour. To excite and evaluate the behaviour of PoultryBot, path segments with different shapes and structures were applied. Furthermore, these path segments were repeatedly applied to see changes over time. It was expected that different conditions would show different robot performance with respect to the amount of control actions needed and the need for human interventions, but that this performance would remain constant over time.

5.4.1.1 Experimental outline

To identify changes due to long-term application, a closed tour was driven for a prolonged period of time, such that each path segment was traversed several times, with the duration of the experiment only being limited by available battery power. Since two sets of batteries were available, this experiment was executed twice, and the results will be referred to as the first and second tour. Each tour took about 1.5 hours to complete and consisted of 12 full cycles of the given path. The given path was constructed by placing 30 waypoints and connecting these using straight lines. It contained 5 clearly different segments, each representing a specific type of condition encountered in practice: Segment 1. Border navigation along the house wall (Blue); Segment 2. Diagonally traversing the house (Red); Segment 3. Sweeping the area, in lateral direction (Green); Segment 4. Diagonally traversing the house (Purple); Segment 5. Sweeping the area, in longitudinal direction (Yellow). The given path with the individual segments are indicated with the bold straight lines in Figure 5.5. Total length of the given path, measured as the Euclidian distance between the waypoints for a single cycle, was 94.2 meter. For proper referencing in this experiment, PoultryBot's location was also tracked using a Trimble S6 Total Station, to assess the accuracy of the localization method under these conditions. As using different path segments over extended timespans potentially increases the chance of failure, the accuracy of the localisation observed in this experiment also serves as upper limit for the localisation accuracy.

5.4.1.2 Analysing performance

The navigation performance of PoultryBot was analysed based on the observations of collisions and human interventions. All events were registered by the observer and divided into one of the following five categories to indicate the type of the intervention needed:

- Continued driving autonomously while touching an object;
- Human intervention using remote control, to retract PoultryBot once after a collision;
- Human intervention using remote control, to steer PoultryBot away from the obstacle once, such that it was set free after a collision;
- Human intervention using remote control, to retract and steer away once, to set PoultryBot free after a collision;
- Repeated human interventions using remote control to handle a collision.

Furthermore, the robot log data was used to calculate several performance metrics, including:

- Path length, measured by the sum of the Euclidian distance between the robot's consecutive position estimates;
- Rotation, measured by the absolute sum of the differences in consecutive robot orientation estimates;
- The number of steering events, defined by the number of changes in the steering angle issued to the motor controller;
- Operational time, given by the amount of time PoultryBot was in autonomous mode or in remote control mode (e.g. controlled by a human operator).

In this experiment, PoultryBot's behaviour was evaluated at path segment level. To allow fair comparison between path segments, all performance metrics (except for distance) and interventions were divided by the autonomously driven distance in that segment averaged over all cycles. Statistical inference was done using an Anova test, followed by a multiple comparison step using Fisher's protected LSD method in GenStat 18.1 to investigate differences between path segments.

5.4.1.3 Results and interpretation

Each cycle of the given path took between 6 to 8 minutes to complete, and covered a distance of around 100 meters, which is longer than the Euclidian distance between the waypoints in the given path. For readability, Figure 5.5 shows a subset of the position estimates obtained during the first tour. From this tour, every 10^{th} position estimate is shown for 2 consecutive cycles to illustrate the driving behaviour of PoultryBot. Also the shortest path connecting the waypoints is displayed by straight lines.

Figure 5.5 shows that PoultryBot drove quite well from waypoint to waypoint, especially when sweeping in longitudinal direction (segment 3, yellow) and driving along the outside border (segment 1, blue). It can also be seen that occasionally, PoultryBot deviated clearly from the given path, such as in the lower-middle part of the area. Here, PoultryBot properly deviated from the given path to avoid a collision with the pole present there, and after negotiating this obstacle returned to its given path. Also around segment 2 (in red), such behaviour was observed to avoid a collision with the feeder bin that was present on the first part of this segment. Also passing through narrow passages, such as between poles and walls at the left and right side of the area, did not present any difficulty for PoultryBot. Such actions indicate the ability of PoultryBot to handle the presence of obstacles and variation in the environment. Furthermore, all path segments could be handled by PoultryBot, indicating its capability of dealing with the various types of conditions encountered in practice, as indicated in the introduction of this section. From the observations, the hens present in the environment seemed to have only a small effect on PoultryBot's driving behaviour. They sometimes showed up in the laser data as obstacles, thereby causing PoultryBot to avoid them by steering away from the hens, but without large changes in driving behaviour. In general, behaviour remained similar over time, suggesting long-term application will not lead to an increase of navigation errors.

The localisation accuracy was evaluated over both tours (ground truth not shown). The Euclidian difference between positions estimated by PoultryBot and the reference measurement from the Total Station had a mean value of 0.127 m, with a 95 percentile of 0.319 m. The deviation in Euclidian distance was less than 0.1 m for 63% of the time. This is an improvement on the results in Vroegindeweij, IJsselmuiden *et al*. (2016), and also indicates that the desired accuracy indicated in that paper (<0.1 m for 95% of time) is within reach.

Logged human intervention and robot data are given in Table 5.1, as the mean value with standard deviation over all 24 cycles of the path. Values are separated into the 5 path segments, and all metrics except for distance were corrected for the average distance driven to allow fair comparison. Also here, having driven distances larger than waypoint distances is not necessarily bad, as they might indicate that PoultryBot deviated from its given path to avoid the obstacles present, although they can also result from poor path tracking. Robot speed was similar for all segments (about 0.28m/s) and not included in Table 5.1.

Length of given path differed between segments, with the diagonal traversals (segments 2 and 4) being the shortest (7.3 and 14.8 m) and the border navigation (segment 1) the longest. Compared to this, driven

distance was less than the length of the given path for the border navigation (26.1 vs. 26.3 m), while for other segments it was up to 10% longer than the given path. This difference might relate to the structure of the border navigation segment, where turns are always in the same direction
and with a limited need to avoid obstacles. Thus a slightly shorter path was used here, in contrary to the other segments, which contained more turns and obstacle-avoidance manoeuvres. For the first diagonal traversal (segment 2), the distance driven by remote control was highest (0.8 m) compared to both the segment length and the other paths. Also the second diagonal traversal (segment 4) and the lateral sweeping (segment 5) had higher remotely controlled distance (0.6 m), which indicates that stronger human interventions were needed on these segments. The largest

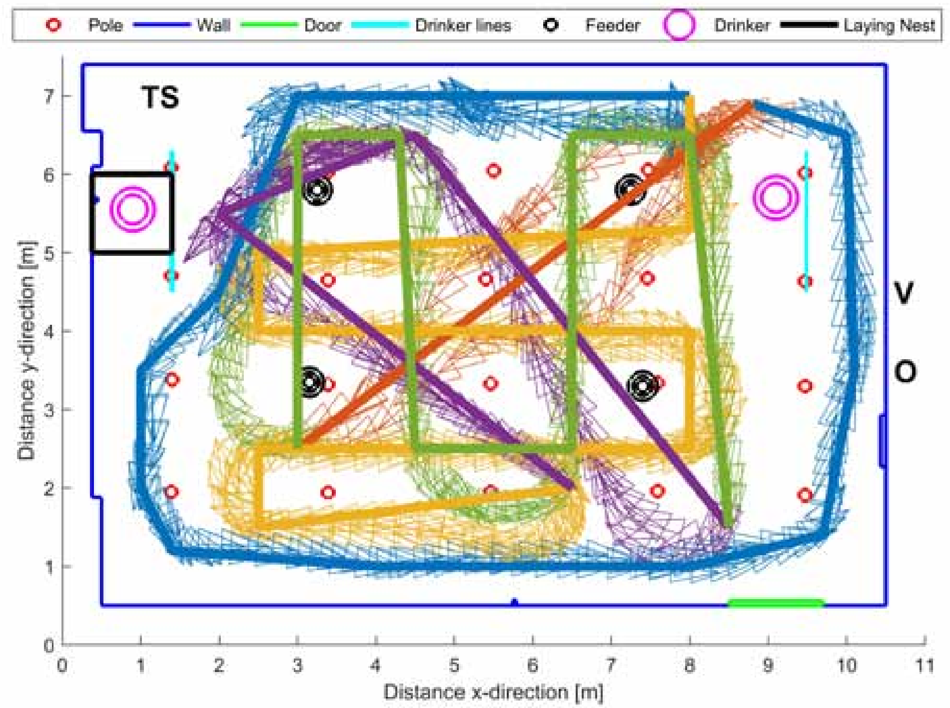

Figure 5.5: Result of two cycles from the first tour of experiment 1. The triangles indicate each 10th estimated robot position, with the colour relating to the path segments. Blue is segment 1 with border navigation, orange and purple are diagonal traversals (segments 2 and 4), and green and yellow are longitudinal and lateral sweeping (segments 3 and 5). The straight lines indicate the shortest lines between the waypoints, with each colour representing a different path segment. TS indicates the position of the total station, V and O the positions of video camera and observer on the elevated platform.

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platform rotations were observed while sweeping longitudinally (segment 5, 0.71 rad m^{-1}) and laterally (segment 3, 0.72 rad m^{-1}), followed by the second diagonal traversal (segment 4, 0.66 rad m^{-1}). A clear relation with path structure can be seen, as the given path also contained the largest rotations (0.5 rad m^{-1}), and the resulting rotation is only 30 to 40% higher than the rotations required to fulfil the given segment. When considering actual platform rotations compared to the required rotation for the given path, segment 2 has most rotations, being almost four times higher than needed for the given path. This high level might be attributed partly to the presence of a feeder bin on the beginning of this segment. In the number of steer events, no relation with path segment type is visible, indicating that larger rotations were more likely the result of distinct turns than of frequent small steering corrections.

Most interventions took place in the diagonal traversal (segments 2 and 4 with totals of 114.8 and 64.6 interventions per 1000 m), while the longitudinal sweeping (segment 3) had fewest interventions (20.0 interventions per 1000 m). This was most likely the result of the waypoints in segment 3 placed in between the housing poles, such that the path was merely obstacle-free, while the diagonal traversals required the explicit avoidance of obstacles. When excluding the ‘Continue’ events, the lateral sweeping (segment 5, 43.9 interventions per 1000 m) performed similar to the second diagonal traversal (segment 4, 56.8 interventions per 1000 m), while the border navigation (segment 1, 22.35 interventions per 1000 m) showed similar behaviour as the longitudinal sweeping (segment 3, 18.5 interventions per 1000 m). Also here, the larger need for intervention at segments 4 and 5 compared to segments 1 and 3 might be related to the number of obstacles that were encountered by PoultryBot on these segments. Minor interventions like ‘Continue’ (keep driving while hitting obstacles) or ‘Steering away’ were most seen during the border navigation segment (segment 1, 25.5 and 4.8 interventions per 1000 m respectively), possibly as result of collisions with the wall. Stronger interventions, like ‘Retract and steer away’, were mainly found at diagonal traversals (segments 2 and 4), while ‘Retract’ actions were also found more in the lateral sweeping (segment 5) but with substantial variation between cycles. The most serious cases, where ‘Multiple’ interventions were required to solve collisions, were mainly seen at the first diagonal traversal (segment 2, 47.0 interventions per 100 m, $p<0.000$), which also had by far the highest number of interventions (114.8 interventions per 1000 m).

This high number of interventions can be explained from the navigation algorithm, where reaching the goal had a higher weight and thus obtained

Table 5.1: Quantitative results of experiment 1, testing long-term navigation performance. Numbers are average values over 24 cycles of the given path, with standard deviation in brackets. Measured values are as given, rotation data and interventions are expressed respectively per meter and per 1000 meter autonomously driven path length. Different superscripts indicate statistical difference at $p<0.05$ using Fisher's protected LSD.

Measured distance, as mean with SD

Path segment	Waypoint distance (m)	Autonomously driven(m)	Remotely controlled driven(m)
1 Border navigation	26.3	26.1 (0.3)	0.2 (0.3)
2 Diagonal traversal	7.3	8.0 (0.6)	0.8 (0.8)
3 Lateral sweeping	21.8	23.7 (0.8)	0.6 (0.6)
4 Diagonal traversal	14.8	16.1 (0.5)	0.6 (0.7)
5 Longitudinal sweeping	25.2	27.0 (1.1)	0.3 (0.6)

Rotations per meter, as mean with SD

Waypoint rotation (radians)	Rotation (radians)	Steer events
0.27	0.56 (0.04) ^{b}	12.5 (1.0) ^{c}
0.13	0.13 (0.08) ^{a}	11.7 (1.7) ^{bc}
0.52	0.52 (0.05) ^{d}	12.1 (1.0) ^{c}
0.40	0.66 (0.05) ^{c}	10.8 (1.3) ^{a}
0.53	0.71(0.04) ^{d}	11.2 (0.8) ^{ab}

 # Interventions per 1000 meter, as mean with SD

Path segment	Continue Driving	Retract	Steer	Retract + Steer	Multiple Interven-tions	Total	Total except Continue
1 Border navigation	25.5 (37.8) ^{b}	11.2 (20.6) ^{ab}	4.8 (12.7) ^{a}	6.4 (18.1) ^{a}	0.0 (0.0) ^{a}	47.9 (48.5) ^{b}	22.3 (26.9) ^{a}
2 Diagonal traversal	5.2 (25.0) ^{a}	31.3 (54.2) ^{bc}	0.0 (0.0) ^{a}	31.3 (65.2) ^{b}	47.0 (60.6) ^{b}	114.8 (108.0) ^{c}	109.6 (97.8) ^{c}
3 Lateral sweeping	8.8 (21.0) ^{a}	33.3 (34.3) ^{c}	0.0 (0.0) ^{a}	8.8 (21.0) ^{a}	1.8 (8.4) ^{a}	52.6 (42.5) ^{b}	43.9 (41.2) ^{ab}
4 Diagonal traversal	7.7 (27.2) ^{a}	28.4 (35.7) ^{bc}	0.0 (0.0) ^{a}	20.7 (34.3) ^{ab}	7.7 (20.5) ^{a}	64.6 (52.1) ^{b}	56.8 (47.1) ^{b}
5 Longitudinal sweeping	1.5 (7.4) ^{a}	6.2 (17.4) ^{ab}	1.5 (7.4) ^{a}	3.1 (10.2) ^{a}	7.7 (23.8) ^{a}	20.0 (30.2) ^{a}	18.5 (30.2) ^{a}

more attention than avoiding obstacles. This frequently led to collisions, especially if an obstacle was close-by on the robot's path to a waypoint further away. Such conditions were indeed present at the start of the first diagonal segment, with an obstacle (feeder bin) being present in the most likely path of PoultryBot towards its next waypoint at the other end of the test environment. Alternatively, if obstacles were further away from the lines that connected the waypoints, navigation was fairly easy and both collision occurrence and the need for human intervention was lower. Also the field-of-view of the obstacle sensor played a role here, since in a number of cases obstacle collisions were observed just after the object has left the detection area. The presented results indicate that PoultryBot could handle various path types, but that path structure, especially the placement of waypoints with respect to obstacles, influenced the results.

5.4.2 Experiment 2: Heuristic effects

In experiment 1, obstacles placed on the shortest line between PoultryBot's position and its target waypoint frequently led to collisions. The second experiment therefore tested whether this relationship between obstacle location and waypoint placement indeed existed, by testing the effect of changing obstacle positions on the driving behaviour of PoultryBot. Furthermore, it was investigated if changing the settings of the navigation heuristic (as explained in Section 5.2.5), especially for the "heading to goal" behaviour, would lead to fewer collisions.

5.4.2.1 Experimental outline

A straight path A (green, see Figure 5.6) was defined by placing 2 waypoints in the longitudinal direction of the test environment, with construction elements on either side of the path (at a lateral distance of about 0.7m to the path). To see if driving behaviour changed when the path was closer to, and thus conflicted more with, these construction elements (obstacles), two additional paths B (orange) and C (red) were defined, also shown in Figure 5.6. To realize this, the waypoints were moved twice, in steps of 0.4m, towards the poles on one side of the path. In these cases, it was expected that either the robot would steer more to avoid the poles, or that the number of collisions would increase. Additional waypoints were used to allow autonomous return of the robot from the end point to the starting position thus allowing repeated execution of the path. This path is indicated by the purple line in Figure 5.6.

Next to moving the waypoints, also the weight factor for "heading to goal" (as defined in Section 5.2.5) in the heuristic was varied in this experiment. As all other weight factors ranged between 0.001 and 0.5, changing the "heading to goal" weight factor from its original value of 3 to 1 and 2 was expected to lead to more steering and better collision-avoidance by PoultryBot. For "heading to goal" weight factor values 2 and 3, each path was repeated 6 times. For a weight factor value of 1, each input path was repeated only 3 times, as during the experiment no clear reduction in the need for human interventions was seen with respect to results obtained when using a weight factor value of 3. Performance was evaluated only for the track between the first and last interior poles in longitudinal direction, which were 8.07m apart. Performance evaluation was done in a similar fashion as described for experiment 1, Section 5.4.1.2.

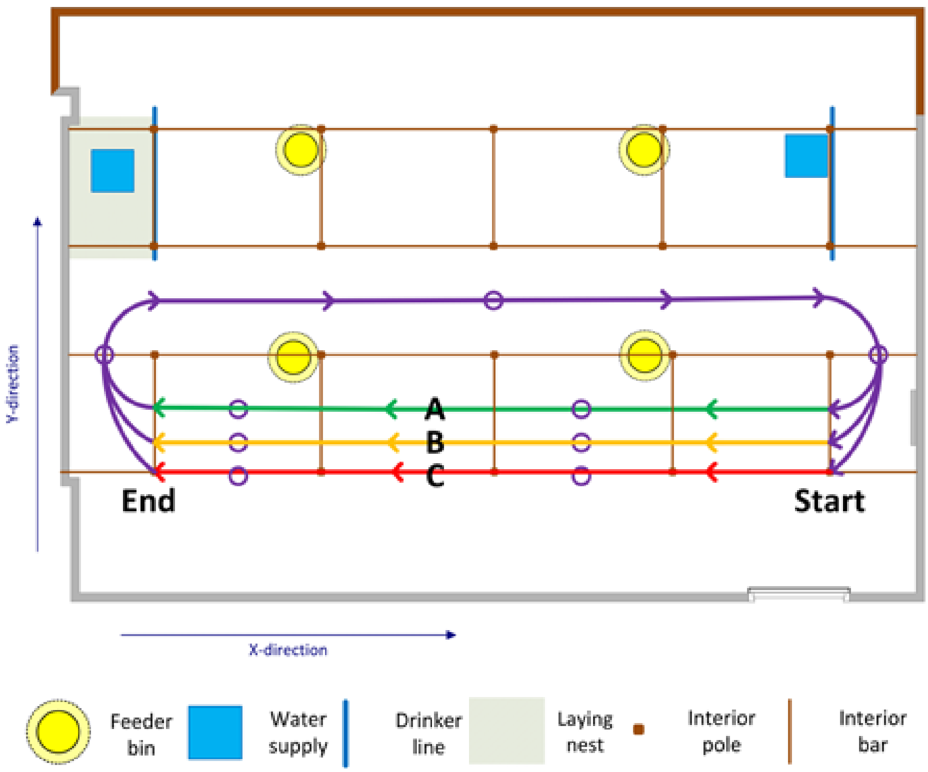

Figure 5.6: Paths for experiment 2, to evaluate the effects of obstacle locations with respect to PoultryBot's path on the driving behaviour of PoultryBot. Waypoints (purple circles) were placed on varying positions A, B, and C with respect to the interior elements. The green, orange and red lines indicate the shortest path between Start and End along the waypoints for trajectories A, B and C. The purple line indicates the path used by PoultryBot for autonomous return from the end-point to the start-point.

5

5.4.2.2 Results and interpretation

An overview of the results is given in Table 5.2, showing the mean and standard deviation of all data obtained from the robot's log file, grouped by weight factor and path. In Table 5.3, the type and number of interventions are given per combination of weight factor setting and given path.

Positioning the robot path such that it conflicted more with obstacles and thereby becoming more complex, increased path length and time required for path completion up to 20 percent (e.g. from 8.16 for path A to 9.74m for path C when using weight factor 3, Table 5.2). Also the amount of steering increased, independent of the weight factor for the "heading to goal"-behaviour. This is visible in Table 5.2 for paths B and C showing more platform rotations and more steering events than path A for all values of the navigation weight factors. For the driven distance, this increase is also clearly significant, when comparing path A to B ($p=0.002$) or C ($p=0.009$), for all settings of the "heading to goal" weight factor. Furthermore, the number of interventions due to collisions increased clearly (Table 5.3), from 1 to 11 for weight factor 3 and from 6 to 13 for weight factor 2, if the

Table 5.2: Autonomous driving results of experiment 2, evaluating the effect of changing the weight factor for "heading to goal"-behaviour and the obstacle placement with respect to PoultryBot's path on the navigation performance of PoultryBot. Data are presented per combination of given path and heuristic setting, and expressed as average with standard deviation over all repetitions.

Autonomous driving

	Weight factor	Path	Repetitions #	Distance (m)		Rotation (rad)		Steer events (#)		Time (seconds)	
				mean	SD	mean	SD	mean	SD	mean	SD
More goal-oriented	3	A	6	8,16	0,05	2,97	0,39	116,3	12,5	26,7	0,5
	3	B	6	8,31	0,10	3,62	0,61	110,8	11,0	28,0	0,9
	3	C	6	9,74	1,38	5,68	0,93	144,3	37,5	37,7	8,8
	2	A	5	8,74	0,60	4,80	1,50	122,6	6,0	32,0	6,0
	2	B	6	8,60	0,66	3,96	1,20	117,8	11,7	30,3	4,0
	2	C	6	9,28	0,44	5,29	0,83	128,5	19,8	35,3	5,2
Less goal-oriented	1	A	3	9,09	0,95	5,97	2,55	110,3	5,7	28,8	1,0
	1	B	3	9,99	1,72	7,21	1,02	160,7	46,6	35,9	8,9
	1	C	3	10,70	1,67	6,29	1,47	151,3	21,0	41,0	8,9

obstacles were positioned more into the robot path. In the type of interventions no clear change can be observed, indicating the interventions to resolve collisions did not become more complex when obstacles were positioned more into the robot path. All of this matches with expectations and the results of the previous experiment, as obstacles on the way of PoultryBot will force it to steer around them, thus increasing time, distance and steering required, as well as the risk for collision. Furthermore, obstacles closer to the robot contour showed only a limited effect, whereas obstacles present in the middle of the robot path caused clear changes in results.

When modifying the weight factor for “heading towards goal” in the heuristic, a decrease of the weight factor seemed to produce longer robot paths (Table 5.2), although effects were smaller compared to that of changing the path. Already with no obstacles (except for hens) present in front of the robot (path A), path length increased with 10 to 15 % when changing the weight factor, e.g. from 8.16 to 8.74 m for a weight factor change from 3 to 2. The total rotation of PoultryBot (in radians) also showed a similar increase, whereas effects on the number of steer events and the

Table 5.3: Intervention results of experiment 2, evaluating the effect of changing the weight factor for “heading to goal”-behaviour and the placement of obstacles with respect to PoultryBot’s path on the navigation performance of PoultryBot. Interventions are presented per combination of given path and heuristic setting, and given as total over all repetitions.

				Interventions						
	Weight factor	Path	Repetitions #	Detour # total	Continued # total	Retract # total	Retract + Steer # total	Multiple # total	Total # total
More goal-oriented	3	A	6	0	0	0	0	1	1
	3	B	6	0	1	1	0	0	2
	3	C	6	2	1	2	2	4	11
	2	A	5	3	1	0	1	1	6
	2	B	6	3	0	2	0	0	5
	2	C	6	4	1	6	2	0	13
Less goal-oriented	1	A	3	3	0	1	0	0	4
	1	B	3	1	0	3	0	1	5
	1	C	3	3	0	3	1	0	7

required time were found to be less clear. Such behaviour seems logical, as with a lower weight for "heading to goal" driving will be less target-oriented, and thus searches more for available free space between objects such as construction elements and hens present in PoultryBot's vicinity. If obstacles were present in the robot path (like path C), the effect of changing the weight factor was smaller and sometimes even opposite, as this path already required more steering. Still, a significant difference in path length was found between a weight factor of 3 and a weight factor of 1 (p=0.006) and 2 (p=0.016) for the "heading to goal"-behaviour. In terms of interventions (Table 5.3), it can be seen that lower weights lead to more detours, where PoultryBot instead of passing between the poles, drove around them. Also, lower weights seemed to require less interventions, especially for the 'multiple'-case. However, this trend was not consistent and sometimes an increase in the number of interventions was seen, so no hard conclusions can be drawn here.

These results showed that the position of obstacles on the path and the setting of weight factors for the heuristic had a clear influence on the driving behaviour of PoultryBot. Moving the robot path closer to obstacles increased both path length and steering behaviour and led to more collisions. Changing the heuristic settings to less goal-oriented behaviour led to longer paths with more steering and a tendency of having fewer collisions with obstacles. This indicates that further tuning of the navigation heuristic can be useful to improve the navigation performance of PoultryBot.

Furthermore, attention is needed for handling obstacle collisions. Currently, these were handled using remote control by the operator, but for autonomous operation these collisions either have to be avoided or solved autonomously. This requires for instance the implementation of automated collision detection and reverse driving behaviour, and possibly also adaptation of the navigation behaviour. Once such solutions are added, this will likely solve most or all of the cases that currently required human intervention, bringing PoultryBot close to fully autonomous operation.

5.5 Evaluating egg collection performance

After testing PoultryBot's navigation capabilities in the previous section, also the egg collection performance was evaluated. In previous work (Vroegindeweij, Kortlever *et al*. 2014) the collection device itself was evaluated in detail. This experiment assessed the egg collection capability of PoultryBot. As previous research indicated that the collection device had difficulty to collect eggs in corners, those locations were not considered in this experiment.

During egg collection, a video camera (Sony DCR-SR78) was positioned in line with the robot's path, to register PoultryBot's behaviour. Furthermore, a GoPro camera mounted to the robot registered a close-up of the egg collection device. In the measurement notes, all egg detections and collection operations were registered. Subsequently, the egg's location (if known) was registered, together with detection and collection results. Furthermore, relevant information like start time of a run, camera and algorithm settings, and specific behaviours and observations were noted as well. All this information was used to evaluate performance of detection and collection in more detail, but especially to indicate causes and possible solutions for current problems or bottlenecks.

5.5.1 Collection procedure

For the evaluation of floor egg collection, a repeatable procedure was used, based on a given path along one of the walls in the test environment. Each collection run was made along the wall in the longitudinal direction of the area, and consisted of 2 parts. In the first part, the wall was to the left of the robot, while in the second part the robot changed direction and had the wall on its right side. Between the two parts, the robot was turned around while driving using remote control by the operator. In each part of the collection run, 2 eggs were present, with the first one (longitudinal locations A and A') between the wall and the second pole, as seen from the start of this part, and the second one (longitudinal locations B and B') between the wall and the open space between the 3rd and 4th pole. To create a collection path that was similar for all eggs, the waypoints before and after each egg were placed in a straight line at about 0.7 m next to the wall and more than 1 m away from the egg.

Eggs were placed on a line perpendicular to this path, and five egg locations in lateral direction were individually tested: in front of the robot, on the robot's edges or outside the robot contour and close to the wall or poles. These lateral locations were numbered 1 to 5 when going from the wall to the pole. In each part of the run, both longitudinal locations (A and B) and a single lateral location were evaluated. Each combination of longitudinal and lateral location (indicated by a combination of the letter A or B and a number between 1 and 5) was repeated for at least 20 correctly detected eggs. In Figure 5.7, an overview of the experiment is given, showing the waypoints, the egg's longitudinal (A or B) and lateral (1 to 5) locations, and the expected driving pattern of PoultryBot.

In preliminary research, egg orientation prior to collection showed limited effects on collection success, as the egg rotates during collection under influence of floor structure and the collection device. Therefore, egg

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orientation was fixed with the egg's major axis aligned with the direction of PoultryBot's given path and their minor end towards the robot. As the hens present during the experiment exhibited egg-eating behaviour, hard-boiled eggs were used to reduce egg eating in case of egg breakage.

Weather conditions outside the building influenced the light intensity in the experimental area, making the use of a single fixed setting of the camera and detection method impossible. Thus, before each measurement series, camera and detection parameters were adapted to the amount of light present at that moment. In this way, the effect of ambient light on the detection and collection results was prevented as far as possible.

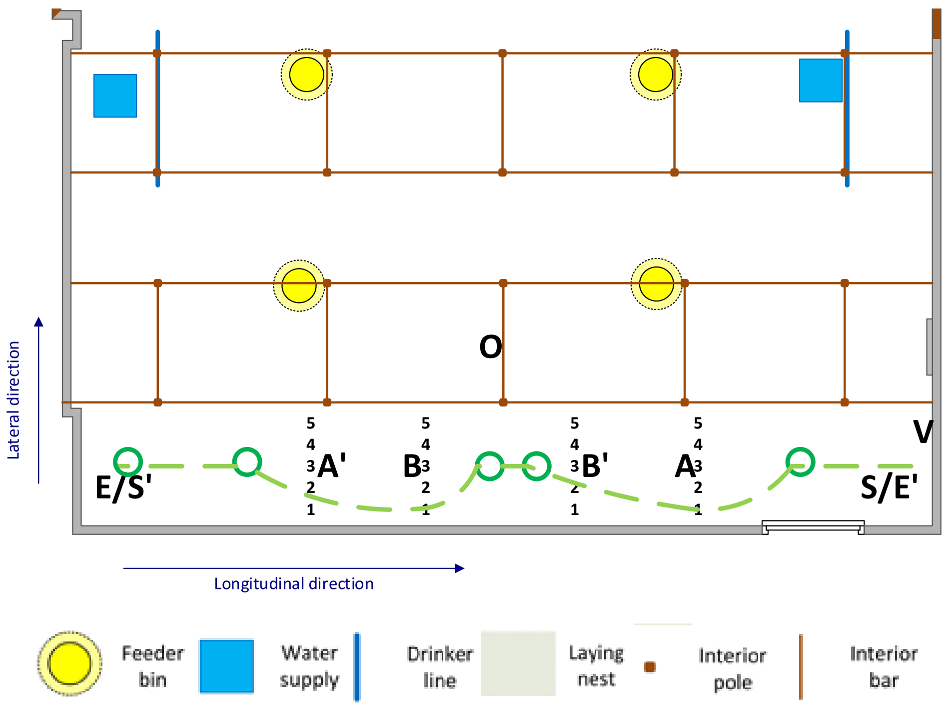

Figure 5.7: Egg locations and waypoints used in the egg collection evaluation. The numbers 1 to 5 indicate the egg locations in lateral direction, while capitals A and B indicate the location of an egg in longitudinal direction. O indicates the location of the observer, V indicates the location of the video camera used for observation of the experiments. Green circles indicate waypoints in the first part of the run, going from the starting point at the right (S) to the end point on the left (E), with eggs located at A and B. The green dashed line indicates the expected robot behaviour for collection at lateral location 1. The second part of the run (not indicated) goes from S' to E', with eggs located on A' and B'.

5.5.2 Data registration and processing

During the egg collection experiments, results were registered separately for egg detection, collection operation, and collection failure. Egg detection potentially yielded one of the following results:

- False negative (FN), i.e. the egg was not detected, and therefore no collection operation was performed;
- False positive (FP), i.e. detected something else than an egg. A collection operation was started, but failed due to the absence of an egg;
- True positive (TP), i.e. egg correctly detected, and egg collection was started.

True negatives (TN) were not registered, as this would include every non-egg object seen by the robot. For an egg collection operation performed on correctly detected eggs (TP), the following options were considered as collection result:

- egg collected correctly;
- collection failure: collection started correctly, but the egg was not collected;
- wrong location of collection (robot was clearly off);
- no start of collection.

In case egg collection failed, one of the following causes for failure was assigned:

A. the collection device ran over the egg without collecting it;
B. the egg was broken by the collection device;
C. the egg left the collection device after collection;
D. the collection device was located just next to the egg;
E. the collection device was lifted before actually reaching the egg;
F. the collection device was lowered after passing the egg;
G. switched to remote control by the operator, as result of a collision with an obstacle.

If the collection operation was ended manually, an asterisk was added to the collection result, independent of the collection result itself. All results were registered by the observer during the experiment, and analysed afterwards as described below.

After the measurements, data from runs that produced unreliable responses due to an unsuitable combination of detection algorithm settings and varying ambient light conditions (see the last paragraph of Section 5.5.1) were excluded from further analysis, and results were clustered per longitudinal location (A or B) and lateral location (1 to 5). As false positives (FP) in detection could not be related to a specific egg or location, they were only assessed in relation to the number of eggs present. Based on this data, the following performance indices were calculated, which are similar to those used in fruit harvesting robots (Bac 2015, Bac, Hemming *et al*. 2017):

- Egg detection success (%): the occurrence of a correct detection (TP) as percentage of the total number of eggs present (TP+ FN);
- False discovery rate for egg detection (%): the number of objects falsely detected as eggs (FP), as percentage of the total number of eggs present (TP + FN);
- Collection success rate (%): the occurrence of each collection result as percentage of the number of correctly detected eggs (TP);
- Collection failure rate (%): the occurrence of each failure type as percentage of total collection failures.

Statistical inference on the results (both raw data and performance indices) was done using an Anova test, followed by a multiple comparison using Fisher's protected Least Significant Difference test in GenStat 18.1 to investigate differences in performance between locations.

Cycle time was not investigated, as it was determined by the fixed driving speed of the robot and the time required for lowering and raising the collection device. It hardly varied in the experiment and/or as result of actual conditions. For each egg, a single collection operation was done. The number of eggs tested varied between 25 and 40 per combination of longitudinal and lateral location, and is indicated in the results in Figure 5.8. Egg damage rate was already investigated in earlier research (Vroegindeweij, Kortlever *et al*. 2014), and not investigated in detail here as it was hardly dependent on operation of the device.

5.5.3 Detection performance

Results for egg detection, given in Figure 5.8, show that the majority of the eggs were properly detected by PoultryBot, although results were dependent on the lateral location of the egg. For clustered longitudinal locations A and B, Figure 5.8 suggests that B-locations (even bars) have slightly more ($p=0.21$) eggs detected correctly compared to A locations (odd bars). As B-locations were more in the middle of the area and light intensity was slightly higher than at the A-locations, this might have positively affected detection rate.

Clear differences in performance can be observed between the lateral locations 1 to 5. In front of the robot (location 3) more than 90% of the eggs were detected correctly, whereas only 65 to 85% of the eggs further to the sides of the robot (locations 1 and 5) were detected correctly. Correct detection at location 5 indeed proved different from locations 2 to 4 (p-values between 0.000 and 0.039), and A1 shows similar results (p-values around 0.05), while difference for B1 could not be proven. When combining data for A and B locations, locations 2 and 3 had significantly more correct detections than locations 1 (p=0.04 and 5 (p<0.000), while results for location 4 seem closer to results for location 1 (p=0.13) but they still differed from results obtained at location 5 (p<0.000).

These results indicate that PoultryBot had more difficulty to detect eggs correctly if they were further towards the side of the robot, such as on lateral locations 1 and 5. The lower detection rate seen for these locations might be explained by the egg being present more towards the boundaries of the camera view. As result of optical properties of the imaging setup, the images contained a radial intensity fall-off, such that eggs further from the image centre appeared darker and therefore were not always detected correctly. For more details on this matter, see (Vroegindeweij, van Hell *et al*. 2018). Also, if eggs were located further away from PoultryBot, there was a greater chance that a hen blocks the view towards the egg. The effect of lateral location on detection performance is relevant for future application, as this affects the scanning range of PoultryBot. From the current results, it can be concluded that about 75% of the eggs within 0.5 meter from the PoultryBot can be correctly detected. However, as locations in a poultry house will be visited multiple times a day and this allows for detection at a later moment, the effect of occasionally not detecting an egg is reduced. In these cases, however, eggs will remain longer in the poultry house, which might still induce undesired effects like additional floor laying and egg eating.

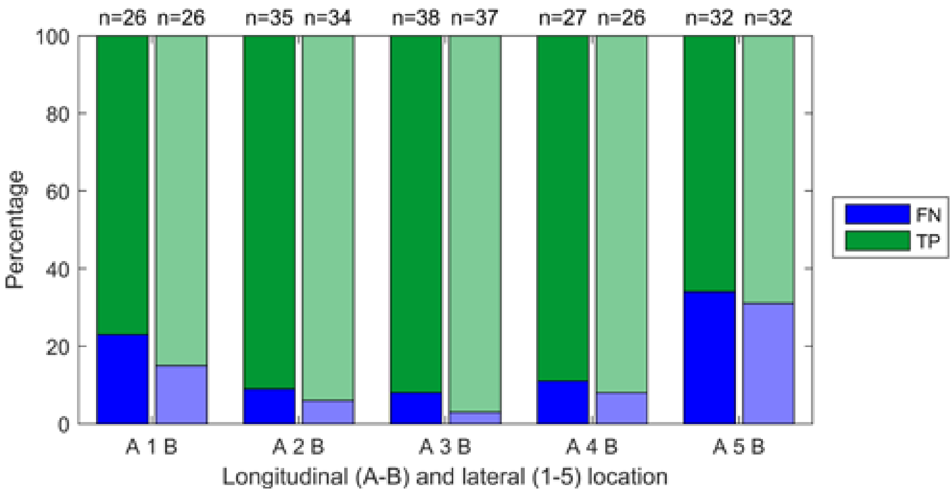

Figure 5.8: Detection results as percentage of the number of the eggs present, expressed per location. Letters A and B indicate the first and second longitudinal location, while numbers 1 to 5 indicate the lateral location, which was perpendicular to robot path. Total number of eggs considered is given above each bar. False positives are not indicated, as they could not be related to a specific position.

False positives could not be related to specific locations and are thus not shown in Figure 5.8. The calculated False Discovery Rate per lateral location (1 to 5) ranged from 21% to 43%. As the false discovery rate varied between 0% and 57% for individual runs, numbers serve as indication only with no clear trends visible. False positive occurrence seemed to be dependent on ambient light levels and camera settings, as there appeared to be a correlation between brighter light conditions and animals close to robot being mistaken for eggs (see Vroegindeweij, van Hell *et al*. (2018) for more details). As fixed intensity thresholds were used for egg detection, and ambient light conditions varied between runs due to variation in outdoor weather, this might explain a large part of the false positives. Furthermore, spots from sunlight, white paint on the wall or feathers on the floor were frequently mistaken as egg by PoultryBot. In commercial poultry houses, these effects are expected to be smaller, as under poultry house conditions both the amount of ambient light and light intensities are much lower.

5.5.4 Collection performance

In general, if eggs were detected, the collection operation started in the neighbourhood of the egg, and more than half of the eggs were immediately collected successfully. Some form of collection failure (i.e. starting the collection operation correctly, but failing to collect the egg) occurred in most other cases, and seems almost complementary to successful collection. Other collection results (clearly wrong location of collection or collection not starting at all) occurred only a few times for correct detections. This is as expected, since eggs won't disappear or move away easily. Cases that did occur, might relate to either a detection error or acting incorrectly during the collection operation, such as the robot passing both waypoints around the egg faster than the control system could respond.

For each correct detection (TP), also collection performance was assessed. Results are given in Figure 5.9, as percentage of the number of correctly detected eggs. For false positive detections, a collection operation was made resulting in 'no egg present'. As no location was known for these cases, they were excluded from the results shown. As shown in Figure 5.9, between 40 to 70% of the correctly detected eggs were collected at once, but clear variation in collection performance can be observed. For statistical comparison of lateral locations 1 through 5, data from longitudinal locations A and B was combined. Eggs in front of the robot (lateral location 3) seemed to be collected correctly more often than eggs at robot edges (locations 2 and 4, $p=0.03$). The number of correct collections at location 1 was also lower than at location 3 ($p=0.08$), but not really different from locations 2 and 4 ($p>0.7$). Location 5, at the other side of PoultryBot, shows a further decrease in performance, especially compared to location 3 ($p<0.001$).

These results might be explained by the behaviour of the robot, as eggs located further away from the initial path required more steering over a short distance to correctly approach the egg. If this was not accomplished in time, the risk of collection failure increased, mainly from incorrectly approaching the egg. The most likely explanation for the results at lateral location 1 being different from those at location 5 is that at location 1 the robot collided with the wall and ending up in front of the egg, such that chances for correct collection increased. This was already observed during the experiments, and can be confirmed when looking at the causes for failure, as shown in Figure 5.100. Here, location 1 has a high amount of human interventions as result of wall collisions, which are not seen at the other locations.

Also between longitudinal locations A and B variation was observed. On locations aside from the robot contour (lateral locations 1 and 5), collection results for the longitudinal locations B (more free space) were clearly worse compared to the A-locations (close to a pole). On the other hand, for lateral locations 2, 3, and 4 (more in front of the robot) the results for longitudinal locations B were slightly better compared with A-locations. This was most explicit for location 4 with $p=0.08$. Although no clear explanations

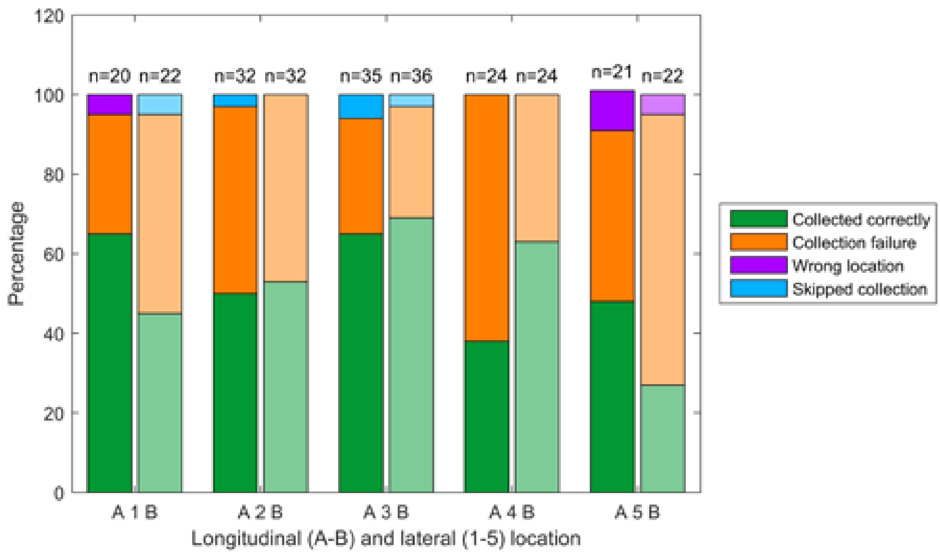

Figure 5.9: Results of the collection operations as percentage of correctly detected (TP) eggs, expressed per location. Letters A and B indicate the first and second longitudinal location, while numbers 1 to 5 indicate the lateral location, which was perpendicular to robot path. Total number of eggs considered is given above each bar.

could be identified for this effect, it might be that the driving behaviour of PoultryBot for collecting the egg at the A-location influenced the collection performance on the B-location. Also, in a number of cases at location A5, the collection operation was ended manually due to collisions with the pole of the interior construction. Based on these results, the location of the egg with respect to obstacles such as a construction pole seems to have limited effect on the collection results. However, waypoint placement and driving behaviour do need improvement here, to make sure no collisions with construction elements occur during or after egg collection.

5.5.5 Collection failures

As up to 60% of the collection operations showed some collection failure, also failure causes were investigated based on observations of the collection operation. Results as percentage of the total number of failures for each location are shown in Figure 5.100. Statistical inference did not show any difference in failure between locations (p-values >0.25), except for the expected difference in obstacle collisions at lateral location 1.

The most frequent failure cause for lateral locations 2 to 5 was the collection device being placed just next to the egg at the start of collection. This occurred less often at location 1, as wall collisions ensured that the robot was directed towards the egg. Frequently, these collisions also resulted in human intervention during the collection operation. Together, these causes account for more than half of the failures, most likely due to a combination of several reasons. First, in the placement of waypoints for egg collection PoultryBot's steering behaviour or obstacle presence were not accounted for. Next, although the navigation method did account for the collection device's position on the robot, steering effects from the heuristic close to the waypoint might still have led to a wrong orientation of the collection device when reaching the egg. As a result, PoultryBot's front wheel might be oriented correctly towards the egg, but the collection device may still have been just next to the egg. Finally, steering corrections applied during collection operation may not always have resulted in the desired move of the collection device, as it had some freedom of movement and frictional forces limited the required lateral shift. Improving the navigation method by better waypoint placement, changing the behaviour of the navigation heuristic and including not only the next waypoint, but also the one after that in the navigation control, are therefore all considered to be desirable. This is likely to reduce these problems and thus improve overall collection performance.

Other failures that occurred frequently, were the egg leaving the collection device after collection (as result of collection device shape), or the collection device being lowered after passing the egg. Lifting the device before actually reaching the egg, moving over an egg without collecting it or breaking the egg during collection happened as well, but was not seen frequently. As loosing eggs mainly occurred on the rear side of the collection device, improving the design of the collection device is expected to resolve this failure cause. Reducing failures like moving over or breaking eggs during collection was more difficult, but their lower occurrence made this also less important. The cases of lowering the collection device after passing the egg, lifting it before actually reaching the egg, or missing the waypoint after the egg and not stopping the collection operation at all, might all have to do with the processing speed of the control method. Improving and speeding up this method would have allowed PoultryBot to respond faster to new observations and changes in position, and thus would have made the navigation and collection control more accurate.

Finally, in some cases the collection operation was not ended automatically such that human intervention was required. As egg collection

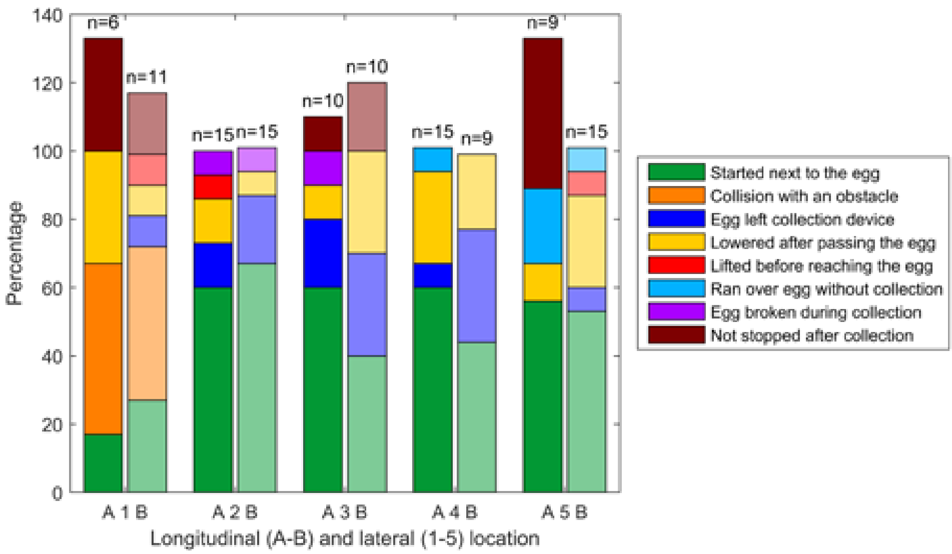

Figure 5.10: Causes for collection failure as percentage of the number of failures, expressed per location. Letters A and B indicate the first and second longitudinal location, while numbers 1 to 5 indicate the lateral location, which was perpendicular to robot path. Total number of eggs considered is given above each bar. Results for not stopping the collection operation in time could exceed 100% score, as an egg could be successfully collected but the collection operation was not ended automatically.

went fine in most of these cases, this explains why these cases exceed 100% of collection failures. This happened especially at location A5 due to collisions with a construction pole, and at lateral location 1 due to collisions with the wall. For the cases that occurred on locations 2 and 3, no direct explanation other than a control error could be identified. To avoid these situations, the navigation method needs improvements in handling obstacles. Furthermore, adding a strict time or distance limit on the collection operation seems useful to assure the collection operation stops in time.

5.6 Combining navigation and egg collection performance

In the previous sections, PoultryBot's capabilities for navigation and egg collection were evaluated in separate experiments. This section gives an integrated reflection on PoultryBot's performance by summarizing the main findings and comparing them with the performance requirements stated in the introduction. Furthermore, it indicates limitations of the current system for application in commercial poultry houses, as well as suitable directions for further development.

5.6.1 Navigation performance overview

The first experiment in Section 5.4 evaluated the long-term navigation capabilities of PoultryBot. Here, PoultryBot proved capable of handling the various path types tested, ranging from border surveying via area sweeping to traversing large areas. Furthermore, it showed its ability to pass through narrow spaces by closely approaching obstacles, but also to deviate from the specified path if this was required to avoid obstacles. As the results of experiment 1 indicated that the occurrence of collisions might relate to the presence of obstacles on PoultryBot's path and the settings of the heuristic used, this was investigated in more detail in experiment 2. Obstacle position with respect to PoultryBot's desired path indeed influenced driving behaviour, with more steering and an increased prevalence of collisions. Also, an indication was found that changing the settings of the navigation heuristic could improve navigation results. During navigation, PoultryBot was able to localise itself with mean accuracy of 0.13 meter, which remained below 0.1 meter for 63% of the time. This approaches the required accuracy of less than 0.1 meter for 95%, but some improvements are still desired in obstacle mapping and handling reference measurements. Although these results sound promising in terms of the requirements stated in the introduction, full autonomous operation of PoultryBot for navigation tasks in commercial poultry houses is not yet possible. Main reasons for this are the number of obstacle collisions observed and PoultryBot's inability to resolve these collisions autonomously.

5.6.2 Obstacle detection and awareness

For achieving the desired operational autonomy of PoultryBot, the first step is to improve its obstacle awareness. In the experiments, several cases were observed were PoultryBot collided with an obstacle just after it had left PoultryBot's field-of-view and was therefore no longer considered in the navigation. Adding or replacing sensors, such that the total field-of-view increases, might solve this problem as obstacles will then remain in sight even after PoultryBot passed them. Also for back-up manoeuvres, additional sensing on the rear side of PoultryBot might be required. Alternatively, a short-term obstacle history can be kept for navigation purposes, which still considers detected obstacles for a certain time after they have left the view of PoultryBot. This approach also allows for a different treatment of so-called hard and soft obstacles (Bac 2015), as for example their retention time or relative importance can now be varied. In that case, PoultryBot should avoid hard obstacles such as construction elements, while soft obstacles such as hens still allow for a certain amount of interaction. Such an approach seems useful, as it was observed that the presence of hens in the environment also influenced the navigation behaviour of PoultryBot. Thus, improving awareness of obstacles in the vicinity of PoultryBot, as well as taking their properties into account, is desirable for further development of PoultryBot. Furthermore, as a collision detection method was missing, this still has to be added to PoultryBot.

5.6.3 Navigation components

Next to improving obstacle awareness, also some navigation components have to be added or improved before PoultryBot can function fully autonomous. For example, PoultryBot's inability to autonomously stop or reverse direction directly influenced current performance, as such manoeuvres are required for autonomous collision resolving. Although the method of Schlegel (1998) does allow for such actions, this was not yet implemented properly in the navigation system of PoultryBot, and needs therefore to be added. In case collisions occur, not only additional navigation behaviours such as reversing direction of motion are required, but also more high-level reasoning that considers adding or moving waypoints to resolve such situations. For example, when during egg collection PoultryBot reaches a dead end or has to collect an egg in a corner, this requires several additional waypoints for a back-up manoeuvre and the indication of a suitable follow-up path. In path planning for car-like robots, methods for defining such manoeuvres already exist (Kiss

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and Tevesz 2014, Csorvási, Nagy *et al*. 2015), which might also be suitable for PoultryBot. If these missing components are implemented as well, PoultryBot is likely able to autonomously handle (potential) collisions, as well as entering corners and dead ends for egg collection.

If these navigation components are added, also the navigation heuristic requires an update, as already suggested from the results of experiment 2. This can be an improved static tuning of weight factors, but it might also be that different conditions require different settings. For example, conditions with an increased risk on collisions might need more obstacle-avoidance behaviour, whereas for traversing an open area more goal-oriented behaviour is desired. Also, handling collisions or backing up might require different settings of the weight factors. Thus, a system where weight factors in the heuristic are made dependent on the desired behaviour under specific driving conditions, might be a suitable improvement for proper functioning of PoultryBot.

5.6.4 Egg collection performance

Next to PoultryBot's navigation capabilities, also its performance in egg detection and collection was determined, and showed a dependency on the egg's location with respect to the robot. In front of PoultryBot, about 90% of the eggs were detected, while more towards the side this decreased to about 65%. On average, some 75% of the eggs within 0.5 meter of PoultryBot were detected. Regarding false positive detections, a range between 0 and 57% was observed, with results being dependent on ambient light conditions. As the images also contained some radial intensity fall-off, improving the optical setup is likely to increase detection performance, as also indicated in Vroegindeweij, van Hell *et al*. (2018). Having more constant ambient light, which is expected to be the case in commercial poultry houses, will also benefit detection performance. With that, the performance comes close to the desired level of detecting 95% of the eggs present, although reaching the maximum 5% false positive detections might still be challenging. If the current detection method does not provide sufficient room for performance improvement, it might also be worthwhile to consider more advanced methods like Conditional Random Fields (He, Zemel *et al*. 2004) for detecting eggs and other objects in images.

In terms of egg collection performance, about 40 to 70% of the eggs could be collected at once. If collection failed, this was mainly due to incorrect positioning of the collection device. The improvements for the navigation method proposed above can already solve part of this, but for egg collection some more improvements of the collection operation are recommended. First, when placing the waypoints used for egg collection, more attention should be given to the robot's current pose, how to approach the egg and the presence of nearby obstacles. Instead of taking the shortest straight line from the current pose towards the egg, a smoother path is desired that can also be followed accurately by PoultryBot, while at the same time avoiding obstacle collisions. Next, the vehicle navigation strategy should be improved further, so that also the orientation of the collection device at the start of collection is included. Finally, the speed of the control loop should be higher, such that the steering actions applied are also performed in time. Next to collection control, also design of collection device needs attention, as part of the eggs escaped after collection. Placing a barrier can easily solve this problem, while adapting the settings of the collection device might also reduce the occurrence of breaking or moving over eggs. With these improvements on collection control and collection device, it is likely that almost all eggs will be collected properly, and the requirement on collection performance can be reached as well.

Still, indicating a dependency between navigation behaviour and collection performance remains complex, for various reasons. First, the robot path contained 2 waypoints between the eggs, to ensure the first and second eggs were approached from a similar direction, but driving behaviour was also subject to animal presence. Thus, paths were never exactly the same and effects of driving behaviour on collection performance varied between experiments. Second, the detection method proved sensitive to the variations in ambient light, leading to more false positives in these cases. As these also lead to collection operations, this affected driving behaviour and egg collection as well. Finally, floor conditions and egg properties do influence collection results but were subject to changes from natural variation, even between subsequent runs. Despite these difficulties, the presented result still provide a good indication of the future possibilities for applying autonomous robots for the collection of floor eggs in commercial poultry houses.

5.6.5 Wrap-up

By improving PoultryBot's obstacle handling and navigation behaviour as indicated above, it will be able to cover all accessible areas of a poultry house. Furthermore, PoultryBot already has large flexibility in its search path, which can contain both long-distance movements, local search actions and other movements, in any combination. These features make PoultryBot capable of handling a wide range of physical environments, path characteristic and navigation behaviours. Furthermore, the obtained localisation accuracy is sufficient to map climate conditions or to register the location of the eggs found, thereby allowing to use this information to inform the farmer on house conditions or for planning PoultryBot's next day's collection path.

By also improving the egg collection operation, PoultryBot will be able to collect almost each egg that is detected and physically reachable. In that case, the exact position of the egg within the poultry house and the position of the egg with respect to PoultryBot's pose will be of limited influence on performance. Given the results from the presented experiments, in the current configuration already more than 40% of the eggs was collected successfully at once, with improper control being the major cause for failure. Using an improved control method likely leads to more than 80% of the eggs properly collected at first encounter, thus approaching the performance requirement on egg collection as stated in the introduction.

All these capabilities make the presented concept a suitable candidate for automating tasks in poultry houses, such as monitoring the animal environment or collecting floor eggs. However, problems or tasks with similar characteristics and requirements can also be found in many other applications, such as cleaning buildings, weed removal or security patrolling. Also here, the flexibility and robustness present in PoultryBot for functioning in dense environments can be a great advantage when creating autonomous applications.

5.7 Conclusion

This work presented PoultryBot, the world's first autonomous mobile robot platform for application in a modern aviary poultry house. PoultryBot was tested under real-life conditions, and proved capable of moving autonomously through this environment. For this, various path types were used, while PoultryBot handled both fixed and moving obstacles during more than 3000 meters of autonomous driving. Egg collection was tested on more than 300 eggs, of which about 46% was successfully collected, while for about 37% of the eggs present some collection failure occurred and only 16% of the eggs was completely missed. The most observed failure cause was the collection device being placed just next to the egg, which can be solved by improving the control algorithms used for navigation and egg collection. These results prove the validity of the PoultryBot concept and indicate that application of smart autonomous vehicles in dense animal environments is possible. Still, improvements on obstacle handling and navigation, the collection method and the reliability of components are required before commercial application of this idea comes within reach.

5.8 Acknowledgements

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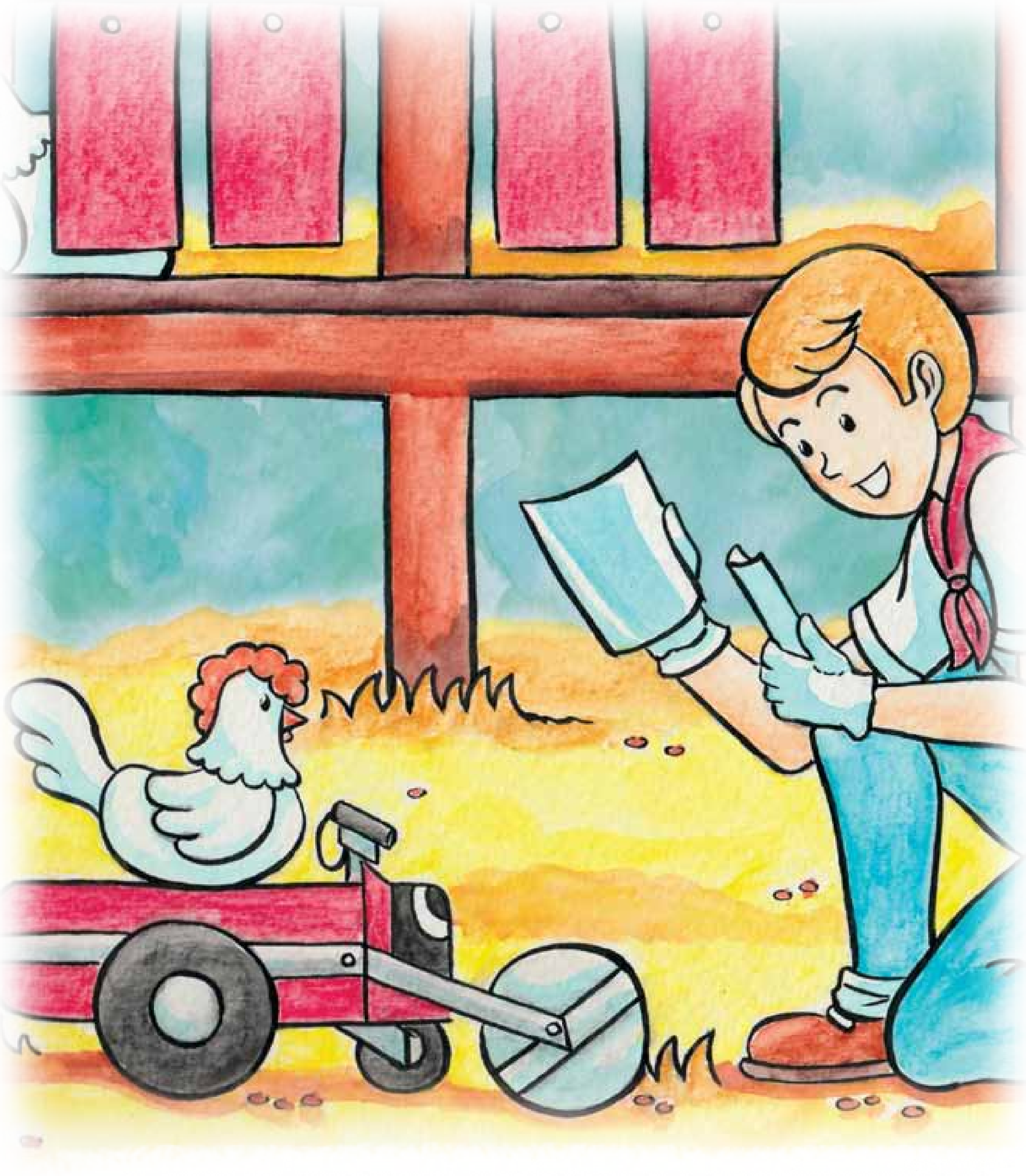

Chapter 6

General discussion

6.1 Conclusion

The central topic of this thesis, as expressed by the objective in Chapter 1, was "*To develop an autonomous mobile robot running in a poultry house environment, capable of performing tasks such as floor egg collection, and test it in a proof of principle experiment to achieve TRL 6*" (See Chapter 1 for a definition of the TRL levels). In chapters 2 through 4 and in Vroegindeweij (2014) subsystems for localisation, path planning, object recognition and actuation were developed and tested. In Chapter 5, these parts were integrated in a mobile platform called PoultryBot, which was subsequently demonstrated and extensively tested in a poultry house environment with hens.

For localisation, in Chapter 2 a particle filter was evaluated in an empty poultry house. By explicitly accounting for uncertainty in sensor data and location estimates, a localisation accuracy was achieved of at least 0.4m for 95% of the time. The particle filter also proved robust against errors and missing values in input data, such that for the localisation system TRL 5 was achieved after Chapter 2. In Chapter 5, multiple odometry data sources were combined to provide the input for the prediction step of the particle filter, and the system was tested and demonstrated successfully in an environment with hens, thereby achieving TRL 6.

For path planning, in Chapter 3 the NURAC path planner was developed, based on a dynamic programming approach and a map containing the probability of floor egg occurrence. Evaluating the resulting paths using an extensive set of simulated floor eggs revealed that the average time between laying and collecting a floor egg was 2.4 hours. This is comparable to a farmer making 2 collection rounds per day, although the robot path visited locations with higher expected presence of floor eggs more frequently, with up to 15 visits per day. These results meet the indicated requirements regarding frequent revisiting of highly suspected floor egg locations to reduce floor egg presence, and the NURAC path planner achieved TRL 4. The resulting paths did not account for the kinematics of PoultryBot, and contained waypoints 0.4 m apart. Preliminary tests of these paths in a poultry house showed they were unsuitable for actual driving by PoultryBot, because waypoint density was too high and some of them were connected by sharp turns. As alternative, in the evaluation in Chapter 5 manually generated paths were used. These also consisted of similar path structures, but with waypoints further apart and without sharp turns. As result, the path planning subsystem remained at TRL 4.

For object recognition, Chapter 4 presented a simple and efficient method based on spectral reflectance properties. This method discriminated between relevant objects for PoultryBot's functioning, such as hens, eggs and litter, with the aim of correctly classifying at least 80% of the pixels.

Using intensity thresholds on monochrome images from a commercial poultry house, which were taken at the most discriminating wavelength (467nm), in the evaluation about 80% of the egg pixels and 40 to 50% of the hen and litter pixels were found to be classified correctly. With this performance, for eggs the object recognition system achieved TRL 5, while for hens and litter technology readiness remained at TRL 4. In Chapter 5, this method was augmented with filtering on size, shape and position of the identified objects to detect floor eggs. With more than 90% of the floor eggs in front of PoultryBot being detected correctly during evaluation and demonstration, the object recognition system achieved TRL 6 for eggs. No attempt was made to improve classification performance for hens and litter, nor was their detection implemented in PoultryBot, thereby the object recognition system remained at TRL 4 for these object categories.

In Chapter 5, also components for egg collection, autonomous navigation and control were added to PoultryBot. For floor egg collection, a bended helical spring was used. This device was previously evaluated in commercial poultry houses (Vroegindeweij, Kortlever et al. 2014), where it achieved TRL 5. For autonomous navigation, the method of (Schlegel 1998) was used, who indicated robust performance of this method in various environments. For system control, all elements were implemented as separately running software nodes, and a finite state machine was used to control PoultryBot's behaviour. Subsequently, PoultryBot's performance was evaluated for navigation and floor egg collection. The following was achieved:

- autonomous navigation in a (complex) poultry house environment for over 3000 meter, including various driving conditions and active obstacle mitigation, and
- autonomous floor egg collection of over 300 eggs, from which 46% was collected successfully, for 37% the collection attempt failed and 17% were missed completely.

Limitations in the vision setup and the implementation of the navigation and control approach prohibited PoultryBot to reach the required level of collecting 90% of the floor eggs present. Lack of attention for the robot kinematics in the path planning method required the use of simpler, manually generated paths with a similar structure as the algorithm-generated paths. The vision setup not recognizing hens and housing elements was circumvented by using the laser scanner for obstacle detection, which proved sufficient for basic navigation, but prohibited distinguishing between these object types. Although path planning and recognition of hens and housing remained at TRL 4 in this research, the presented results indicate that with modifications of these components in place PoultryBot as a complete robotic system could function at TRL 6.

With these results, an answer was found for each of the first four research questions stated in the introduction, summarized as "Where am I", "Where do I go", "What do I encounter" and "How do I perform". Also, it can be concluded that the objective of this research was achieved, as PoultryBot, an autonomous mobile robot for a poultry house environment, was developed and demonstrated to be capable of floor egg collection in a commercially relevant environment. Furthermore, the technical feasibility of such a robot was demonstrated to the research supervisory board, professional media and the general public on various occasions.

6.2 Reaching TRL 7: improvements, additional functions and requirements

As PoultryBot can achieve TRL 6, this leads to the fifth research question: *"How to continue?"* - What is required to advance from the results of this research to the next level on the TRL scale? At TRL 7, a systems prototype is capable of continuous or long-term reliable operation, which is demonstrated in the operational environment with a prototype that is close to the planned operational system. If TRL 7 is achieved, this also means that the prototype can be used for testing of the hypothesis from Chapter 1, to prove the benefits of using mobile robots in a poultry house. In the sections 6.2.1 through 6.2.6, the required functionality and performance for TRL 7 will be explained in more detail for PoultryBot as a whole and for each of the subsystems. Furthermore, it contains a short reflection on the suitability of the current methods and the underlying concepts for reaching TRL 7. Section 6.3 will then reflect on PoultryBot as part of a larger poultry production system.

6.2.1 Missing functionality and new requirements

Based on the experiences and results so far, a set of missing functionalities can be indicated for PoultryBot and the various subsystems. Furthermore, there exist a number of additional requirements that have to be met. On a more general systems level, they can be defined by two core elements: 1) having a reliable and application-oriented design that is modular and maintainable, and 2) use methods that are robust in dealing with variation and uncertainty. The first element deals with the initial design of the system's hard- and software, such that it is adapted to application requirements, but also make sure that all elements operate reliable individually and in combination, and can also be maintained properly. The second element focusses more on the selection of data processing and control methods, such that they are explicitly able to handle the variation in data and situations that result from applying a mobile robot in a poultry house. As both elements have direct implications on the subsystems, missing functions and additional requirements will be given for each of the subsystems separately.

6.2.2 Vehicle and system design

For autonomous operation, several hardware functions have to be added to the design, such as a charging facility, collision checking and egg transport and storage. In the development of PoultryBot, limited attention was given to vehicle design and component selection, as mainly already available components were used and emphasis was on proof-of-principle tests. However, this also introduced some legacy in the hard- and software design of PoultryBot.

Thus, for the next prototype, a new design of both hard- and software has to be created, which fits poultry house applications such as floor egg collection. This requires the dimensions of PoultryBot to be adapted to those of the poultry house environment. It should also be modular, such that single components can be replaced and new functionality can be added. From a safety perspective, the egg collection device has to be integrated more into the robot. Also, the outer shell of the robot has to be smooth and cover all robot parts, such that it does not hurt the animals and can be cleaned and disinfected easily.

For dealing with uncertainty in the conditions, also PoultryBot's environmental awareness should increase. This requires not only maximizing the view coverage around PoultryBot, but also introducing redundancy in sensing to avoid PoultryBot functioning improperly due to failure of a single sensor (Murphy and Hershberger 1996). In both the design of PoultryBot and the selection of individual components, also future commercialisation of PoultryBot should be considered, to avoid choosing components that are unsuitable for commercial production of the system in later stages.

The current approach and methods used for development of the control software were focussed on ease of use by students with limited training. In later stages of the project, this turned out to have some significant limitations, so improvements in design and robustness of the control software are required. First, all processing tasks should become separate software instances with limited interdependency that all run concurrently, such that failing elements can be isolated and restarted without affecting other elements. Second, the used code should be modular and maintainable, also for complex elements, to allow tracing of changes in the code and adaptation of individual elements without breaking code elsewhere. This accommodates adding of new processing elements and functionality in later stages. Finally, attention should be paid to the execution speed of individual processing tasks, to ensure they fit application on a mobile robot with limitations on available computing power and that processing tasks that are critical for safe operation can finish their calculations in time.

To achieve the desired improvements in the design of PoultryBot and its control system, using a structured design approach like (Siers and van den Kroonenberg 2004, Cross 2008) is recommended. For a more reliable control architecture, the Robot Operating System (ROS)(Quigley, Conley *et al*. 2009) seems a suitable candidate.

6.2.3 Localisation

For localisation, the initial high-level requirement was to have robust localisation in environments with a repetitive structure and a large number of moving objects, such as found in poultry houses. The particle filter used for localisation explicitly accounted for uncertainty in measurements and data, and proved successful for localisation of PoultryBot in Chapters 2 and 5. More general, this explicit accounting for uncertainty (as done with probabilistic approaches) seems very suitable for use in autonomous systems that operate in highly dynamic environments with an higher level of uncertainty. However, there exists no standard approach for selecting the methods and parameter values for individual processing steps in probabilistic methods, which also take into account requirements from the application and the environment at hand. As a result, a trial and error approach is still required when implementing such methods, thereby consuming significant amounts of time and resources. For speeding up the integration of such probabilistic methods, it would be helpful if robotics research publishes also algorithm settings and calculation results with more quantitative details.

During such a trial-and-error based evaluation process, as was applied in Chapters 2 and 5, also new requirements emerged. For example, the large number of animals around the robot likely introduces more noise from moving obstacles in the data used for updating the particle filter. As result, increasing the fraction of information related to fixed obstacles in the data used for the update step is required. This includes a need for fusing data from multiple sensing sources for both the prediction and update step of the particle filter. Next, in the current implementation, the filtering step strongly reduces the spread in the particles. As this negatively affects localisation performance and demands introducing more noise in the prediction step, it is required that this algorithm step is improved. Although not required for reaching TRL 7, also the addition of Simultaneous Localisation and Mapping (SLAM) functionality (Lu, Hu *et al*. 2009) is desired. Given the repetitive structure of the environment, the currently used house design drawings can easily be used and seem reliable enough for reaching TRL7 and application in practice. However, for quick introduction to new environments, especially for testing purposes, and to allow the robot to detect and learn changing conditions, having SLAM functionality is desired.

To remove part of the sensing uncertainty resulting from hen presence, filtering or preselection can be applied (Burgard, Cremers *et al*. 1998, Levinson, Askeland *et al*. 2011), but also fusing laser data with information from other sensors like ultrasound sensors or cameras (Rivera-Rubio, Alexiou *et al*. 2015) seems interesting. To retain more particle spreading in the filtering step, a stronger correction of particle weights or making the correction dependent on the effective sample size (Doucet and Johansen 2009) can be used. Also, more adaptive algorithm behaviour can be implemented by using Adaptive MCL with KLD-sampling (Fox 2003) or Augmented MCL (Fox, Burgard *et al*. 1999).

6.2.4 Path planning

For path planning, the initial high-level requirement was to have a floor egg collection path that reduced the time floor eggs were present at the floor of the poultry house. As this time is unknown in practice, several secondary requirements were derived, such as frequent revisiting of locations with a high probability on floor egg occurrence and covering the whole house each day. Furthermore, the method had to be capable of handling narrow passages between separate housing sections (i.e. local minima) and generate new paths overnight, so it can account for yesterday's floor egg production. Especially these features (frequent revisits of highly suspected floor egg locations, handling narrow passages, and a guarantee on finding a path with relatively efficient calculations) determined the suitability of the NURAC method. Whether or not the calculated result was truly optimal (which was one of the initial reasons for choosing a DP approach) proved of less importance, as the underlying problem of floor egg occurrence features intrinsic variation and uncertainty. In that case, using a truly optimal solution includes the risk of making the system unsafe or unstable under practical conditions while a non-optimal solution is likely to be more robust in a practical application.

Although the results of the NURAC planner seemed promising in a simulation setting, applying the resulting paths on PoultryBot showed that these paths could not be executed, mainly as result of sharp turns and high waypoint density. To solve this issue, also the kinematic properties of PoultryBot have to be accounted for in the planning procedure, to ensure that the paths resulting from the NURAC planner can also be executed by PoultryBot. To adapt PoultryBot's path to the actual locations where floor eggs are found, also the feedback loop between floor egg collection and the floor egg model used by the NURAC path planner (as proposed in Chapter 3) should be closed. This will increase operational effectiveness further, such that PoultryBot "*improves both the quality of floor egg collection and prevents an increase in floor laying*". Finally, experimental evaluation of the paths calculated by the NURAC on PoultryBot is still required to see if they indeed have the desired effects on animal behaviour.

To remove sharp turns in the paths that result from the NURAC planner, a cost criterion that accounts for the kinematic properties of PoultryBot can be added to the planning algorithm. Initial tests with increased costs for larger turning angles reduced the number of sharp turns (> 45 degrees) by 70%, while using larger distances between waypoints also seemed to have a positive effect (Langerwerf 2017). Alternatively, a 2-step approach using a generic planner to visit floor egg suspected locations combined with local sweeping actions can be used.

6.2.5 Object recognition

For problems like object recognition for the control of a mobile robot, where performance criteria like calculation time, energy supply and robust implementation are relevant, using simple methods seemed an interesting approach. In Chapters 4 and 5, such a method was applied for PoultryBot, where it turned out that this approach resulted in more problems than initially expected when dealing with the complex conditions and inherent variation of a poultry house. For example the distribution of ambient light within the image varied considerably, causing a reduction in performance of the method tested and thereby compromising it's suitability for PoultryBot. Thus, to create environmental awareness for PoultryBot, significant improvements in performance of the object recognition system are required, together with the addition of some new functionalities.

First, the object recognition system should be able to deal with the variation in light distribution that is present within a poultry house, without compromising detection performance. Next to that, it should also be capable in handling the variation in conditions between houses, such as in housing interior, lighting types and animal breeds. Second, the number of object types recognized and the detection performance should increase. For hard obstacles like housing interior, the number of false negatives should be close to zero, to avoid collisions. For soft obstacles like hens and target objects like eggs, a low number of false positives is desired to reduce unnecessary actions and increase PoultryBot's performance. Also objects that are currently ignored in the recognition approach, such as roughage bins, pecking stones and stray objects, have to be detected by PoultryBot.

To achieve this, a shift from pixel classification to more state of the art methods for object recognition and labelling might be a suitable step. For example, Faster R-CNN (Regional Convolutional Neural Networks) (Ren, He *et al*. 2015) can be used for object detection using bounding boxes, while Mask R-CNN (He, Gkioxari *et al*. 2017) can also add semantic segmentation on pixel level. For training such methods, data-driven feature learning (like Zeiler, Taylor *et al*. 2011, Shao, Liu *et al*. 2014) seem preferable over using knowledge-based, hand-crafted features like colour, texture and shape. Furthermore, the training data used for the object recognition method should sufficiently cover all variation that PoultryBot will encounter in practical applications.

Next to its direct application for robot control, the object recognition system can also be used to obtain information on house and animal status, which the farmer can use for management purposes. For this, the requirements on calculation speed are less strict as this can also be done off-line, but they might require a higher reliability of the results. Furthermore, this application requires the handling of a wider range of objects and object parts and a greater level of detail in the detection results. With respect to system development, it would be beneficial if the methods used to create environmental awareness of PoultryBot are also capable of this task. However, if this leads to comprising performance for at least one of the applications, it might be better to use separate approaches or processing elements for this.

6.2.6 Navigation and control

The first requirement for navigation and control to achieve long-term reliable operation, is to improve obstacle awareness, as part of the navigation errors in Chapter 5 were caused by incorrect sensing. This requirement was already indicated in Section 6.2.2 on vehicle and system design, by stating that sensor coverage and redundancy should be increased. If done so, multiple sensing sources will provide data on the same objects, which requires proper sensor fusion to merge this data. Furthermore, for navigation purposes this information should remain in memory for some time after the object disappeared from the sensor's view as a result of robot movement, as they can still impact the navigation behaviour. Also, attention should be paid to failure detection, such that incorrectly functioning sensors are detected and their data can be excluded from usage by PoultryBot.

Next, the implementation of the navigation method should be improved, by adding the ability to drive backwards. In planning and performing special manoeuvres, such as floor egg collection, more attention should be paid to the presence of obstacles along the robots trajectory. Instead of hard-coding these special manoeuvres, an online local planner should be added to deal with special conditions that are unknown beforehand, such as handling collisions or approaching eggs in corners or near obstacles. In this planner, kinematic properties of the robot should explicitly be accounted for. Furthermore, as a significant part of the failures of floor egg collection could be attributed to the speed and accuracy of the control system, a faster execution of all operation-critical elements is required, to ensure PoultryBot responds in time to changing conditions.

Also the behaviour of the hens requires attention in the navigation method. In general, PoultryBot can ignore the presence of hens while driving, as they are expected to move away if PoultryBot gets close by. However, when they regard PoultryBot as a rooster, or are ill or dead, this is not the case. To allow PoultryBot to continue its journey safely while guaranteeing animal welfare, such cases have to be detected correctly and in time, and should be followed by a proper response from PoultryBot.

For handling the increased amount of obstacle information that results from the required sensing improvements, a more probabilistic or time-based approach is desired. For example, a single obstacle map can be used that contains not only location of the obstacle, but also the detection source, time and reliability of the information. Approaches like the Vector Field Histogram-methods (Borenstein and Koren 1991, Ulrich and Borenstein 1998, Ulrich and Borenstein 2000), the Curvature Velocity Method (Simmons 1996) and the Dynamic Window Approach (Fox, Burgard *et al*. 1997) seem able to do so, but might have limitations in handling more complex vehicle shapes. To deal with animal presence close to PoultryBot and create space for PoultryBot to drive, it might be useful to implement some form of ‘nudging behaviour’ in the robot control (Daley, Joffe *et al*. 2017). Alternatively, animals can be lured towards other areas of the hen house, for example by spreading additional feed, to create sufficient space for PoultryBot to operate.

6.3 PoultryBot as part of a larger system

Next to the more technical developments discussed above, also some non-technical topics require attention when advancing the current results to TRL 7. As PoultryBot is continuously present among the laying hens in the poultry house and actively interacts with them, also their response to PoultryBot should be considered in the development process. Furthermore, since technological innovations relating to animals and food production face on-going attention from society, this topic should be addressed properly in the continuation of the developments as well. Finally, the commercial feasibility should be considered, as well as potential implications of this concept on the design and management of poultry farms.

6.3.1 Animal response to PoultryBot

Regarding animal behaviour in response to a mobile robot, initial research by Vroegindeweij, Boots *et al*. (2014) indicated hens had not much fear for and quickly got used to a robot in their environment. Similar results were found by Usher, Daley *et al*. (2014). Also during technical tests of PoultryBot in a commercial poultry house the hens initially kept some distance, but within several hours after PoultryBot's introduction their avoidance behaviour decreased clearly. They returned to normal behaviour, only avoiding the robot when it approached them very closely (within 0.5 meter) (Boots 2013).

In the experimental environment used in Chapter 5, this behaviour was more pronounced, with hens losing all fear for PoultryBot (and also for the humans present during the proof of principle tests). Frequently, also curious behaviour was observed, with the hens closely following PoultryBot while driving. At stand-still, they immediately approached it, followed by pecking at and jumping on top of it. Sometimes, they remained on top when PoultryBot started to drive again, but as the smooth cover hampered their stability they jumped off after a while. These observations are positive from an animal welfare perspective, as there is no fear or abnormal behaviour observed from the laying hens. PoultryBot can even be seen as an enrichment of environment and animal welfare, as it stimulates the intrinsic curiosity of the laying hens.

6.3.2 Societal acceptance of PoultryBot

Acceptance by society and adoption by farmers are crucial to make this development successful. This does not start after the technical development is finished, but is preferably integrated in the whole development process. Excellent examples of such integration of societal stakeholders in technical developments are given by the development of innovative housing systems like Rondeel, Windstreek and Eggsphere (Projectteam Houden van Hennen 2004, Janssen, Nijkamp et al. 2011, Weeghel, Groot Koerkamp *et al.* 2011).

Acceptance by farmers and society also achieved attention in the development of PoultryBot, although on a smaller scale. First, the research described in this thesis was guided by a supervisory board consisting of representatives from poultry practice, related suppliers and engineering companies. They ensured that the research outcomes were not only scientifically relevant, but also suitable for uptake by poultry practice. This was done by the board providing valuable feedback on ideas and application, as well as indicating the need for demonstrating the project outcomes both in a lab and under practical conditions. Secondly, the outcomes of the project were widely communicated, not only in the scientific community but also to society during and after the project. From 2011 until 2017 9 videos of PoultryBot were published on YouTube, PoultryBot appeared more than 10 times in professional poultry press, 6 times on regional and national radio and television, 3 times in newspapers (including 1 national front page appearance) and was present on more than 10 trade shows and networking events, next to a range of appearances in other publications. So far, only positive reactions regarding the idea of PoultryBot and its applications were received from the public.

Although this sounds very promising in terms of societal acceptance, involving all relevant stakeholders in the continuation of this development still needs significant attention. This starts with keeping poultry practice and technology partners involved, to ensure the development results have a feasible application on commercial poultry farms. Next, society and animal welfare organisations should be consulted on their ideas regarding the use of robots in animal houses. Although from a technical perspective not crucial for reaching TRL 7, societal acceptance of robot technology for livestock production is a prerequisite to make this development successful. Thus, the response of both society and animal welfare organisations towards PoultryBot and its successors should be actively sought for. Organising focus group sessions (Barbour and Kitzinger 1999, Greenbaum 1999) in which these stakeholders actively reflect on this matter, seem particularly useful for this. The resulting opinions and ideas should be included in the development of PoultryBot's successors and their market introduction, to ensure also society accepts this development.

6.3.3 Commercial feasibility of PoultryBot

To make PoultryBot a success, also the commercial perspective of the concept should be evaluated. Already in 2012, representatives of the poultry business were consulted on the commercial feasibility of PoultryBot, and assessed the initial ideas on floor egg collection. This was followed by a first analysis on the financial costs and benefits of PoultryBot by Boots (2013), indicating a break-even for a single robot at an investment price €29.000 using an economic lifetime of 5 years and including time and costs needed for maintenance. Based on these results and input from poultry practice and technical experts, the commercial feasibility of PoultryBot was evaluated in more detail. This showed that continuation of this development into a commercial product could be profitable within 5 years and would require a total investment of about 2.5 million euro. To assess the market demand, in spring 2016 a study was done by Livestock Robotics and Wageningen Livestock Research (Timmerman, van Emous *et al.* 2017). Financial feasibility calculations indicated a savings potential of €0.29 per animal place per year which equals about €11.700 for a flock of 40.000 hens. In a separate internet survey, farmers indicated they were willing to invest on average €1.04 per animal place with an expected payback time of 4 years (Timmerman, van Emous *et al*. 2017). These results indicate the commercial feasibility of PoultryBot.

6.3.4 Implications of PoultryBot on design and management of poultry farms

Additional to the application of mobile robots for floor egg collection, there exist a wider range of applications in the livestock domain (and beyond that) for such autonomous systems. After years of reduced attention for the individual animal, the continuous presence of a mobile robot among the animals allows again for more intensive monitoring of animal health and welfare (up to 24/7), but also measuring climate conditions at animal level and checking the technical status of the house. Based on that, a range of new actuation tasks may be added, such as using manipulation of the litter to control its quality, dead bird retrieval, and even performing interactions with individual animals to increase their welfare. Even more, if robots take over the daily activities that require human presence in the livestock house, current designs that explicitly allow human presence are no longer needed. This opens up the possibility for a complete redesign of the housing interior, such that the livestock house can be adapted even further towards the animal needs.

6.4 Concluding notes

With these technical and non-technical reflections, an answer is provided to the fifth research questions, "How to continue?". Together with Chapters 2 to 5, this indicates that the objective from Chapter 1, "*To develop and test an autonomous mobile robot for a poultry house environment*" is reached and the underlying research questions are all answered. By implementing the proposed improvements, PoultryBot will reach TRL 7, which then allows the evaluation of the hypothesis posed in Chapter 1, "*Automation and robotics can have significant benefits when taking over tasks from humans in a poultry house. For a labour-intensive task like the collection of floor eggs, using an autonomous mobile robot improves the quality of floor egg collection and prevents an increase in floor laying.*" Also, a new range of applications around monitoring of animal and house state emerges then.

Thus, with the development and performance evaluation of PoultryBot, the world's first autonomous mobile robot for poultry houses, not only the objective of this thesis is reached, but it also contributes to opening up a completely new field in the domain of agricultural robots: that of Smart Mobile Livestock Robots.

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Summary

In the Netherlands, laying hens are nowadays mostly housed in aviary housing systems. Here they have the freedom to express their natural behaviour, such as nesting, dust bathing and perching. In these aviary systems, a significant part of the daily work for the care of the animals is mechanised or automated. Still, a number of activities continue to require human labour, such as inspection of animals, retrieval of dead hens and the collection of floor eggs. These tasks account for about 20 to 40% of the daily work time-budget, and have to be executed under physically demanding conditions with limited flexibility in work schedule. For poultry farming to remain a viable business in the future, improvements in labour quality and sensing opportunities are required. Nowadays, the use of automation and robots to replace undesired labour and improve sensing opportunities increasingly gains attention, also in agriculture. In line with these trends, the use of an autonomous robot for tasks like floor egg collection was proposed at the start of this thesis. Such an autonomous robot needs to be flexible and adaptive to changing conditions. This demands full freedom in mobile robot behaviour, while it also needs to be aware of its environment and have the ability to interact with it. Irrespective of the final application, this requires a mobile robot to have capabilities like localisation, path planning and object recognition, but also navigation and actuation. No proof of concept of the required mobile robot capabilities for poultry house applications was available at the start of the research and therefore, the main objective of this thesis was identified as:

"To develop an autonomous mobile robot running in a poultry house environment, capable of performing tasks such as floor egg collection, and test it in a proof of principle experiment to achieve TRL 6".

The steps required to fulfil this objective form the main line of this thesis.

Chapter 1 starts with providing a more detailed review of the background and approach of the research. The following chapters review existing methods for several core elements, to see if they were suitable for use in a poultry house environment. If necessary, also new methods were developed and tested.

The question Where am I?" plays a central role Chapter 2, where probabilistic localisation using a particle filter was evaluated for use inside poultry

houses. Localisation in this environment requires a method being capable of handling uncertainty and ambiguities in sensor data, environment and position estimates. Being commonly used in mobile robots, a particle filter is well capable of doing so, and can also combine data from various sensing sources.

Literature review describes multiple options for each processing step of the particle filter, and multiple alternatives were implemented and evaluated. For testing their suitability and performance in a poultry house environment, data obtained by driving PoultryBot in a commercial poultry house without animals was used. Using a 3-stage evaluation procedure, 9 particle filter settings were evaluated on 21 trajectories. After each stage, a qualitative and quantitative comparison was done to select the most suitable settings.

As a result of this procedure, it was found that using 300 particles combined with the Field update model with learned parameters could reach an accuracy of 0.37m for 95% of the time, with a mean error of 0.2m. Although performance was slightly worse (0.42m) for the alternative approach using a Beam model in the update, this difference was not significant. As this is well below the required accuracy of 1.0m for 95% of the time, a particle filter can be considered suitable for localising PoultryBot in its future application. Furthermore, insight was gained into the behaviour of the methods and the effect of parameter settings, such that the most suitable methods and settings could be selected for future implementation.

Chapter 3 aims to answer the question “Where do I go?”, especially with respect to the collection of floor eggs. When using a robot, a dedicated collection path is required that minimizes the time eggs are present on the floor. This translates into frequently revisiting locations where floor eggs are laid, but also assuring that at the end of the day the whole house is covered so no eggs remain in the house for more than 24 hours.

As existing path planners could not provide this functionality, a novel path planning algorithm was introduced to generate non-uniform repetitive area coverage (NURAC) paths, based on floor egg probabilities. First, a spatial map was developed that describes the probability of floor egg occurrence at each location in a poultry house. Using this map, paths for floor egg collection were planned with a dynamic programming approach that covers the complete house floor area and frequently revisits locations with a high potential on floor eggs. These paths were compared with the paths used by a farmer for floor egg collection, and both methods were quantitatively evaluated with help of a simulated set of floor eggs.

With respect to the average time eggs were present on the floor, the robot path resulted in an average of 2.2 hours, which is comparable to the 2.4 hours of a farmer collecting floor eggs twice a day. With respect to the structure of the path and the number of visits to locations with a high floor egg potential, the robot paths outperformed the farmer with up to 15 visits per location. Using different starting locations for the path did not influence collection performance.

The presented results are promising for the use of a robot to collect floor eggs, and will result in a reduction of the demand for manual labour. Extending the floor egg model with feedback information, i.e. by updating the floor egg probabilities based on the locations where floor eggs are actually found, could further improve the results.

Chapter 4 deals with the environmental awareness of PoultryBot to answer the question "What do I encounter on the way to my goal?". The required response of PoultryBot differs between the various object categories that are present in a poultry house, as floor eggs need collection, housing elements should be avoided and hens can initially be ignored. A correct detection of and discrimination between these object categories is therefore required. For this, a simple and robust method for pixel-wise classification of images based on differences in spectral reflectance properties was presented.

First, of four relevant object categories, hens, eggs, housing elements and litter, the spectral reflectance was measured at wavelengths between 400 and 1000 nm. The resulting distribution of reflectance values was determined for each combination of object category and wavelength band measured. Next, the wavelength band with lowest overlap between all object categories was selected around 467 nm, with 16% overlap for chickens vs. eggs, 12% overlap for housing vs. litter, and lower overlap for other combinations.

Subsequently, images were taken in a commercial poultry house, using a standard monochrome camera and a band pass filter around 470 nm without additional lighting. After pre-processing, each pixel was assigned an object category based on its intensity, and classification performance was evaluated. Based on pixel-wise evaluation on 87 of the acquired images, the requirement of 80% correctly classified pixels was almost reached for eggs. For hens and litter, 40 to 50% of the pixels were classified correctly, while for litter performance was rather low with 15.6% of the pixels classified correctly. Unequal distribution of ambient light led to overlapping intensity distributions, which influenced performance. Still, this seemed a feasible starting point for implementing egg detection on PoultryBot. Improving light distribution in the images, using a region of interest and including morphological processing are all likely to further improve these results.

In Chapter 5, the components from the previous chapters were integrated in PoultryBot, together with a navigation method and an egg collection device. In this way, a functioning proof of principle of this technology was created, and subsequently evaluated under practical conditions, to answer the question “How do I perform?”.

PoultryBot’s navigation performance was assessed using different paths, like area sweeping and surveying close to walls. By confronting PoultryBot with obstacles on different positions with respect to its path, also obstacle handling was investigated. PoultryBot proved capable of navigating autonomously through the area covering a total path length of over 3000 meter, while avoiding obstacles and dealing with the hens present. The placement of obstacles on different positions with respect to PoultryBot’s path and the setting of navigation parameters showed clear influence on PoultryBot’s driving behaviour. Path length and steering actions increased if obstacles were closer to the path and/or if navigation parameters were set to less goal-oriented behaviour.

For floor egg collection, performance of detection and collection of floor eggs was assessed on 5 predefined egg positions off to the robot path. Over 300 eggs were tested, and in front of the robot, over 90% of the eggs were detected correctly, while towards the sides of the robot this number reduced to 65% of the eggs present. From all eggs tested, 46% were collected successfully, 37% were not collected successfully as result of collection failure, and only 16% were missed completely. The most observed failure was the collection device being placed just next to the egg.

By improving the obstacle awareness of PoultryBot and adapting the control algorithms for navigation, obstacle handling and floor egg collection, the performance for both navigation and egg collection can be increased even further. With these adaptations, it is expected that PoultryBot will be able to cover all accessible areas of the poultry house, while collecting almost all eggs that are detected and physically reachable.

The final question that remains is “How to continue?”. Thus, Chapter 6 summarizes the results and benchmarks them against the Technology Readiness Levels (TRL’s) as defined in Chapter 1. From that, it is concluded that with some modifications in place for path planning and recognisings hens and housing, PoultryBot as a complete robotic system could function at TRL 6, in which a prototype system is demonstrated in a relevant environment. With this, also the objective from the introduction, "to develop a proof of principle of an autonomous poultry house robot", was achieved. By reflecting on current performance, also missing functionalities and requirements are indicated for advancing to TRL 7, in which continuous or long-term reliable operation of a near-final prototype is achieved.

To proceed beyond a proof of principle test at TRL 6, two main requirements demand further attention on a systems level: 1) having a reliable and application-oriented design that is modular & maintainable, and 2) use methods that are robust in dealing with variation and uncertainty. To achieve this, a new design of PoultryBot is required, which includes currently missing elements like autonomous charging, increases sensing opportunities, and has a more modular layout of the control software. By explicitly accounting for uncertainty, the particle filter for localisation fits well to the application of PoultryBot, but some small improvements are desired on the update and filtering methods for the particles. In simulation, the NURAC path planner results seem promising, but require inclusion of robot kinematics before they can be tested in practice. The object detection method, that was characterized by its simplicity, requires more significant improvements, especially for dealing with variation in ambient light and the recognition of multiple object categories. For navigation and control, improved obstacle awareness and navigation behaviour are required, also to guarantee safe and reliable operation in the interaction with animals. Investigating the animal response on PoultryBot's presence, the commercial potential of the PoultryBot concept and the responses from the general public on the application of PoultryBot all had positive results. This clearly proves the possibility of smart mobile robots in dense animal environments, and the PoultryBot concept for autonomous floor egg collection in commercial poultry houses in particular.

With that, an answer is provided to the fifth research questions, "How to continue?", and is indicated how PoultryBot can reach TRL 7. With that, not only the objective of this thesis, "To develop and test an autonomous mobile robot for a poultry house environment", is reached, but it also contributes to opening up a completely new field in the domain of agricultural robots: that of Smart Mobile Livestock Robots.

Dankwoord

Met dit dankwoord komt er een voorlopig einde aan een wetenschappelijk traject, dat bijna 11 jaar geleden begon. Hoewel ik blij ben dat mijn proefschrift nu klaar is, voelt dit ook erg dubbel, omdat ik een erg leerzame en interessante periode in mijn leven nu toch echt moet gaan afsluiten. In deze tijd is heel veel gebeurd op technisch en wetenschappelijk gebied, met onder andere de PoultryBot als een mooi resultaat. Ook in mijn persoonlijke leven heb ik in deze tijd mogen groeien. Hoewel het onmogelijk is om iedereen die hieraan een bijdrage geleverd heeft te bedanken, wil ik toch een poging wagen om de belangrijkste personen even in het zonnetje te zetten.

Het eerste idee voor de PoultryBot ontstond toen ik met een 3-tal medestudenten (Harmen Wollerich, Theo van der Zwaag en Tim Kool) deelnam aan het Field Robot Event van 2007. Een van de opdrachten was het bestrijden van onkruid, voorgesteld door gele golfballen. Na de eerste ideeën over spuiten en schoffelen, is er vervolgens een golf-ballen-opraapwagen in elkaar geknutseld (jongens: bij deze krijgen jullie de credits voor het idee!). Op basis daarvan ontstond, dankzij een losse opmerking in de gang, het idee voor het oprapen van grondeieren in pluimveestallen. Met wat snelle aanpassingen van de software bleek dit simpel te demonstreren, wat resulteerde in een 2e prijs voor de Freestyle opdracht. Daarmee was het niet klaar, maar begon voor mij het avontuur pas echt, met een optreden op de Agritechnica 2007 ("Die Holländer sammeln Eier") en een artikel in vakblad Pluimveehouderij als eerste hoogtepunten.

De volgende fase in de ontwikkeling van de PoultryBot was het verder uitwerken van dit idee binnen mijn masterthesis. Onder de goede begeleiding van Gerard van Willigenburg en Peter Groot Koerkamp heb ik daarin de eerste stappen mogen zetten. Eerst is een model opgezet voor de verspreiding van grondeieren, op basis van bestaande kennis van het gedrag van kippen. Vervolgens is hiermee ook een routeplanner ontwikkeld voor het verzamelen van grondeieren. Samen vormen deze elementen de basis van hoofdstuk 3 uit deze thesis.

Nadat ik in juni 2010 door Eldert van Henten mijn MSc-diploma uitgereikt had gekregen, meldde Peter Groot Koerkamp bij de borrel dat hij zojuist akkoord had gekregen om mij aan te stellen als tijdelijke medewerker bij FTE. Daarbij boden jullie mij niet alleen een aantal erg leerzame onderwijstaken aan, maar ook de mogelijkheid om het idee van de PoultryBot verder uit te werken, wat uiteindelijk resulteerde in dit promotieonderzoek.

Nu was mijn insteek vooral praktisch (ik wil een robotje maken), en niet meteen gericht op een wetenschappelijk onderzoek. Jullie hebben mij dan ook flink moeten coachen en sturen richting het eindresultaat dat er nu ligt. Dat was voor mij niet altijd makkelijk, en het heeft me af en toe best wat moeite gekost om mijn meer pragmatische en praktijkgerichte aanpak te laten varen voor een wetenschappelijke benadering. Toch denk ik dat dat dankzij jullie goede sturing uiteindelijk heel aardig gelukt is, en ik wil jullie dan ook heel erg bedanken voor alle moeite, tijd en energie die jullie in mijn persoonlijke ontwikkeling hebben willen steken!

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Eldert, bedankt voor de praktische begeleiding, met name bij het schrijven van de papers en uiteindelijk deze thesis. Dankzij jouw scherpe oog en goede analyse heb ik daarin een flinke leerslag mogen maken, en is de kwaliteit van het resultaat flink verbeterd. Ook van jouw ervaring in het omgaan met mensen, variërend van afstudeerder tot journal-editor, heb ik veel kunnen en mogen leren. Peter, jij keek vaak wat meer vanaf de zijlijn mee, en juist daarmee zorgden jouw reflecties op de grote lijnen, gecombineerd met een soms wat meer pragmatische aanpak en een goede kennis van de pluimveesector voor een mooie aanvulling. Het resultaat werd daarmee niet alleen wetenschappelijk sterker, maar bleef tegelijkertijd ook toepasbaar voor de pluimveepraktijk.

Ongeveer halverwege het promotietraject, in januari 2014, kwam Joris IJsselmuiden erbij als dagelijkse begeleider. Joris, hoewel het misschien niet allemaal werkte zoals we vooraf verwachtten, hebben jouw ondersteuning en de wat kortere lijntjes zeker hun vruchten afgeworpen. Niet alleen voor het schrijven van mijn teksten, maar ook op het gebied van softwarecode, algoritmes en methoden heb ik het nodige van jou geleerd. Vooral het werken met Git als versiebeheermethode is iets waar ik nog alle dagen profijt van heb!

Sam Blaauw, als IT en robot-specialist binnen FTE heb je ook aan dit project een onmisbare bijdrage geleverd. Dat begon met het vervullen van speciale IT wensen die ik had voor mijn padplanning uit hoofdstuk 3 en de uitgebreide simulaties voor de plaatsbepaling in hoofdstuk 2. Jij richtte de binnenkant van de PoultryBot op een nette en gestructureerde manier in, zodat we daarmee nog een aantal jaren door konden. Ook gaf je uitgebreide ondersteuning bij het uitvoeren van experimenten in de werkplaats, de kippenstal en uiteindelijk ook 'ons' eigen stalletje op Droevendaal. Zonder jouw kennis, ervaring en gestructureerde manier van werken, met aandacht voor zowel grote lijnen als details, was de ontwikkeling van de PoultryBot nooit zover gekomen. Zelfs nu nog maak je jezelf onmisbaar, door mij binnen Livestock Robotics te ondersteunen met jouw IT-vaardigheden, technische kennis en scherp en kritisch inzicht. Bedankt ook dat je mijn paranimf wilde zijn!

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De ontwikkeling van PoultryBot, en daarmee ook deze thesis, was niet mogelijk geweest zonder de bijdrage van een grote groep studenten. In verschillende stadia van hun loopbaan hebben zij ideeën uitgewerkt, onderdelen ontwikkelt, aangepast en getest en resultaten gepubliceerd. Dit gebeurde niet alleen in de vorm van een BSc of MSc thesis aan de WUR of later als afstudeerder bij Livestock Robotics, maar ook in groepsopdrachten, onderwijsprojecten, door het op de achtergrond laten draaien van mijn simulaties op hun afstudeer-pc, of zelfs als bijbaantje naast hun studie. Hun werk uitgebreid benoemen wordt teveel, maar wordt daarom niet minder gewaardeerd: Arjan Verduijn, Bas van Kooten, Bastiaan Vergouw, Bernard Russchen, Bram Overbeek, Dini Ras, Elbert van Leeuwen, Elianne van Esbroeck, Emiel Bergwerff, Ernst-Jan de Vries, Gerco Schopman, Jacob-Jan Boonzaaijer, Jan-Willem Kortlever, Joris van Rodijnen, Jort Schutte, Heleen ten Have, Koen Vermue, Lars Flikweert, Maaike Vollering, Marleen Hermelink, Marnix van Koeveringe, Matthijs van Haperen, Natasja Boots, Ragnar Groot Koerkamp, Reamon Langerwerf, Rick van Essen, Rik Aelfers, Rob van Olst, Roel Dohmen, Roy Raedts, Sander Bouwknegt, Sander van Leijsen, Sergey Kleymenov, Sjoerd van Wijk, Steven van Hell, Thijs van Beers, Tijn van den Aker, Tim Rijssemus, Tom van de Ven, Wiger Aantjes, Wilco Verhoijsen, en Yeb Andela: BEDANKT!!!

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BAT04, als techneuten waren en blijven we een hechte groep, waarin we al bijna 14 jaar de mooie en minder mooie kanten van het leven met elkaar mochten delen. Ons jaarlijkse weekendje weg (ook al was ik er niet altijd bij) blijft daarbij toch wel een hoogtepunt, zeker gezien alle goede gesprekken en mooie discussies die dan gevoerd worden.

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Dennis, al sinds 2004 trekken we samen op, en daarmee kennen wij elkaar langer dan dat we onze vrouwen kennen. We begonnen in periode 1 (en volgens mij ook al tijdens een meeloop-dag) met het samen maken van wiskunde-opgaven, wat werd gevolgd door groepsopdrachten, een Almanakcommissie en een project voor Martin Gauss waarin we samenwerkten. Ook onze BSc-thesis deden we bij dezelfde begeleider. In 2008 belandden we in hetzelfde afstudeerhok en hebben we, met een paar korte onderbrekingen, tot voorjaar 2016 in hetzelfde kantoor gezeten. In die tijd hebben we samen van alles meegemaakt, met gezamenlijk onderwijs, gebruik van elkaars code en kennis en goede gesprekken over ons scherm heen. Ook daarbuiten we zagen elkaar, bijvoorbeeld bij klus- en verbouwactiviteiten en weekend-bezoekjes, maar ook op elkaars bruiloft mochten we een rol vervullen. Bedankt ook dat jij paranimf wilde zijn. De laatste jaren is ons contact door alle veranderingen in ons beider leven (andere banen, gezinsuitbreiding) helaas wel iets minder geworden, dus het afronden van deze thesis lijkt me een goede reden om elkaar weer eens vaker op te zoeken.

Uiteraard verdient ook mijn familie een plek in dit rijtje. Pa en Ma, jullie wil ik allereerst bedanken voor jullie opvoeding, en het meegeven van wat voor jullie belangrijke normen en waarden zijn. Ook voor de ruimte, mogelijkheden en ondersteuning die jullie daarin boden om mijn eigen keuzes te maken heb ik altijd erg gewaardeerd. Dankzij jullie achtergrond is mijn interesse voor landbouw en techniek al vroeg ontstaan, met deze thesis als één van de mooie resultaten. Fijn dat jullie huis nog altijd een warm nest is waar we op terug mogen vallen!

Ma, bedankt voor alle goede zorgen in al die jaren en al het praktische werk wat je voor mij hebt gedaan! Hoewel je de nodige ervaring hebt in DTP-werk, blijkt het vormgeven van een PhD-thesis toch van een hele andere orde, en daarmee een flinke kluif. Bedankt dat je dit ondanks alles toch hebt willen doen! Ik hoop dat we de lijst met klussen die we samen hebben mogen doen nog veel langer kunnen maken.

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Gerrit, Janny en Coralie, aan jullie veel dank voor het opnemen van mij als schoonzoon en zwager in de familie en de vele gezellige momenten die we met elkaar hebben mogen beleven. Ik hoop dat we daar nog slechts een klein deel van gehad hebben!

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Curriculum Vitae

Bastiaan Abraham Vroegindeweij was born on the 19th of November 1986 in Lienden, the Netherlands, as son of a poultry farmer. Between 1988 and 1995 he lived on one of his family's farms, where he had his first experiences with poultry farming and agricultural technology. During his secondary school (1998-2004) and university studies (2004-2010), he was active on his family's farms in various jobs, ranging from executing daily work to maintenance activities and managing a farm site during holiday periods. Furthermore, he worked at 2 contracting companies in agriculture and construction, where he gained a wide practical experience in using and maintaining all kinds of machinery.

In 2004, he started with the BSc programme in Agrotechnology at Wageningen University, from which he graduated in 2008. In 2007, he participated with 3 fellow students in the Field Robot Event, where his team received an overall 3rd price. Furthermore, they received the 2nd price for their freestyle task, presenting a concept of robotic floor egg collection, which eventually turned out to be the starting point of this thesis. Bastiaan continued his MSc in Agricultural and Bioresource Engineering at Wageningen University, which he completed in 2010 (cum laude). In his major thesis at the Systems and Control Group, he developed a path planning algorithm for a floor egg collection robot, which was nominated for the 2010 KIVI NIRIA control engineering price, awarded the 2010 NVTL thesis price and forms the basis of Chapter 3 in this thesis. His minor thesis at the Farm Technology Group was on designing a user interface for herd health control, while he was also involved in a project on localisation of animals. Furthermore, he did an internship at Moba on the detection of internal defects in eggs.

After graduation, he started working as a Research and Teaching Assistant at the Farm Technology Group of Wageningen University, where he contributed to the preparation of and teaching in the courses Engineering Design, Biosystems Design, Greenhouse Technology and Livestock Technology. Furthermore, he continued his work on a mobile robot for poultry houses. This led to the start of the PhD project Automation for Poultry Production at the beginning of 2012. In the context of this project, the development of the PoultryBot was executed and this thesis was written.

After the employment of Bastiaan with Wageningen University ended at the end of 2015, he started in 2016 the spin-off company Livestock Robotics to continue the development of PoultryBot into a commercially viable product. Livestock Robotics' mission is to "Improve life, for Farmer and Animal", by providing the farmer automated assistance in his daily tasks, such as the collection of floor eggs and observing the status of his animals. The expected result of using such technology is a reduction in undesired labour for the farmer and improved awareness of and care for the well-being of the animal.

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Gail Damerow and Bastiaan Vroegindeweij (2016). *Egg collecting robot gathers eggs from the chicken coop floor.* Cackle Hatchery Blog, 16-2-2016. http://blog.cacklehatchery.com/egg-collecting-robot-gathers-eggs-from-the-chicken-coop-floor/

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WIAS Training and Supervision plan

Description	Year
Basic package (3.0 ECTS)	
WIAS Introduction Course, Wageningen, The Netherlands	2012
Course Ethics and Philosophy in Life Sciences, Wageningen, The Netherlands	2012
International Conferences (3.6 ECTS)	
6^{th} European Precision Livestock Farming conference (ECPLF), Leuven, Belgium	2013
International Conference on Agricultural Engineering (AgEng), Zurich, Switzerland	2014
IEEE/RSJ International conference on Intelligent Robots and Systems (IROS), Hamburg, Germany	2015
Seminars and Workshops (1.4 ECTS)	
Speeding up MATLAB and handling large datasets, Maarssen, The Netherlands	2011
WIAS Science day, Wageningen, The Netherlands	2012
WIAS Science day, Wageningen, The Netherlands	2013
Vision, Robotics and Mechatronics, Veldhoven, The Netherlands	2014
NI Days, Utrecht, The Netherlands	2014
Presentations (5.0 ECTS)	
Oral presentation at ECPLF 2013, Leuven, Belgium	2013
Poster presentation at WIAS Science day, Wageningen	2014
Oral presentation at WIAS Science day, Wageningen	2014
Oral presentation at EurAgEng 2014, Zurich, Switzerland	2014
Poster presentation at EurAgEng 2014, Zurich, Switzerland	2014
Oral presentation at IROS 2015, Hamburg, Germany	2014
In-depth Studies (11.5 ECTS)	
Biosystems Instrumentation, Viborg, Denmark	2011-2012
Basic Statistics, Wageningen, The Netherlands	2013
Professional Skills courses (2.7 ECTS)	
Course Techniques for Scientific Writing, Wageningen	2012
Course supervising MSc thesis work, Wageningen	2012
Conversation skills in one to one guidance, Wageningen	2012
Job assessment, Wageningen	2015

Research Skills Training (6.0 ECTS)	
Preparing own PhD research proposal	2011
Didactic Skills Training (17.0 ECTS)	
Greenhouse Technology, preparing course materials and exams	2010-2011
Biosystems Design, Lecturing and Preparing course materials	2010-2014
Supervising 6 MSc and 13 BSc students	2011-2015
Livestock Technology, Lecturing and Preparing course materials	2012-2015
Management Skills Training (2.0 ECTS)	
Livestock Technology Course Coordination	2012-2015
Education and Training total	**52 ECTS**

1 ECTS credit equals a study load of approximately 28 hours

Colofon

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