

Object segmentation in poultry housings using spectral reflectivity*

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Abstract— We present a simple and robust method for pixel segmentation based on spectral reflectance properties. Of four object categories that are relevant for PoultryBot, a mobile robot for poultry housings, the spectral reflectance was measured at wavelengths between 400 and 1000 nm. From this information, the distribution of reflectance values was determined for each combination of object category and wavelength band measured. From this, the wavelength band could be selected where the overlap between objects was lowest. This was found to be around 467 nm, with 16% overlap for chickens vs. eggs, 12% overlap for housing vs. litter, and lower overlap for other combinations. Images were taken with a standard monochrome camera and a band pass filter around 470 nm in a commercial poultry house, to test segmentation using this method. Preliminary results indicate that this method is a promising direction for future work.

I. INTRODUCTION

A. Background

In current poultry production systems in western Europe, but also in increasing amounts in other parts of the world, laying hens have freedom to move around. Compared to cage housing, this requires more advanced management, and more manual labour under unfavourable conditions, for example for the collection of floor eggs [1, 2]. In previous work, a poultry house robot (*PoultryBot*) was introduced that should assist in such tasks. For this robot, localisation and path planning methods were presented and evaluated in [3, 4]. In order to allow autonomous function of such robot, it should also be aware of which objects surround it. In this work, we explore the possibility of using spectral information for this task, by analysing the spectral features of objects that are common in poultry houses. Environmental conditions in a poultry house are described in [1, 4, 5]. With respect to the application of vision methods, the low amounts of light (around 5 to 20 lux), in combination with a crowded environment are the most problematic. When functioning inside a poultry house, four main object categories are of relevance for PoultryBot: 1) eggs, being target objects that have to be collected, 2) chickens, being moving obstacles that can be ignored while driving, because they move away from the robot themselves, 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.

B. Object detection

For the detection of objects around a mobile robot, various methods exist, such as tactile feedback and distance sensors. Most methods however, rely on vision systems as

they can provide much more information on what kind of obstacle is observed. Main disadvantage of vision sensors is that sophisticated processing is required to come up with correct and reliable results under varying conditions. This not only relates to computation time, but involves also more complex algorithms, which might still suffer from variation in objects and environment. In the computer vision domain, much work is done on improving the methods used, by evaluating them on standard sets of images. Common methods make use of color, texture, shape or SIFT/SURF, combined with classifiers like support vector machines or neural networks to locate and classify features or objects. More information can be found in [6], while [7] is one of many examples present. Another variety of vision methods takes advantage of spectral information on objects. In agriculture, this method has been applied for example to distinguish between various kinds of green plants [8, 9]. Van Henten et al. [10] used a known difference between the spectral reflectance of cucumbers and leaves to distinguish these two object types in cucumber harvesting. In egg quality inspection, the transmission spectrum of eggs is used to assess internal quality parameters, like age and contamination [11–13]. Although methods based on spectral properties require more effort and complex equipment in the development stage, the resulting method is usually more simple and robust, and works with common and cheap equipment like monochrome cameras. Furthermore, if only specific wavelength bands are used, the results are less sensitive towards the color and intensity of the environmental light, as long as it is evenly distributed over the area. If required, other object detection methods can still be added in a later stage to increase detection performance.

With respect to our problem of object detection for PoultryBot, already some information on spectral properties of the relevant object categories can be found in literature. Prescott and Wathes [14] 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 hybrids. Furthermore, they showed spectral results of various materials present in commercial poultry houses. Thus, their results provide a good starting point for our research. Spectral characteristics of hen eggs were used mainly for transmission measurements to determine the quality of shelled eggs [11, 12]. Less work has been done on spectral reflectance of eggs. In [14], only the spectral reflectance of a brown egg was reported. Gloag et al. [15] presented also other egg colors (although from a different bird), with similar results.

C. Contribution and paper outline

To see whether these results still hold in our conditions, we sampled spectral reflectance of the four object categories

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relevant to PoultryBot. Based on the sampled spectral reflectance, we segmented images from a monochrome camera with a wavelength filter into these four categories. For a reliable operation of PoultryBot, it is desired that in the initial stage, at least 80% of the pixels (so not objects) in these four categories are correctly segmented. Most likely, this will lead to at least partial detection of the objects present in the image. Further processing can then be used to ensure that all objects are correctly identified. Finally, objects can appear in more than one image, so their chance of being detected is not completely depending on the results of processing a single image only.

Our main contribution is a generic method to develop simple and robust segmentation based on spectral information. Furthermore, we demonstrate its applicability to the segmentation of four object categories present in a modern aviary poultry house with white hens. Although other objects and environments (like greenhouse crops or arable fields) could be tested as well, we decided to limit ourselves to the poultry house. In Section II, we present the methods and materials used. In Section III, we offer the results, which are then discussed in Section IV. Conclusions and indications for future work are given in Section V.

II. MATERIALS & METHODS

The approach used in this work consists of the 10 steps below, and leads from the selection of relevant objects to the definition of threshold values for image segmentation.

1. Define which objects are relevant.
2. Measure the spectral reflection for each object category at all relevant wavelengths.
3. Select which measurements have to be included in the sample for each object category.
4. Find the distribution of reflections for each combination of wavelength and object category, based on the selected measurements.
5. Find the wavelength with the largest discriminative power, i.e. the one with the least overlap in reflection between the object categories.
6. Select a suitable band pass filter for this wavelength.
7. Acquire images using this band pass filter and a standard monochrome camera.
8. Find the distribution of intensity values for each object category in these images.
9. Use this information to define threshold values for segmentation.
10. Segment the image on pixel-level using these thresholds.

A. Materials tested

In step 1, the four main object categories considered relevant in this research were *eggs*, *chickens*, *housing*, and *litter*. As representatives of these, 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 this, the objects were placed on a white cardboard plate in the imaging setup. Other instances of the object categories (like brown eggs and feathers and clean wood shavings) were also measured in step 2, but not used in further processing.

B. Spectral measurement setup

The data on spectral reflection was collected using a hyperspectral line scan setup, based on the one mentioned in [16, 17] and shown in Fig. 1. This setup used 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. Data was binned by 2 cells spatially and 4 cells spectrally, and the 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 camera/spectrograph and the light source were attached to a stepper motor, such that they moved over the object with a fixed step size (0.5 mm), and an area with a length of 150 mm and a width of about 300 mm was measured. Before measurements, the camera and light source were on for at least 20 minutes to avoid start-up effects. Furthermore, a dark room was used to avoid influence from ambient light. In the setup, the reflectance of the object R is normalized from the measured intensity I . It is corrected for the background noise B , and expressed as fraction of the white reference W using

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

which is based on [17]. This normalization was performed automatically in the ISAAC2 software that controlled the imaging setup. 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.

C. Processing methods used

Processing of the spectral data was performed using Matlab. For each object category, between 38000 and 45000 pixels were manually selected from the acquired spectral

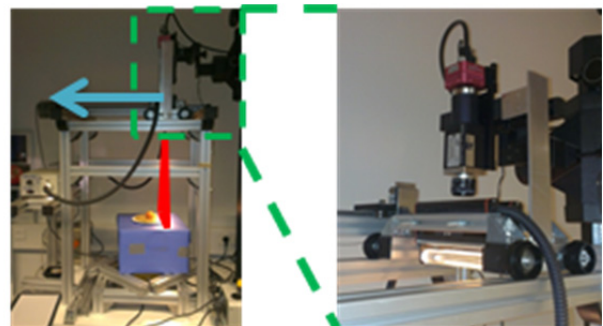


Figure 1: The hyperspectral imaging setup used for the experiments in step 2. On the left, the full setup is shown, with an indication of the linear motion of the camera (blue arrow) and the scan line (red triangle). The blue box is used to place the sample upon, in this case a brown egg on wood shavings. On the right, a close up of the moving construction for the camera, spectrograph and light source.

data. By using such a large number of pixels, the sample set covers more of the variation in the objects. For this, reconstructed RGB images were used to identify the objects, on which rectangles were drawn manually to select pixels to include in the sample (step 3). From these samples, the reflectance distribution at each wavelength band was determined (step 4). Next, a normal distribution was fitted on this data. From these results, the percentage of overlap between the distributions was calculated, for both the measured and fitted distributions. This was done for all 192 wavelength bands by Riemann integration of the overlapping area on the measured distributions and by trapezoidal integration on the fitted distributions. Next, the total amount of overlap per wavelength band was calculated by summing the values of all object categories. Based on this, the wavelength band could be selected where the sum of the overlap between the four groups was lowest (step 5).

D. Application of filtering at the selected wavelength band

The next step was to evaluate whether the chosen wavelength band was also effective under the conditions found in a commercial poultry house. Thus, images were acquired under such conditions, in the same poultry house as used in [3, 4]. In the house, animals of the same breed as used for the collection of the spectral data (Dekalb White) were present. Ambient light intensities were measured using a Voltcraft MS-1300 photometer, and ranged between 5 and 15 lux.

For image acquisition (step 7), a standard monochrome camera and a band pass filter at the selected wavelength band suffice. Thus, a band pass filter (470 nm, with a spectral width of 85 nm FWHM) was attached to an Ueye UI148xSE monochrome camera equipped with a lens with 4 mm focal distance. Frame rate was set to 3 fps, with the diaphragm fully opened and a fixed gain was applied inside the camera. Additional light was added to the scene using a 14-led white-blue light source, to better distribute the measured pixel intensities over the available sensor range.

Processing was performed with LabVIEW and started by taking the square root of each pixel, to correct for the uneven

illumination in the images. Next, the threshold levels for the various object categories were empirically determined from the images using visual feedback (step 9). Using these intensity values, pixel-wise segmentation was applied, to distinguish between the object categories (step 10). To improve the segmentation results, and allow for object detection, more (advanced) processing steps can be added in a later stage. Furthermore, a corresponding ground-truth image was obtained by manually labelling all pixels in the image into 5 categories: eggs, hens, housing, litter, and unknown.

III. RESULTS

The hyperspectral imaging (step 2) resulted for each pixel in a stack of 192 wavelength bands a 2D frame. From this, explanatory pictures like Fig. 2 could be made to inspect the results, before continuing to process them. Fig. 2 shows on the left side an RGB image (reconstructed from the wavelength bands), containing the four main object categories. On the right side, the spectra corresponding to locations indicated on the left are given. It can be seen that eggs had the highest reflectance, followed by chickens, housing and litter, although the latter two switch order in the second half of the spectrum. Furthermore, the difference between litter and both eggs and chickens was large at lower wavelengths, but reduced with increasing wavelengths. For housing and litter, the difference was initially small, but increased at larger wavelengths.

In step 3, multiple pixels for the same object category were selected, as described in Section IIC. The resulting reflectance distributions for the four object categories and two wavelength bands are shown in Fig. 3, together with normal distributions fitted to this data (step 4). Clear differences exist in the distribution of data. Litter and housing have narrower distributions than chickens and eggs. In addition, there is some overlap between litter and housing, as well as between feathers and eggs. Furthermore, this overlap turns out to differ between the various wavelength bands.

In step 5, overlap between all combinations of object types was quantified for each wavelength band, as described in section IIC. The least overlap was found for wavelength

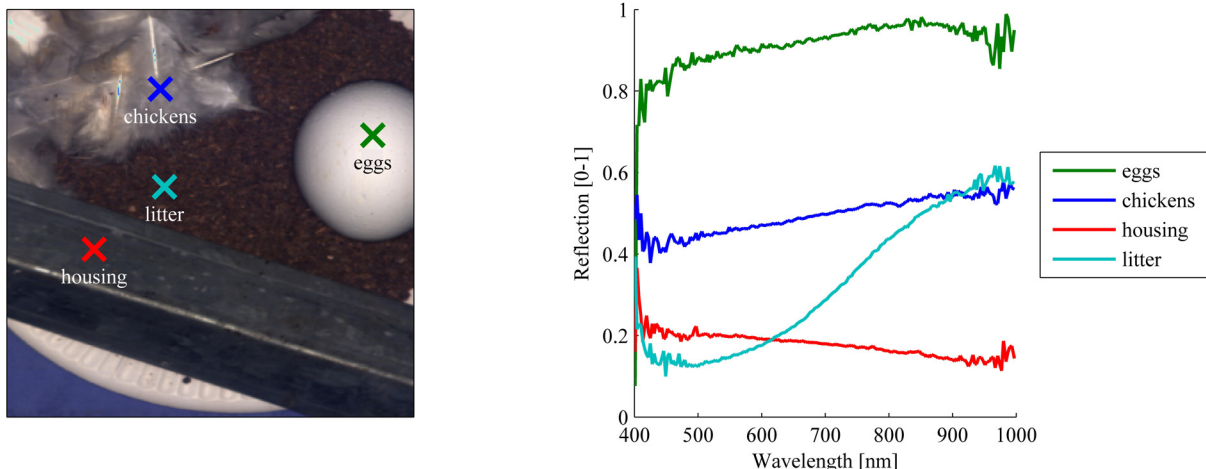


Figure 2: Results of hyperspectral imaging for the four object categories. On the left side an RGB image reconstructed from the spectral data, on the right side the spectra that correspond to the locations indicated on the left.

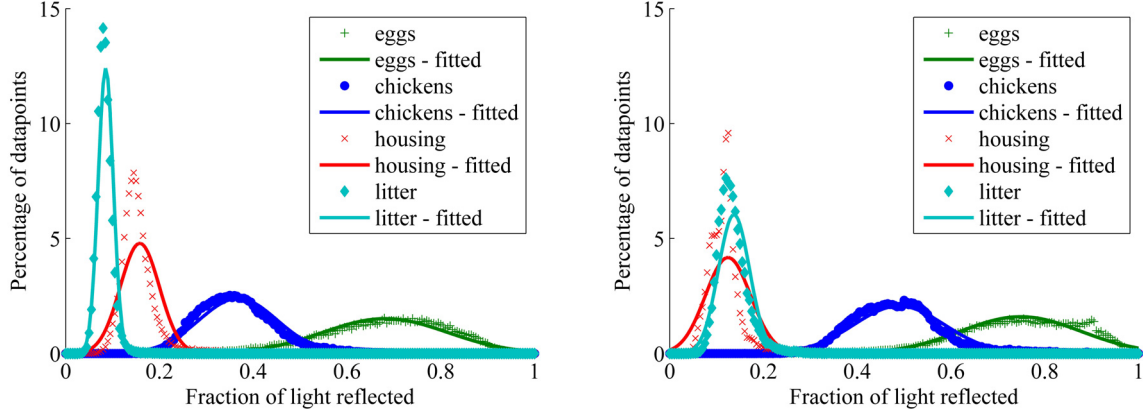


Figure 3: Distribution of reflectance for the 4 main object categories, at the 467 nm (left) and 663 nm (right) wavelength bands. Points indicate measured data, while lines represent the fitted distributions.

TABLE I. RESULTS OF WAVELENGTH SELECTION, SHOWING THE OVERLAP BETWEEN VARIOUS CATEGORIES IN PERCENTAGES. DATA IS PRESENTED FOR BOTH MEASURED AND FITTED DISTRIBUTIONS, AT THE BEST WAVELENGTH BAND (467 NM) AND A LESS SUITABLE WAVELENGTH BAND (663 NM).

Wavelength	Data type	Eggs vs. Chickens	Eggs vs. Housing	Eggs vs. Litter	Chickens vs. Housing	Chickens vs. Litter	Housing vs. Litter	Summed
467	measured	16.2	1.7	0.0	6.9	0.2	11.5	36.5
467	fitted	14.2	0.2	0.0	8.8	0.3	18.1	41.6
663	measured	23.0	1.0	0.3	2.7	0.8	78.1	105.7
663	fitted	24.4	0.0	0.0	1.1	0.6	79.1	105.3

bands between 430 and 515 nm. Among this range, the lowest overlap is found at the 467 nm band. In Table I, the overlap percentages are given for the best wavelength band (467 nm) and a clearly deviating one (663 nm), on both the measured and fitted data. Data in Table I corresponds to Fig. 3. There are clear differences in overlap between both wavelength bands and the various object combinations. At the 467 nm band, the overlap is quite evenly distributed over the categories, whereas at other wavelength bands, it has moved more towards one or two combinations. Most overlap is found between eggs vs. chickens and housing vs. litter, whereas the combinations eggs vs. housing, eggs vs. litter and chickens vs. litter have hardly any overlap.

Based on the lowest amount of overlap, a band pass filter around 470 nm was selected for image acquisition in the poultry house (step 6-7). Two of the acquired images are shown in Fig. 4, together with the preliminary results from segmentation (step 9) and the associated ground truth. The artificial illumination pattern that is visible in the images affected the segmentation results. For example, part of the litter was segmented as hens or housing and some mixing of object categories was present on pixel level. In some images, housing objects had similar intensities as hens and litter, and could thus not be segmented separately. Also, ambient light intensity varied considerably within some images, which made accurate setting of the threshold values difficult. Depending on the object category, the requirement of correctly segmenting 80% of the pixels in the correct group seemed possible.

DISCUSSION

In the results, significant variation in the reflectance can be observed at the ends of the measured spectra. A likely explanation is the limited amount of light available at these wavelengths, especially around 400 nm, as the light source emitted hardly any UV light. Combined with limited sensitivity of the camera chip at the ends of its spectral range, this might result in reflectance values that are largely determined by sensor noise [17]. Prescott and Wathes [14] indicate similar findings from their measurements, especially around 400 nm. They did not indicate whether this originated from technical limitations of their setup instead or if it was a specific feature of the sample measured. To investigate whether any relevant features are present in the wavelength range below 450 nm, it is advised to add a UV light source to the hyperspectral imaging setup. However, the amount of UV available in a poultry house is limited, and artificially adding UV light might have undesirable consequences for animal welfare. Thus, investigating or using UV wavelengths seems of limited use for our case.

Furthermore, measurements on housing material were performed using relatively clean materials. In the poultry house however, it can be expected that there is some contamination with dust and poultry droppings. As result, the reflectance of objects might vary from the values presented and the spectral response might change. Also, reflectance of housing was constant throughout the spectrum, but sensitive to the angle towards the light source during hyperspectral imaging. Thus, this requires substantial attention when using

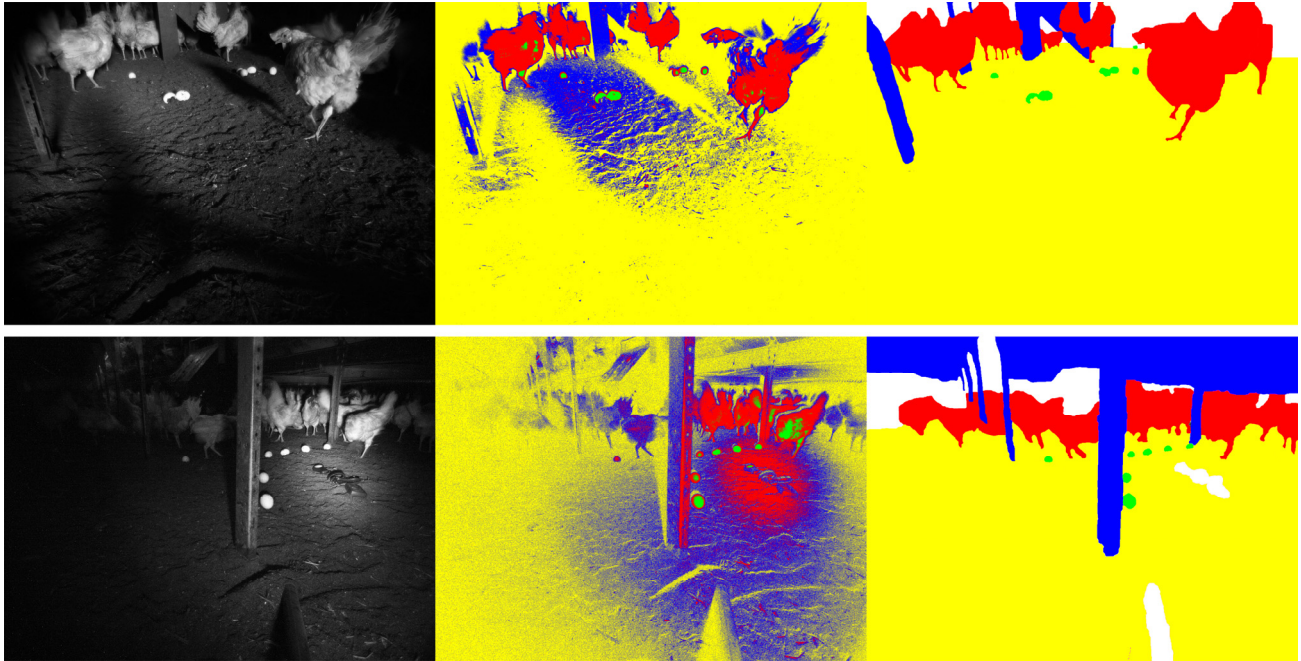


Figure 4: First segmentation results. From left to right: original image (brightness increased by 100), segmentation result, ground truth.

the presented approach and data to test and develop methods for practical applications.

For the selection of the most suitable wavelength band, the sum of the overlap percentage was used. Here, segmentation was weighted equally for each object combination. For practical applications however, it might be relevant to apply different weight factors, to allow better discrimination of objects that are of higher importance. For improving the segmentation results, using multiple spectral bands simultaneously seems also promising. In this way, separate wavelength bands can be selected for different object categories, such that differences in reflectance become more distinct. Initial testing on segmentation for brown eggs indicated that overlap could be reduced from 40 to 10% using this method.

Initial results from applying this approach in a poultry house show that segmenting multiple object categories using this method is quite promising. However, still some difficulties arise, especially with respect to the light distribution in the image and setting the thresholds for the segmentation of housing. Both problems might be related, and have to do with the low amounts of ambient light. Thus, additional illumination was required. As a result, illumination spots appear, which require correction during processing. Also, they lead to a wider range of intensities for a single object category than was expected from step 4. Thus, object categories tend to overlap more, which makes it more difficult to segment them correctly. Possible options to deal with this are the adding of more homogeneous illumination or an improved illumination correction to improve the input image. As processing is currently done using a very simple threshold, segmenting by more advanced methods like considering adjacent pixels or using fuzzy methods to relate pixels to multiple object categories might be used as well.

Such methods can be combined with morphologic image processing like erode, dilate and shape filtering to reconstruct object shapes and thus improve the final classification result. The first results of the method presented are promising, and can be extended to reach the desired level of 80% correctly segmented pixels. Future work will address improvement of results by adding more advanced processing, and evaluation under a wider range of conditions.

CONCLUSION

In this work, a simple and robust segmentation method based on spectral reflectance properties was presented. Spectral reflectance of four object categories that are relevant for PoultryBot (eggs, chickens, housing and litter) was investigated in the range between 400 and 1000 nm. Between the four object categories that are relevant for PoultryBot (eggs, chickens, housing, and litter), clear differences could be observed in the amount of reflectance. At the wavelength band around 467 nm, the overlap of the four object categories was found to be the lowest, and was 16% for chickens and eggs, 12% for litter and housing, and lower for the other combinations. Images taken in a commercial poultry house, using a standard monochrome camera and a band pass filter around 470 nm, indicated that pixel-based segmentation of the object categories is possible using this method. First results showed that the desired level of 80% correctly segmented pixels seems possible, making this method a promising direction for future work.

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