Agricultural Research Department
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Detection, classification and localisation of cucumber fruits within their environment by computer vision

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SUMMARY

Detecting and locating the position of a mature cucumber are essential for robotic harvesting of cucumber fruits. Therefore, it is desirable to develop a sensing technique which can detect mature cucumbers within their environment. This has been the subject of this research.

In most of former fruit detection studies, the difference in colours or brightness between fruits and the other parts of the plant has been used to detect the fruits within their environment or to determine the positions of the fruits. However, it is difficult to apply the same procedure to cucumbers as cucumbers have a colour close to that of their leaves and stems and may be (partly) hidden by their big leaves. Consequently, a sensing technique has to be found which would be capable of detecting cucumbers based on features different from their environment. Therefore, various imaging techniques have been reviewed and some have been proposed for their use in a harvesting robot.

More research and a study on reflection properties of cucumbers and cucumber leaves, finally showed that the imaging technique of using some selected frequencies in the near-infrared range is the most promising imaging technique capable of detecting cucumbers within their environment. In agreement with literature, it has been found that reflectance of cucumbers in the near-infrared range is different in comparison with their leaves.

Unfortunately, experiments in a greenhouse have not taken place and, consequently, it cannot be proved practically that the imaging technique of using near-infrared reflection is the way of detecting cucumbers within their environment. However, considering the results which have been obtained by literature and measurements made in laboratory, on the contrary, suggest there is an opportunity for this imaging technique and, in fact, only correct measurements in a greenhouse would be needed to prove its feasibility.

Further, as cucumbers do not ripen at the same time, every cucumber has to be evaluated for ripeness prior to harvesting. The evaluation of cucumbers within their environment seemed to be a complex task, due to possible occlusion of cucumbers and influences of the unpredictable changing agricultural environment. Although, in the case of clearly visible cucumbers the maturity of a cucumber can be estimated from its volume by measuring its length and diameter (based on a two-dimensional image). The easiest way to determine the maturity of cucumbers seemed to be to harvest all cucumbers at a certain height.

Another difficulty in developing a robot to selectively harvest cucumbers is the localisation of individual cucumbers. This specification is basic prerequisite to guide a harvesting device towards a cucumber, while avoiding collisions with obstacles. While three coordinates are normally required to describe the position of a cucumber within the plant, it has been shown that the output of an imaging sensor, a two-dimensional image, is sufficient to define the location of the cucumber. However, in the case of occluded cucumbers the localisation seemed to be dependent on the possibility of the imaging sensor to detect these occluded cucumbers and the use of an additional ranging technique to guide the harvesting device towards them while avoiding obstacles.

As a result, in this research a first step has been made towards the development of a harvesting robot of cucumber fruits.

PREFACE

Many agricultural tasks have been mechanised for several decades now. Harvesting of soft fruits, however is an exception and has still remained exclusively manual. Meanwhile, the cost of manual harvesting of these kinds of fruits has become a larger part of the fruits final price (labour is even the main cost of fruit production in greenhouses). In the same time, the fruit prices have regularly declined, due to international competition, and a serious lack of qualified labour has appeared for the harvesting task. Therefore, in the present situation, to consolidate the competitivity of the Dutch horticulture the quality of the production systems has to be improved and the labour costs have to be lowered.

Based on this motivation the aim of this project is the development of a harvesting robot of cucumber fruits. Cucumbers are chosen because this fruit has received only little attention for robotic harvesting (only in Japan). At the end of the project a prototype will be presented which can be tested in field.

This research captures only the part of the project that deals with the detection of mature cucumbers within their environment. The detection technique will be based on computer vision.

During this research several people have contributed directly or indirectly to my work. I would like to thank my supervisors Jos Balendonck, Zweitze Houkes and Paul Regtien, for giving me the opportunity to do this research and for their time, valuable inputs and advice, during very busy times for themselves. Further, I would like to thank the department of instrumentation and measurement technology at the Institute of Agricultural Engineering (IMAG) for her assistance, especially Jan Kornet and Peter Nijenhuis, and making available some of her equipment.

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René Groenen

CONTENTS

1 INTRODUCTION

'[...] Agricultural harvesting mechanisation is currently limited to crops which ripen at the same time and which do not require individual and delicate treatment. Mobile robotic systems have been proposed for the selective harvesting of easily-damaged fruits and vegetables. Such robotic systems could increase production efficiency and profitability, and improve overall fruit quality [...]' (Benady, 1992).

However, a robot operating in an agricultural environment will need to receive, classify and analyse sensory inputs in order to navigate successfully, detect and locate the fruits, determine the maturity stage of the fruit and develop efficient plans for execution of tasks.

The selective harvesting of cucumbers is an example of an agricultural process which would benefit from robotic manipulation. Cucumbers are delicate and fresh soft fruits which do not ripen at the same time. Thus, every cucumber has to be detected separately and evaluated for ripeness prior to harvesting.

1.1 Background

In horticulture harvesting of soft fruits (like citrus, apples, peaches, cucumbers, etc.), mainly those which are destined for the fresh market, is still a manual task. However, manual harvesting is a very labour intensive operation and determines a significant percentage of the total cost of fruit production. Furthermore, with the lack of labour for this kind of work, the decline of fruit prices and increasing demand for better fruit quality by consumer there is a valid justification for evaluating alternative methods to manual harvesting (Nienhuis, 1995 and Rabatel, 1994).

Some technology already exists for harvesting fruit intended for processing and for fruit capable of absorbing relatively strong impacts and pressure without impairment of its quality (like walnuts, almonds and filberts). This technology is primarily based on automated fruit detachment using machines which shake the fruit off the tree (or plant), by vibrating the trunk or separate branches, or strip the fruit off by means of an air or water jet (United Nations 1987, p. 1). However, the application of this technology to soft fruit is limited because of possible damage to the fruit (bruising and crushing).

Today's automated harvesting in which the plants are mown down with the fruit still on them and subsequently threshed in order to separate the fruit, also called the 'once-over' method, wouldn't be a solution also. This because of the lack of selective harvesting, which is an important requirement for soft fruits since the fruits do not ripen at the same time (especially for year-round soft fruits like cucumbers, tomatoes and paprikas).

Fortunately, robotic technologies now offer a solution to automate the harvesting of soft fruit. The basic idea is to harvest the fruit individually, like a human harvester, to avoid any damage and to use the possibility of selective harvesting (to choose the mature fruits in between the non-mature ones), but now using a robotic manipulator. Although the harvesting operation is '[...] a very intricate process, involving a multitude of tasks which require dynamic, real-time interpretation of the environment and execution of various sensing dependent operations, advances in microprocessor and microelectronics in recent years make the application of robotics feasible [...]' (Sarig, 1993).

The challenge of developing a robotic system for soft fruit harvesting has been taken up by researchers at several places in the world (Sarig, 1993). The major problems that have to be solved with a robotic harvesting system are detecting and locating the fruit, determining the maturity stage of the fruit and detaching it according to prescribed criteria, without damaging either the fruit or the tree (or plant) (Benady, 1992). In addition, the robotic harvesting system has to be an optimal and cost-effective alternative method to manual harvesting (see appendix A).

1.2 Goal

Cucumber harvesting for the fresh market is very labour intensive in comparison with harvesting of other fruits in horticulture. Cucumbers should be selectively harvested when the size and maturity are suitable for the market. However, the cucumbers grow so fast that one half day's delay of harvesting may damage its price in the market. Some farmers even harvest in midnight in order to obtain a higher price. Hence, it is beneficial to automate the harvesting of cucumbers (Amaha, 1989). In this project it is this soft fruit which has to be harvested by the harvesting robot.

Before being harvested the cucumber has to be detected, classified and located by the robot first. It is this part of the system which covers this research. The goal of this research is namely to derive sensing systems which are able to:

- Detect and far locate the cucumber within its environment;
- Classify the cucumber (determine its maturity stage);
- Precise locate the cucumber (for handling and cutting).

However, the accent in this research will address mainly the first point and to a lesser degree the last two points.

Furthermore, especially the use of computer vision as the major sensing technique has to be evaluated. This because of the recognition of the potential of this technique for the guidance or control of agricultural processes (Tillett, 1990). It is capable of providing large amounts of scene information and its operational range covers small and large areas over a broad range of distances (Dobrusin, 1992). The envisioned computer vision system will have to encompass the sensing and the processing tasks, detect and classify (possibly providing an indication of the cucumbers maturity) the cucumber after which the cucumber can be located. This and maybe other sensing techniques will be developed by using literature and experimental research.

As already mentioned, no automatic harvesting system is available yet. Therefore, such a system has to be developed right from the start. The system requirements are:

- The final harvesting results should be at least as good as the results produced by human harvesters;
- The system should be economically justifiable;
- For logistic and economic reasons the harvesting operations should not cause additional operations in the cultivation carried out in the greenhouse;
- For some time the system should be able to operate without human supervision;
- The specifications mentioned in appendix A.

In addition, this research is limited to applications to the high-wire cultivation method which has almost no curved and bruised (deviating) fruits (see appendix B). The harvesting robot will be adapted to the physical properties of the cucumber plant in this cultivation method. No studies will be done in possibly changing the cultivation method in which the robot could work more easily. For example, the inclined trellis method (with its disadvantage of low production and very high cost price) used in Japan (Kondo, 1994).

1.3 Overview

Although, the project is restricted to the harvesting of cucumber fruits. It can be expected that the developed sensing technique(s) (or its achievement) will be (partly) useful for the harvesting of other soft fruits, like tomatoes and paprikas. Because of this similarity it has been chosen to start this research with a general approach after which more and more attention will be focussed at the chosen fruit: the cucumber.

Hence, in the next chapter, first, the practical use of image analysis for the harvesting of fruit is described. In chapter 3, various imaging techniques will be reviewed and their potential for the detection of fruits within their environment will be discussed. Finally, after this preliminary and general research an appropriate imaging technique will be chosen for its used in cucumber detection, which is described in chapter 4, and which will be tested by experiments in chapter 5. Further, as cucumbers do not ripen at the same time every cucumber has to be located separately and evaluated for ripeness prior to harvesting. This is described, respectively, in chapter 7 and chapter 6. In chapter 8, the results are discussed, conclusions are drawn and ideas for future research are given.

2 IMAGE ANALYSIS IN THE AGRICULTURAL ENVIRONMENT

Image analysis and interpretation by computers, also called computer vision, has many potential applications for guiding or controlling agricultural processes (like grading, quality control, pruning, harvesting, etc.) (Tillett, 1990). The practical use of image analysis for an agricultural process will require the system ~~to~~ output data to guide or control a robotic system. A lot of applications in this area are at an early stage, being developed under laboratory conditions. Methods of extracting information from the image and using it to make correct decisions are studied. For practical use a lot more research is required to include the flexibility, robustness and speed necessary for the system to work under the varying conditions of the application and without human supervision (Sarig, 1993).

Thus, although there is a lot of research being done, most of it concentrates on specific applications using, on the whole, very simple image analysis algorithms. These image analysis algorithms will be successful under certain constrained conditions, but for more flexibility and robustness there are generic problems to be overcome. These problems mostly relate to the variability of the agricultural objects being viewed and the lack of controllability of the agricultural environment.

2.1 Image analysis for the harvesting of fruit

There are many processes in agriculture where decisions are made based on the appearance of a product. The harvesting of fruit is a particular example, which depends mainly on human visual detection. All these applications involve agricultural objects, which have a natural variability. Consequently, any process or task which interacts with the agricultural objects has to be sufficiently flexible to deal with this variability. Humans use their eyes to achieve the required flexibility (Edan, 1995).

Recently, advances in computer technology have produced an increase of interest in image analysis systems, also called computer vision. Researchers have demonstrated the technical feasibility of using an image analysis system to guide a robotic system in the harvest of fruit (Slaughter, 1989). But, as yet, there have been relatively few industrial applications of image analysis systems and very few within the agricultural industry (Sarig, 1993).

Already existing industrial image analysis detection applications (to guide a robotic system) have potential use to automate the harvesting of fruit. However, they cannot simply be applied to the agricultural environment because of such problems, as already mentioned, as the variability of fruits and the difficulty in interpretation of the uncontrollable environments. These difficulties make it necessary to develop an image analysis system for the harvest of fruit from the very beginning. Basic techniques developed for industrial applications can be applied. However, for most steps in the development of an image analysis system, modifications are necessary in order to make them suitable for agricultural applications. To find an image analysis system for the harvesting of fruit, first an introduction and overview of the actual image analysis process is given.

2.2 Image analysis

Generally, an image analysis system consists of an image sensor, a computer containing the electronics for a frame grabber and frame store, a lighting system, a display monitor and a terminal allowing the user to interact with the computer. The image sensor generates a signal representing the image of a scene, which is passed to the frame grabber. The frame grabber samples the signal and converts it to a digital form (the quantization). The image is stored in the frame store of the computer, linked with suitable electronics to a display monitor. This allows the image to be displayed to the operator (see figure 2.1).

A stored image can be processed using algorithms written in the form of a computer program. The choice of algorithms which are appropriate depends greatly on the type and quality of the image.'[...] In machine-vision systems, the success of the image processing and analysis phases is highly dependent on the quality of the information in the images. This, in turn, is highly dependent on the quality of the lighting, optics, and sensor used to capture the image [...]' (Burke 1996, p. 1). The algorithms may be very simple, such as counting the number of white pixels, or very complicated involving such things as the matching of models of likely objects to the image. The output of the algorithms may be quantities, such as lengths or areas, or scores associated with some references. The computer program has to combine this information with preprogrammed knowledge of the required task to draw out specific conclusions such as whether an object appears in the image, where it is, what size it is and if it is of sufficient quality. This will provide the final interpretation of the image, in order to guide or control further systems.

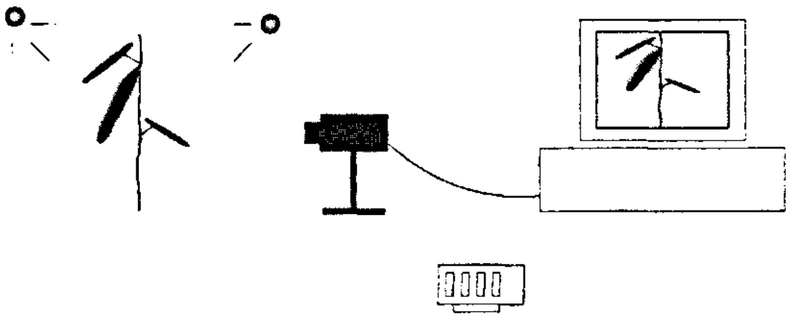

Figure 2.1. Example of an image analysis system

There are three essential subsystems in which the image analysis system can be divided:

- Image acquisition;
- Image processing;
- Image interpretation.

These three subsystems are very interdependent and one subsystem can be considered entirely in isolation from the others. The next three sections discuss some of the possible techniques in each subsystem.

2.3 Image acquisition

The first subsystem in the image analysis system is image acquisition. The image acquisition encompasses the proper selection of light sources, sensors and supporting optics, and their positioning with respect to the scene being imaged. If this is done correctly, the result should be an image with maximum information utility. Because an image analysis system is mostly contrast based the goal of the image acquisition is to acquire an image with high contrast between background information (noise) and any object features containing the needed information required to perform the required task. Thus, the information to be extracted has to be defined with respect to the overall image analysis system goals (Dorf 1990, p. 1101).

In specifying the image acquisition to satisfy a set of image analysis system goals, one has varying degrees of control over the system's lighting, sensors and optics, all within the constraints of the specified task environment. For example, with respect to sensor specifications one can select for spectral response, sensitivity, speed and resolution, as will be discussed in the paragraphs below.

2.3.1 Lighting

The quality and quantity of the illumination of a scene are important factors that often affect the complexity of succeeding image analysis algorithms. The importance of the light source and its application is often undervalued with respect to the image analysis system. It is generally far easier to control lighting than to deal with the uncontrollability of analysing an image dependent only on ambient light. Furthermore, arbitrary lighting of the environment is seldom acceptable, resulting in low contrast images, specular reflections, shadows and extraneous details. A proper lighting system illuminates a scene such that the complexity of the resulting image is minimised, while the information required is enhanced (Paulsen, 1986).

'[...] The source of illumination must provide the image analysis system with the best possible image of the object, e.g. the highest contrast between the features of interest and the background. The illumination source must be selected to match a given application's needs with respect to spectral content, source size, efficacy, directionality, reliability/service life, cost, steadiness of output and intensity [...]' (Burke 1996, p. 128).

One of the first considerations in selecting a light source is the spectral distribution required by the application. What wavelengths are needed? Most image analysis systems use visible light to illuminate the scene, but there are other types of light sources, including acoustic scans, X-rays, infrared, etc. Generally, the spectral range of the light source which should be used depends on the required task and the sensor requirements. Figure 2.2 shows the spectral responses of several types of light sources. In addition, illumination at unwanted spectral wavelengths can result in a source of problems (like glare, heating, etc.).

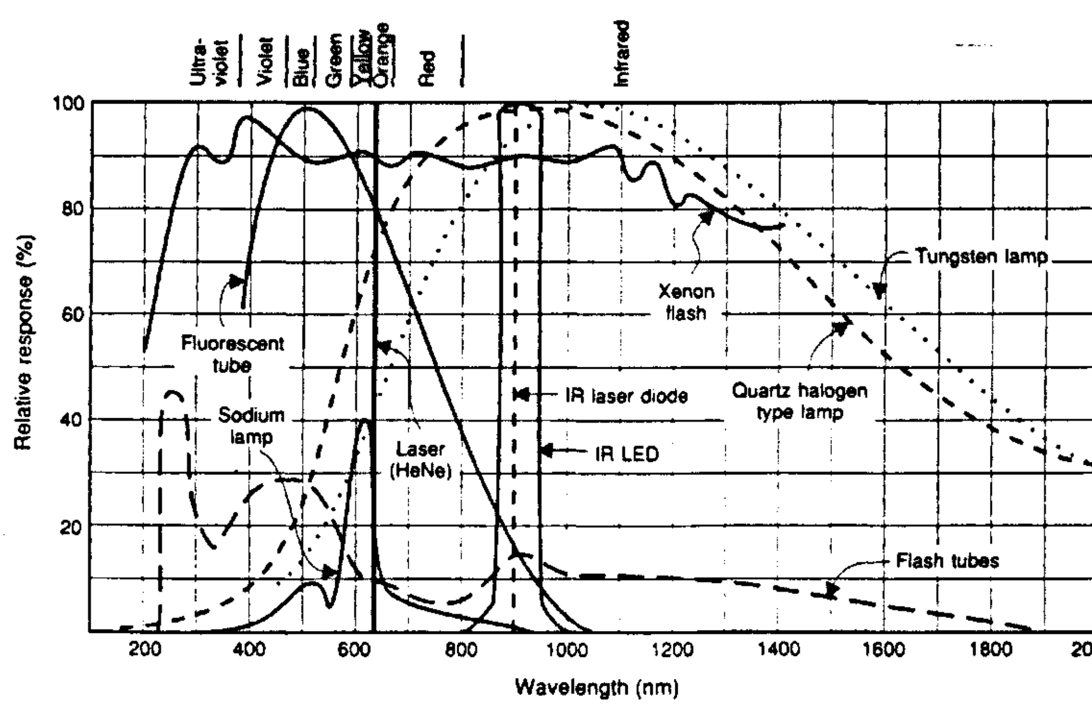

Figure 2.2. Spectral response of several light sources (Burke 1990, p. 129)

Further, how intense should the light source be? This depends greatly on the reflectivity of the object, the sensitivity of the sensor and how large the area is which has to be illuminated (Burke 1996, p. 127-129 and Paulsen, 1986).

In addition to considerations as the radiance of a light source, attention has to be given to the setup of scene illumination. One can seldom manipulate the object in the scene. In fact, the object features (size, reflectivity, colour, temperature, etc.) are usually what have to be measured by the image analysis system. But, one can often control the locations and orientations of light sources and sensors relative to the object. By controlling these positions, features of interest can be given enhanced contrast to background information. This can be done, for example, by using the following lighting possibilities (Burke 1996, p. 109-124):

- Backlighting;
  To produce high contrast images.
- Frontlighting;
  To enhance the spectral features of the object.
- Structured lighting.
  To yield direct three-dimensional information about the object.

Generally, the type of lighting which should be used depends greatly on the required task and often cannot be determined straight at the beginning. The traditional way of deciding which type of lighting is best is to make preliminary tests. Further, the more control one has over lighting, background and orientation and position with respect to the object the easier subsequent analysis will be (Tillett, 1990).

2.3.2 Optics

The characteristic interactions between light source and scene are the primary source of information present in the image acquired by a sensor. On the other hand, the optics in an image analysis system (like lenses, mirrors, prisms, polarisers, filters, etc.) are the primary means of modifying and controlling the information, both between the light source and scene and between the scene and sensor (Dorf 1990, p. 1102).

There are actually two distinct optical subsystems within the image acquisition: the illumination optics (between the light source and scene) and the imaging optics (between the scene and sensor). Imaging optics are mostly used to gather and concentrate the energy (information) being emitted/reflected from the object. For example, the primary function of a lens is '[...] to gather enough energy from the object to form an image of good contrast while maintaining a sharp optical image on the surface of the sensor. This image should have sufficient resolution for the required task (which also determine the resolution of the sensor) and adequate irradiance to permit a good contrast image [...]' (Burke 1996, p. 285-286). The imaging optics selected will interact strongly with the sensor selected, sometimes compensating for limitations in the sensor and sometimes expanding its capabilities into new sensing paradigms.

The function of the other optical subsystem (the illumination optics) is the manupilation of the radiance of the light source. Often a light source does not have either the required radiance, sufficient area or it cannot be positioned properly, etc. Optical components can then be used to change the characteristics of the light source. Like changing the intensity of the light source (concentrating it by the use of lenses or reflectors), diffusing the light source and varying its spectral characteristics (Burke 1996, p. 108).

It can be concluded that the flexibility in the optics can be very useful in the image acquisition.

2.3.3 Sensors

'[...] The sensor is the image acquisition component most often overlooked for design manipulation. In the past, the sensing component of the image acquisition subsystem has been seen as a constraint rather than a design variable. More recent technological advances have now given the computer vision system designer a very flexible arsenal of sensing tools. It is now possible to select from a wide variety of specialized sensors [...]' (Burke 1996, p. 107).

Sensors can be classified into two categories: contact and non-contact. A contact sensor measures the response of an object to some form of physical contact. This group of sensors responds to touch, force, torque, pressure, temperature, electrical or magnetic quantities. A non-contact sensor measures the response brought by some form of electromagnetic radiation. This group of sensors responds to light, X-rays, radar, acoustic, electric or magnetic radiation (Dorf 1990, p. 890).

The primary task of the sensor in an image analysis system is to convert scene information (after properly illuminating the scene and collecting and focusing the energy onto the imaging sensor) into electrical signals suitable for image processing. Thus, the sensor represents, as Burke (1996, p. 540) has noted, '[...] the primary point of connection between the environment being examined and the image processing system [...]'. This conversion process is never ideal. The sensor is therefore of particular importance with respect to how faithfully it senses or converts the scene information and how it can present the transformed information to the image processing subsystem.

To generate an acceptable image (one that contains enough information to accomplish the required task), appropriate parts of the electromagnetic spectrum can be sensed. However, most image analysis systems senses reflected visible light, but as seen in previous paragraphs, the utilization of reflected radiation from non-visible sources such as ultraviolet, acoustic scans, X-rays, infrared, etc., can also be used and may be more appropriate. Further, to select a sensor that will satisfy the required detail in the image analysis system the resolution characteristics of the sensor with respect to greyscale, spatial and temporal domains have to be viewed (Dorf 1990, p. 1101-1102).

In general, it is important to know the salient characteristics of the sensors, their advantages and limitations and how these impact on the required application. Further, the sensors which may be used will mainly be determined by the goals of the image analysis system. Lack of information about the image analysis system goals and their fit to the capabilities of the sensors can easily lead to overly complex sensing systems that are costly and slow or to overly simplistic sensing systems that simply do not work.

2.4 Image processing

Image processing is the manupilation and analysis of the acquired images. It can be considered to consist of three parts (Dorf 1990, p. 1096):

- Image enhancement;
  Operations using the original image to create other images, finally resulting in an image that contains only desired information.
- Segmentation;
  Process of separating objects features of interest from the background, partitioning an image into various regions.
- Feature extraction.
  Operations that extract feature information from the enhanced and/or segmented image.

2.4.1 Image enhancement

Image enhancement improves the degradation of the image (low contrast, blurred, noisy) through operations which transform an image into a 'better' image or one more suitable for subsequent processing. There are three fundamental enhancement operations: pixel or point transformations, neighbourhood transformations and image or global transformations (Dorf 1990, p. 1103-1104).

Pixel transformations
Single pixel operations transform an image pixel by pixel, based on one to one transformations of each pixel's value. Like scaling, addition or subtraction of a constant to each pixel, inverting, etc.

Neighbourhood transformations
The operations transform an image by replacing each pixel with a value generated by looking at pixels in that pixel's neighbourhood. Like filtering, smoothing, etc.

Global transformations
In this case, an operation is performed on an entire image. Like smoothing, subtraction, multiplication, etc.

2.4.2 Segmentation

An important step in image processing is the segmentation of objects features of interest from the background. The simplest way to segment an image is by using a threshold. '[...] Segmentation, using grey level thresholding can be performed extremely fast since the operation is easily handled in hardware at standard video rates. Once a binary image has been constructed, a quick and simple Boolean operator is sufficient to determine if a pixel is object or background [...]' (Slaughter, 1989). The main difficulty with thresholding is to choose a threshold which distinguishes object feature from background. When the object feature and its background have highly contrasting colours, colour can sometimes be used to segment the image. This generally results into a much more refined segmentation, since it is based on several features rather than a single one (Tillett, 1990). However, in many situations the contrast between object feature and background is poor and a more complex approach is required.

There is a large set of techniques documented in the image processing literature such as edge detection, texture analysis and region growing and splitting which can be used to segment an image. However, these techniques tend to be complex and time-consuming. Faster techniques involving joining edge segments will give partial segmentation of the image, but to understand the results of the segmentation, knowledge on a higher level is required. The higher level contains, for example, knowledge about the objects' size, shape and connectivity between the elements to form objects. In this way clusters of pixels are labelled as elements of an object or disregarded as noise or background.

2.4.3 *Feature extraction*

Feature extraction is the process of deriving some values from the enhanced and/or segmented image, containing the objects features of interest. These values are usually dimensional (like area, length, width, perimeter, convex hull area, moments), but may be other types such as roundness, density ratio, intensity and shape. In addition, measurements of features with dimensions always implies the need for calibration. The advantage of dimensionless features is that no calibration is needed. The features which have to be measured strongly depend on the application.

For simple images, feature extraction may be easy once the image is segmented. The length, width, area, principal axes, moments and so on of an object feature in the image will be easy to measure once the edge is defined. These features can be described mathematically and have a clear meaning. In the case of more complex features it will be difficult to describe them mathematically and locate reliably. These features are application dependent and require some knowledge of the application either implicitly or explicitly included in the computer program (Dijkstra 1994, p. 31-35).

2.5 *Image interpretation*

After feature extraction, the results of the image processing have to be interpreted to provide the output of the image analysis system. The interpretation is based on one or more features processed in a linear or non-linear mathematical model, called the decision model. In some situations the simple features are all that are required, but often more refined conclusions have to be drawn. Application specific knowledge has then to be included to make sensible evaluations of the features found. The simplest way of including knowledge involves cluster analysis (the clustering of points in the feature space). Regions can be distinguished which belong to a certain object based on similarity to some reference. In the case of a homogeneous distribution in the feature space (no clusters can be distinguished) the use of a linear model would be a possible solution. For the development of such a linear model, multiple linear regression analysis can be used as a method for finding weights which have to be combined with features. However, these techniques require well understood and constrained conditions. For more flexibility there has to be a more general inclusion of knowledge, allowing it to be applied over varying conditions. For these non-linear cases, decision models can be developed using fuzzy logic (like artificial intelligence) and neural networks (Dijkstra 1994, p. 35-36).

2.6 *The development of an image analysis system for the harvesting of fruit*

On the basis of the different subsystems in an image analysis system for the harvesting of fruit, a strategy for the development of such a harvesting system is needed first.

The harvesting system has to result into the detection of mature fruits within their environment, called the Harvesting System Detection Output (HSDO), after which the fruits can be located. This detection output determines among others the goals of the harvesting system. These goals are called the harvesting task. In turn, the harvesting task determines the setup of the harvesting system, because the harvesting task determines which fruit features have to be used to result into the HSDO. In figure 2.3 the subsystems (including the image flow and knowledge flow) are shown in the harvesting system development stage.

It can be seen that there are two layers:

- The lower level (system knowledge);
  representing the image flow with the features.
- The higher level (human knowledge).
  representing the knowledge flow.

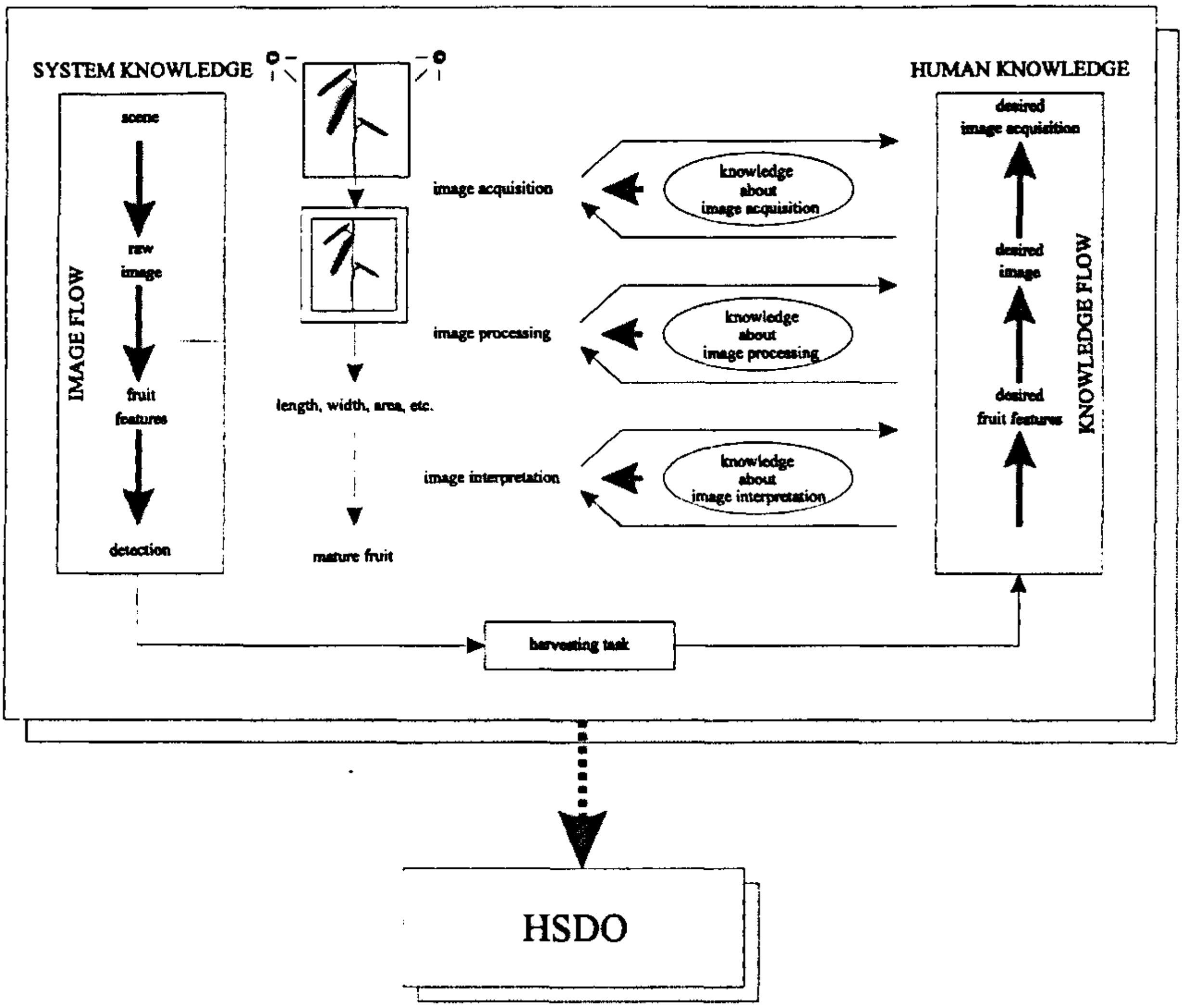

Figure 2.3. Image and knowledge flow in the harvesting system development stage

The human knowledge about the harvesting task is embedded in the knowledge flow, while the system knowledge about the harvesting task is embedded in the image flow. The knowledge flow goes from the total impression of the agricultural environment to a single feature of the fruit. Humans are able to detect fruit within its environment, based on comparison. However, they are not able to measure features of a single fruit without tools. The image flow goes from the single features of a fruit to the total impression of the agricultural environment (the detection, maturity estimation and localisation). As the image analysis system is capable of measuring single features of a fruit. However, it is not able to detect mature fruit within its environment without additional knowledge.

Thus, the harvesting system needs knowledge for the detection (and finally locating) of the mature fruits within their environment (HSDO). Therefore, during the development stage of a harvesting system the two flows have to interact with each other in the subsystems. A combination of the desired output of a subsystem with the knowledge about the subsystem leads to the desired input of that subsystem. So, knowledge about the image interpretation combined with the harvesting task results into a list of desired fruit features. Knowledge about image processing combined with the desired fruit features results in the characteristics of the input image. The input image has to contain information about the desired features. Knowledge about image acquisition combined with the desired image characteristics results into an image acquisition (see figure 2.3) (Dijkstra 1994, p. 37-39 and Edan, 1995).

Further, an important requirement of a harvesting system is its operation without human supervision. For a proper system operation, control is needed over the decisions of the harvesting system. In figure 2.4 an automatic harvesting system is shown. Each subsystem makes decisions in the image flow. The status of the decision is reported to the 'supervision layer'. If an error status is reported by one of the subsystems the analysis is stopped and the image has to be recaptured. In this way the system is prevented from taking false decisions from incorrect images.

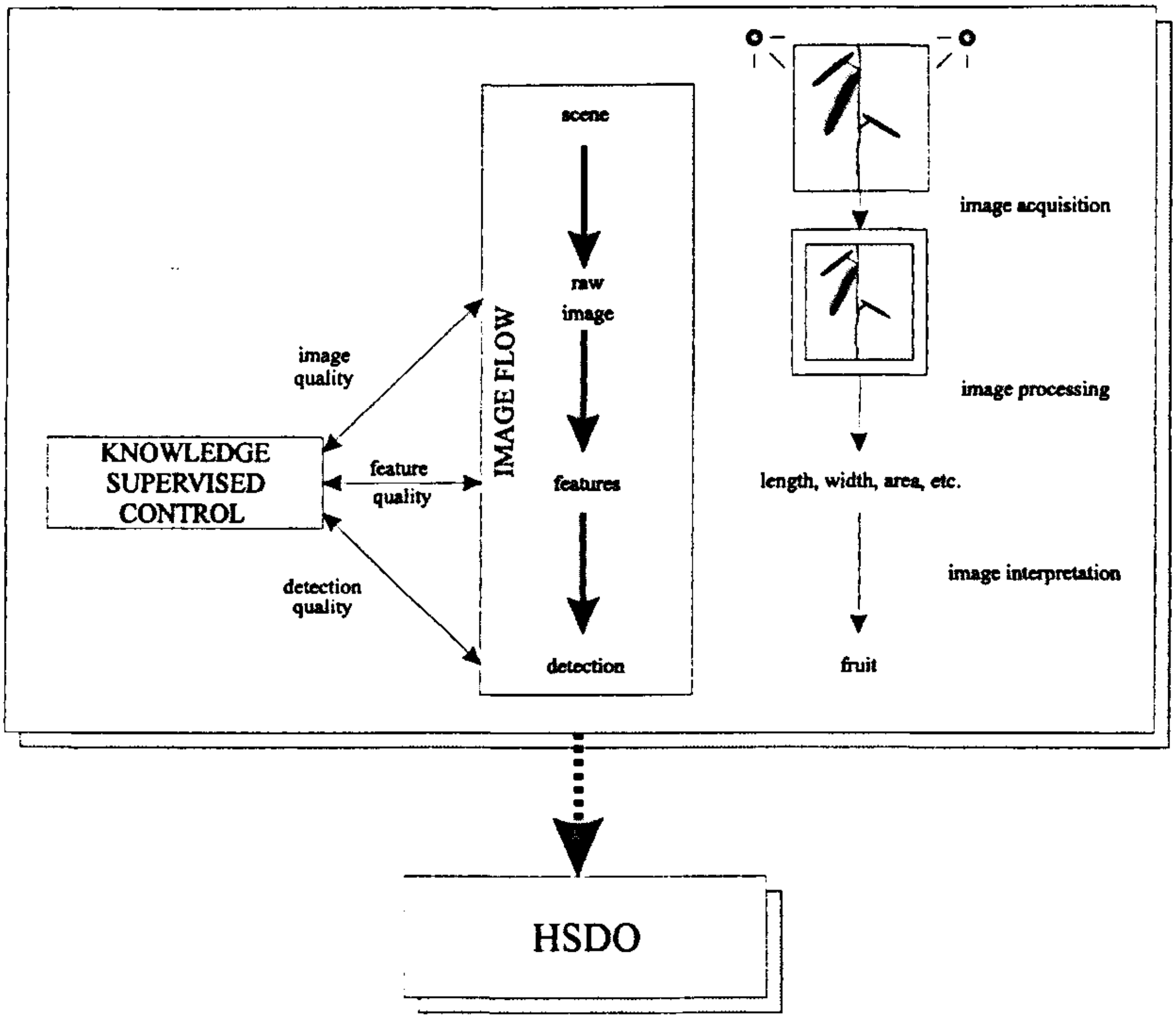

Figure 2.4, An automatic harvesting system

2.7 *Practical considerations*

In all subsystems, errors will be introduced into the measurements. The several sources of error will have their influence on the reliability of the harvesting system output. Some sources of error (like insufficient resolution, too large variation in the distance between sensor and fruit, etc.) can be minimised by choosing a correct setup. Other sources, mainly caused by the agricultural environment (like the variability of fruits, occlusion of essential fruit features, variation in illumination, motion of the fruit, etc.), are difficult to influence and have to be taken into consideration during measurements. Consequently, for practical use the harvesting system has to achieve requirements in flexibility, robustness and speed necessary for the harvesting system to succeed in the agricultural environment (Burke 1990, p. 689 and Tillett 1990).

Therefore, the image processing has to be flexible and robust in the sense that they allow for changes in illumination (sun direction, clouds), variability in the fruits and uncontrollability of the agricultural environment. The image processing should work reliably under all the extremes likely to be encountered. This may require 'extra' algorithms to control the system and guide error recovery.

Also, the sensors have to be robust to the likely conditions in the agricultural environment, such as temperature changes, dirt, dust, extreme humidity, etc. Further, they have to work many hours a day with little attention paid to maintenance.

Besides, the speed of the harvesting system may be a critical part of the automatic harvesting process (has to work in real-time). To some extent the speed can be increased by using more expensive hardware, but much more increases can be achieved by making sure only necessary processing is done. Techniques for segmenting the image and extracting the important fruit features as soon as possible allow further processing to be restricted to these segmented images. However, reducing the amount of further processing may, of course, adversely affect the robustness of the image processing. Another method of increasing speed is by using parallel processing (Burke 1990, p. 1076).

In addition, the flexibility in the harvesting system may allow it to be used for similar processes, such as the harvesting of similar types of fruits.

2.8 *Conclusions and discussion*

In this chapter the application of image analysis in the agricultural environment, in this case for the harvesting of fruit, has been discussed. In industry different applications have already been developed. However, they cannot be directly applied in agriculture because of the difference in objects and controllability of the environment. Therefore, most steps for an image analysis system for the harvest of fruit have to be developed from the very beginning. Knowledge and fruit features are required to meet the mature fruit detection goal.

To setup a harvesting system a harvesting task has to be formulated (to determine which fruit features have to be used to result into the HSDO). An important part of the development of a harvesting system is the information about fruit features that have to be measured and their processing in a decision model to come to the detection of the mature fruit. If desired fruit features are not measurable in the input image, other useful fruit features and/or another setup (like changing the sensor) have to be chosen. Further, the use of the different subsystems in an image analysis system reduces the complexity of the harvesting system setup.

The strength of using image analysis in the harvesting of fruit is its ability to measure many fruit features in an objective way. However, for the detection of the mature fruit it requires considerable additional knowledge. Humans, on the other side, are good in analysing complex images and comparing them with each other. Consequently, during the development stage of a harvesting system the two have to interact strongly which each other.

Errors in the harvesting system setup could result in a nonsatisfactory Harvesting System Detection Output (HSDO). The errors can occur in all subsystems and, consequently, require for practical use of the harvesting system to include flexibility, robustness and speed necessary for the harvesting system to work in the agricultural environment and without human supervision.

3 DETECTION OF THE FRUIT WITHIN ITS ENVIRONMENT

The first major harvesting task of the harvesting system is to detect the fruit within its environment.'[...] While humans can recognize familiar objects from almost any angle, over a broad range of distance and lighting, and incorporate hearing and other senses to aid in the vision operation, it is most difficult to replicate this intricate process by machine vision [...]' (Sarig, 1993). Unfortunately, the fruit features (to meet the fruit detection) are not well defined since they vary in shape, size, texture and colour. Furthermore, the fruit features are dependent on environmental influences, such as changing illumination conditions (clouds, sun direction), shadows or occluding leaves, which may change or hide the fruit features. In addition, the locations of the fruits are random. While this all doesn't present a major obstacle for human vision it may be a considerable technical challenge for an image analysis system.

Nevertheless several researchers have attempted, with reasonable success, to develop an image analysis system capable of detecting fruits within their environment (Amaha, 1989; Balerin, ?; Benady, 1992; Bracy 1992; Dario, 1994; Dobrusin, 1992; Edan, 1995; Fujiura, 1992; Hayashi, 1996; Kondo, 1994; Kondo, 1994; Kondo, 1995; Moltó, 1992; Namikawa, 1988; Plá, 1993; Rabatel, 1994; Rabatel, 1995; Sarig, 1993; Sevila, 1991; Slaughter, 1989; Tillett, 1995; et al.).

3.1 Detection of the fruit

In horticulture the environment of fruits is complex and loosely structured. The fruit locations are random and the fruits can be difficult to detect and reach (may be hidden by leaves). The shape, size, texture and colour of the fruits are variable and the environmental conditions (in field and in greenhouses) are hostile due to changing illumination (clouds, sun direction), shadows, dust, dirt, temperature changes and extreme humidity (Edan, 1995). The uncertainties in the fruits location, shape, size, texture and colour (the fruit features) necessitate a sophisticated image analysis system which has to detect fruits that may partially be occluded in constantly changing environment conditions. In addition, imaging sensors tend to be the most suitable technique for dealing with these problems (Sevila, 1991).

The fruit features which should be interpreted in the image interpretation, used in the harvesting system for the detection of fruits (the harvesting task), depend on the character of the fruit of interest. The resulting desired fruit features, which have to be measured, may be detected (in the image processing) by examining intensity levels in a grey level image of the agricultural scene. As intensity levels result from two components: the reflectance properties of the fruit within its environment and the ambient illumination. However, grey level thresholding requires that in the image the fruit features and their environment have different levels of intensity. The threshold is then the intensity level that allows fruit to be detected within its environment.

Unfortunately, due to among others the natural variability of the illumination conditions during the day the fruit features are not easily to detect within their environment. Under daylight conditions, the following problems are usually encountered:

- In scenes with light and shadow, fruits located in the dark area are difficult to detect;
- Direct sunlight is reflected from leaves, making them appear brighter than fruits in the shadow;
  '[...] In the laboratory, with a proper selection of filters, a fruit can be distinguished from leaves, whereas in the field the sky, clouds and soil may sometimes be classified as fruits. A fruit in sunlight may appear brighter than a leaf in sunlight, while in the shade a leaf could appear brighter than a fruit [...]' (Sarig, 1993).
- Throughout the day the illumination varies, due to changes in the incidence angle of the direct sunlight and the passage of clouds.

Although there is a lot of research being done in this area (Moltó, 1992; Plá, 1993; Rabatel, 1994; et al.), most research in the detection of fruits have employed controlled illumination, in which the image analysis system does not run the risk of the extremely variable conditions that occur in field or in greenhouses. So used Dobrusin et al. (1992) grey level imaging to detect melons. However, the performance was improved by adding knowledge and some melons could not be detected because of occlusion by leaves and other melons.

Research on oranges, peaches and other colourful fruits have found that fruit can possibly be distinguished from occluding leaves by colour (Rabatel, 1995 and Slaughter, 1989). The technique of colour segmentation gives good results when in the image the fruit features and their environment have highly contrasting colours. Colour filtering was used by Rabatel et al. (1994) in an image analysis system for harvesting apples and by Balerin et al. (?) and Hayashi et al. (1996) for harvesting tomatoes. However, in the case of clusters of fruit problems may arise in segmenting these clusters into single fruit (Bree, 1994). Further, avocado, apples (as 'Granny Smith'), melons and, of course, cucumbers may have colours close to the plants leaves and stem. These fruits are, therefore, difficult to detect within their environment based on intensity or colour only.

Texture can also be used (as a desired fruit feature) to detect fruits within their environment (as it impacts the reflectance). Some fruit have textures different from their leaves. Some are smooth while others are rough. Texture analysis has been used (Dobrusin, 1992 and Qiu, 1991) and might be a way to detect some specific fruit (like using the different edges intensity (netting) in melons and leaves).

Another feature characterising a fruit is its shape. The main problem of shape analysis techniques is to expose the edges in noisy images or in images which are 'contaminated' with occlusion. Under these conditions, edge detection techniques are likely to give only partial information on the desired edges and a large amount of extra unwanted edge information from its environment. Techniques which are suitable for this situation must include some knowledge of the fruit. Parts of edges can then be linked together by using knowledge of the expected fruit. Or in the case of a topdown approach a model of the fruit can be matched to the image. However, the model must be allowed to deform or change to match the likely variations of the fruit. Another useful technique may be the Hough transform technique which is specially designed for applications with noise and occlusion. So used Whittaker et al. (1987) the circular Hough transform for the detection of tomatoes.

Much of the research mentioned above has been directed towards the interpretation of images obtained in the visible range. Relative little attention has been given to improve the information collected by the image analysis system or in examining other techniques which could be used to generate an image which highlight desired fruit features even better.

There are several reasons for the large interest in the use of the visible range of the electromagnetic spectrum. Firstly, the image obtained corresponds closely to our own perception and secondly, because more and more attention has been paid to this kind of cameras their performance have been increased and lowered their prices. Moreover, these cameras have become smaller and more robust, making them more attractive for incorporating in robotic systems (Bull, 1993 and Sevila, 1991).

Although detection techniques using the visible range give acceptable results, they do not include the possibility of detecting fruits which have a colour close to that of the rest of the plant. Furthermore, the output of the sensing is a two-dimensional (2D) image, whereas the agricultural environment has a three-dimensional (3D) nature. The plants have volume that is filled by stems, leaves and fruits, which may obstruct the fruit. The desired fruit features may be distorted by occlusion so that sometimes they cannot be detected at all. Under these circumstances, it is therefore difficult for an imaging sensor, working in the visible range, to detect fruit within its environment. However, as already mentioned, there are other imaging techniques which can give additional or more specific information about desired fruit features to that obtained in the visible range. A few of these techniques will be described below and its potential for the use in the detection of fruits within their environment will be evaluated.

3.2 Imaging techniques

3.2.1 Imaging techniques using electromagnetic spectrum

For clarity, first a general description of the electromagnetic spectrum will be given. One of the characteristic quantities of an electromagnetic wave is its wavelength (λ). The electromagnetic spectrum is known to exhibit wavelengths from less than 10^{-10} µm to over 10^5 km which are commonly and conveniently divided into the following bands: long electrical oscillations, radio waves, microwaves, infrared, near infrared, visible light, ultraviolet, X-rays, gamma rays and cosmic rays. Further, three different processes characterise the interaction of an electromagnetic wave with an object, namely:

- Reflection;
- Absorption;
- Transmission.

When illuminating an object part of the radiation is reflected by the surface (specular reflection) and the remaining radiation is transmitted into the object. From the transmitted energy part is absorbed (i.e. the conversion from electromagnetic energy into other forms of energy such as heat, chemical changes or luminescence), part is reflected back to the surface (diffuse reflection) and part is transmitted through the object (see figure 3.1) (Heijden van der 1994, p. 9). The magnitude of these quantities, which vary with the wavelength, are dependent on the physical condition and the chemical composition of the object.

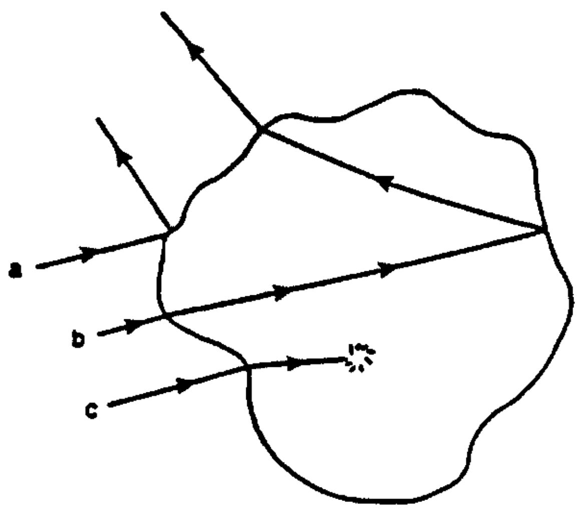

Figure 3.1. A schematic diagram of the interaction of radiation and an object: (a) specular reflection; (b) diffuse reflection; (c) absorption

The potential of some of the electromagnetic bands to generate useful images (for the detection of fruits within their environment) based on reflectance and transmission quantities (it is hoped that the fruits to be detected respond differently to the wavelength in comparison with their environment) is discussed in the next section.

3.2.1.1 Radio wave detection and ranging (radar)

'[...] In radar systems, a short duration electromagnetic pulse (in the frequency range of 3 kHz to 300 MHz) is transmitted from an antenna. A proportion of the electromagnetic pulse will be reflected back to the antenna by discontinuities in the dielectric constant of the propagating media. The amplitude of these reflections are measured with respect to time and displayed graphically. If the antenna is subsequently moved it is possible to obtain an image of the reflecting discontinuities [...]' (Bull, 1993). This approach has been used for several agriculture related measurements. For example, in detecting and monitoring the movement of insects (Beerwinkle, 1995), mapping well defined discontinuities in the soil profile using ground penetrating radar (Weiler, 1995) and remote identification of crops (Holmes, 1990 and Buiten, 1993). The latter may offer the most interesting opportunities for the detection of fruits. Furthermore, radar has its own source of radiation (is an active sensor) and is not largely affected by the natural variability of the illumination conditions during the day. Radar has also the advantage of being able to measure the distance or range to the object (using the principle of time-of-flight (TOF)).

In literature (Buiten 1993, p. 203-217; Holmes, 1990 and Skolnik, 1980) it can be found that, in general, the amount of reflected energy (the radar sensitivity) is determined by the type of the object, i.e. the physical and electrical properties (the electrical properties are described by means of the dielectric constant which is closely linked to the moisture content), the size, the roughness of the object and also the orientation of the object towards the antenna (the incident angle). Further, some research (Brakke, 1994; Buiten 1993, p. 34 and Chun, 1995) suggested that in addition to the foregoing aspect of reflected energy, the polarization characteristics of an object may also be important for detection applications. As the polarization and the phase of the impinging polarized wave will be changed by the object, pertaining to its specific structure (i.e. size, shape and roughness) and its physical and electrical properties. Depolarization may occur at a rough surface (rough with respect to the wavelength of the transmitted wave) for example. In addition, although few studies have been made to the use of this technique, undoubtedly polarimetry will become of great significance in the future, but the full potential still has to be assessed (Buiten 1993, p. 34 and 43).

From the preceding generalizations and discussions made by Holmes et al. (1994) on parameters affecting the reflected energy from vegetation, it follows that with respect to the detection of fruit within its environment the crucial features in determining the proportion of the reflected energy are the biomass, the dielectric constant and the geometry of the plant and its components (stem, fruits and leaves), which in turn depend on the character of the plant of interest and its physiological age.

However, research (Lewandowski, 1994) and field experiments (Holmes, 1990) have demonstrated that radar sensitivity (the reflected energy) from different objects become more distinct by using frequencies that span the natural electromagnetic resonance of these objects. For example, detection of a 10 cm tall object should be based on waves containing frequencies in the neighbourhood of 3 GHz. Because the wavelength range of radio waves is approximately from 1 m to 100 km this limits its use for the detection of the 'small' fruits. More research in this area is required to fully exclude the use of radio waves. However, radar also operates at lower wavelengths, the microwave range (which is discussed in the paragraph below), and it may be suggested that this range is likely to give more opportunities for the detection of fruits. As it will have the same interesting features, as discussed with radio waves, because of the generality of radar. Because of this, the use of radio waves for the detection of fruit within its environment is no longer investigated in this research.

3.2.1.2 Microwaves

First, it is important at this stage to discriminate between active and passive forms of microwave sensors. Active microwave sensors provide their own source of energy and measure the reflected (the radar sensitivity, as described in the above paragraph) or transmitted energy, whereas passive sensors measure the microwaves emitted by the objects. This paragraph restricts itself to active microwave sensors. In addition, because of the very long integration time and the poor resolution of passive microwave sensors this imaging technique will not be considered at all (Buiten 1993, p. 49-60 and p. 155).

Bull et al. (1993) found when microwave energy, with frequencies of 300 Mhz to 300 GHz, passes through agricultural objects the energy is strongly absorbed and reflected by water molecules. Transmission of microwave energy may therefore be useful to determine the quantity of water in an object between the microwave source and detector. However, this measurement can be ambiguous as a high density object of low moisture content will give the same response as a low density object of high moisture content. This limits the usefulness of microwave transmission as an imaging technique. For example, one investigation (Timm, 1989) which attempted to detect the presence of pits in tart cherries using microwave transmission found that the size difference in the cherries has a more profound effect on the transmission than the presence or absence of fruit defects. Furthermore, the sensing of this imaging technique, is by physical contact which precludes its use for fruit detection.

However, microwave transmission techniques have been successfully used to determine the microwave permittivities of fruits and vegetables (Nelson, 1994). In general, the microwave permittivities or dielectric properties of objects are important because these properties determine the nature of interaction of electromagnetic energy with the objects at microwave frequencies. The object permittivity influences the propagation of electromagnetic waves through the object, reflections of waves from the surface of the object and the attenuation of the wave energy as it traverse the object. The permittivity is represented as $\epsilon = \epsilon' - j\epsilon''$, where the real part ϵ' is the dielectric constant and the imaginary part ϵ'' is the dielectric loss factor. The dielectric constant ϵ' influences the electric field distribution and the phase of waves travelling through the object, whereas the energy absorption and consequent attenuation is influenced principally by the loss factor ϵ''. In fruits both ϵ' and ϵ'' are highly correlated with moisture content, because the permittivity of water greatly exceeds that of the dry matter of fruits (usually present in fruits in small quantities) (Nelson, 1994).

Unfortunately, measurements of dielectric properties on fruits are not straightforward and, largely for that reason, are not common in literature. As with most biological materials, considerable variation can be expected in permittivity values among different kinds of fruits and more important within given kinds. Moisture content is a dominant variable that influences the permittivity values, but there are also other sources of variation (Nelson, 1994). More research on the permittivity and loss factors are essential for an understanding of the attenuation of microwaves by fruits (in comparison with their environment) and for the use in their detection.

One of the properties of radiation in the microwave range is that its able to penetrate into an object. For the detection of fruits this provides a potential for studying not only the surface of the plant directly in front of the sensor, but also behind it. As was demonstrated in a recent study of surveying vegetation by radar remote sensing (Holmes, 1990). It was found that the penetration depth of an incident microwave depends on its polarization and frequency, such that the optical thickness of the vegetation increases with increasing frequency. Further, vertically polarized radiation (by observing from above) is much more strongly attenuated than horizontally polarized radiation and there is a marked increase in the attenuation of the vertically polarized radiation with increasing incidence angle. Horizontally polarized radiation, on the other hand, penetrates deeply into the vegetation and shows negligible dependence on incidence angle (see figure 3.2 and 3.3).

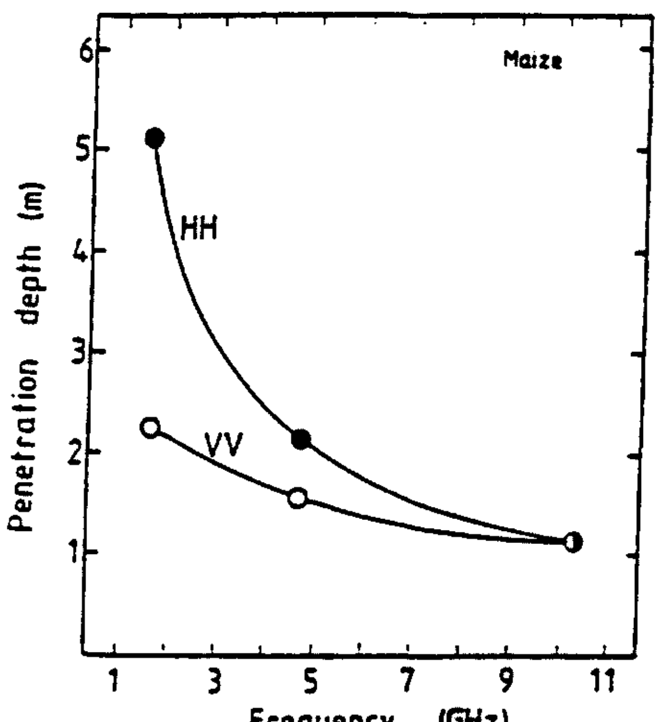

Figure 3.2. Wavelength dependency for microwave penetration into corn canopy. Penetration depth is defined as the depth at which the incident power is reduced to 37% of that incident. The data presented are for incidence angle of 40°, LAI (leaf area index) = 2.8, plant height = 2.7 m, leaf volumetric moisture content = 0.65, stalk volumetric moisture content = 0.47 (Holmes, 1990)

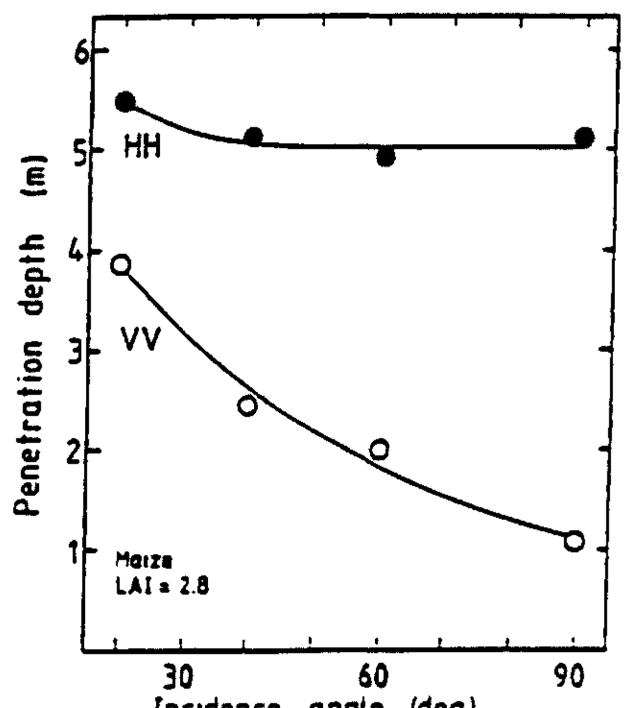

Figure 3.3. Polarization and incidence angle dependency for microwave penetration into a corn canopy. Penetration depth is defined as the depth at which the incident power is reduced to 37% of that incident. LAI = 2.8, plant height = 2.7 m, leaf volumetric moisture content = 0.65, stalk volumetric moisture content = 0.47 (Holmes, 1990)

An important practical aspect of this type of observation is that vertically polarized data provide information which is predominantly related to the physical characteristics of the vegetation, whereas the horizontally polarized radiation is largely penetrating the vegetation and therefore providing information on the vegetation behind it. However, this statement must be considered in the context of the wavelength used. Longer wavelengths tend to penetrate deeply into vegetation, whereas shorter wavelengths are scattered at the surface. As a result, discrimination between polarizations may be impossible at shorter wavelengths (see figure 3.2). The detection can be further enhanced by using cross-polarization or multi-polarization (cross- and like-polarization) analysis (Holmes, 1990).

From the phenomena mentioned above, it follows that for the use in the detection of fruits within their environment it is necessary that multi-polarization and multi-frequency data should be fully exploited. This should be done at different growth stages. Such information can then be used for the formation of a reflection model of fruit in relation with its environment.

Research in using microwave reflectance as an imaging technique has already been done for soil moisture content. There it was concluded that the predominant factors affecting reflection are the morphology (roughness and texture) and the dielectric constant (moisture content) (Whalley, 1991 and Fall, 1990). But, what actually happens to the microwave at the soil surface is still not understood. The dielectric properties are usually unknown and other quantities, unrelated to these properties, are used in the current soil descriptions. Further, the surface and medium quantities are usually badly described and difficult to determine separately. Hence, it is very difficult to create a reflection model. These limitations and difficulties should be noted to avoid misinterpretation of the results.

It can be concluded that the use of microwaves might be a way to detect fruits within their environment. However, research on using microwave reflection as an imaging technique of soil moisture content has shown that this technique can be highly problematic as the microwave reflection depends not only on one parameter but on different and very complex parameters, which would result in a very complicated and time-consuming research to understand the process.

3.2.1.3 Near-infrared and visible range

'[...] There is a certain consensus in the literature on the optimal bands necessary to acquire characteristic spectral information about vegetation. These bands are situated in the visible (green and red) and the near-infrared (NIR) part of the electromagnetic spectrum [...]' (Buiten 1993, p. 178).

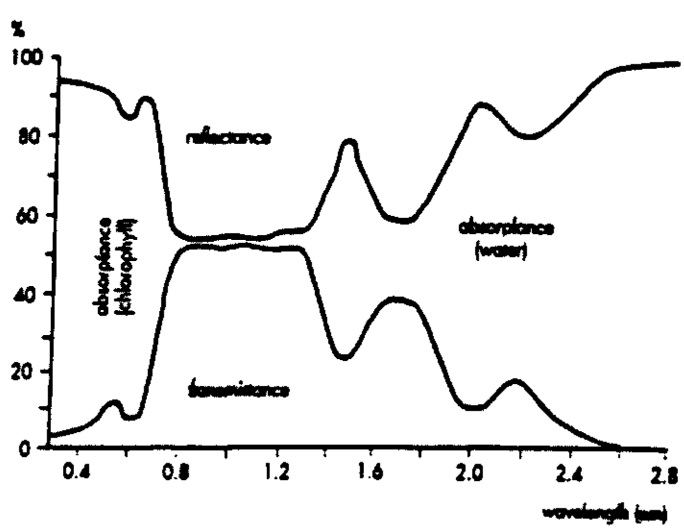

Figure 3.4. Average course of reflectance, absorptance and transmittance of a green healty plant leaf as a percentage of the irradiation (Buiten 1993, p. 91)

The characteristics of vegetation and their influence on remote sensing have recently been reviewed by Buiten et al. (1993). In their work the reflection of vegetation in the near-infrared and visible range has been dealt within detail. It was found that differences in reflection can provide information on vegetation.

It is not intended to repeat the information in this current work but to emphasise only the areas in which there is a potential for the detection of fruits within their environment. In order to show clearly the difference between the two frequency ranges first the two ranges are treated side by side, then, to maintain the generality of this research, each range will also be dealt separately in a broader context.

'[...] A general characteristic of vegetation is its green colour during most of the growing season. The green colour is caused by the pigment chlorophyll [...]' (Buiten 1993, p. 89). In the visible range (0.4 μm to 0.7 μm) various pigments in vegetation, such as chlorophyll, xanthophyll (yellow) and carotene (orange), influence the reflection. In most plants two types of chlorophyll (a and b) determine to a large extend the reflection, mainly by absorption of blue ($\pm$0.45 μm) and red light ($\pm$0.65 μm) and to a lesser degree of green light ($\pm$0.54 μm) (provided the plant is functioning well) (see figure 3.4). The other leaf pigments, xanthophyll and carotene, absorb mainly in the blue region of the spectrum. However, they are not visible since chlorophyll (usually present in leaves in large quantities) also absorbs in the blue. Differences in pigment content, causing differences in hue, may so be useful for detection applications (see figure 3.5).

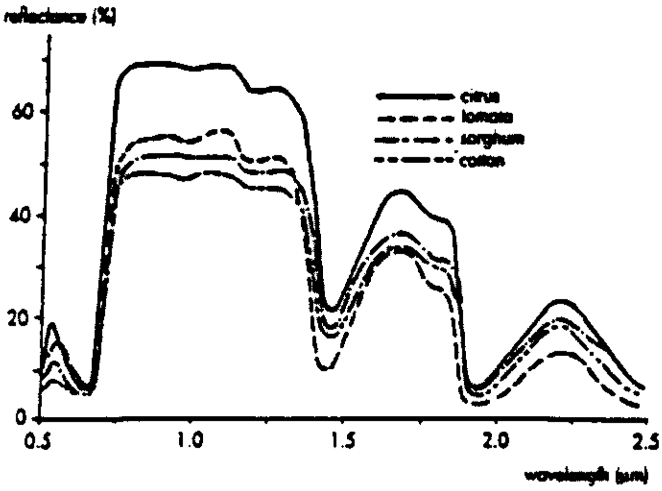

Figure 3.5, Spectral reflectance of representative leaves of four agricultural crops measured with a Beckman DK-2A laboratory spectrometer (Buiten 1996, p. 94)

Another characteristic of vegetation which causes differences of reflection is the structure of the plant. Examples are the position of the leaves and their distribution. Because of this, information on reflectance acquired by measurements on individual leaves only cannot be applied directly to the whole plant.

Further, differences in reflection may originate from differences in the surface of the vegetation. For example, leaves may be covered with wax or have a hairy coat. Also, the growth stage of the plant has an influence on the reflection. This may be caused by differences of structure as well as by differences in colour.

Under field conditions one has to take account of even more factors influencing the reflectance. Examples are the conditions of nutrition, water supply and infections of the plant causing an immediate change in both the signature of the leaves and the plant structure.

In contrast with the visible range the first part of the near-infrared range (0.7 μm to 1.3 μm) is mainly determined by the absence of absorption by pigments (see figure 3.4). This means that the radiation passes through the leaves or is reflected. From various reflectance curves in literature (measurements on individual leaves) it is apparent that approximately 50% of the NIR energy is reflected by the leaf. However, figure 3.5 shows that this percentage varies widely for different plants. Various experiments have tried to obtain insight into which parts of the leaf are responsible for the reflection. It has been established for this range of wavelengths that a leaf becomes very transparent if the air channels between the cells of the leaf are filled with fluid (see figure 3.6).

In the second part of the near-infrared range (1.3 μm to 2.5 μm) a great part of the radiation is absorbed by water in the cells (see figure 3.4). The figure shows, like figures 3.5 and 3.6, that the absorption peaks fall at 1.4 and 1.9 μm. In addition, weak absorption bands of water also occur at 0.96 and 1.1 μm.

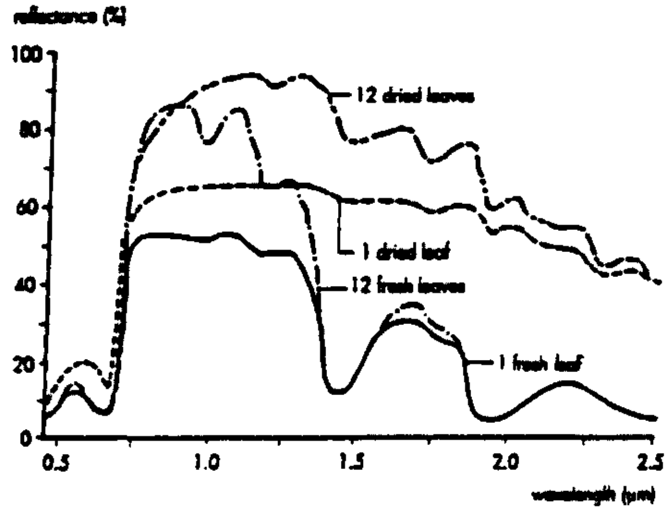

Figure 3.6, Total reflectance of fresh and dried cotton leaves measured with a laboratory spectrometer (Buiten 1993, p. 96)

Measurements on leaves with differences of moisture content gave the reflectance curves shown in figure 3.7. The reflectance in the range of 0.7 to 1.3 μm as well as in the range of 1.3 to 2.5 μm increases with a decreasing moisture content. Thus, the ratio of the minimal reflectance caused by water and the maximum reflectance in the adjacent region of the curve can provide information on the moisture content.

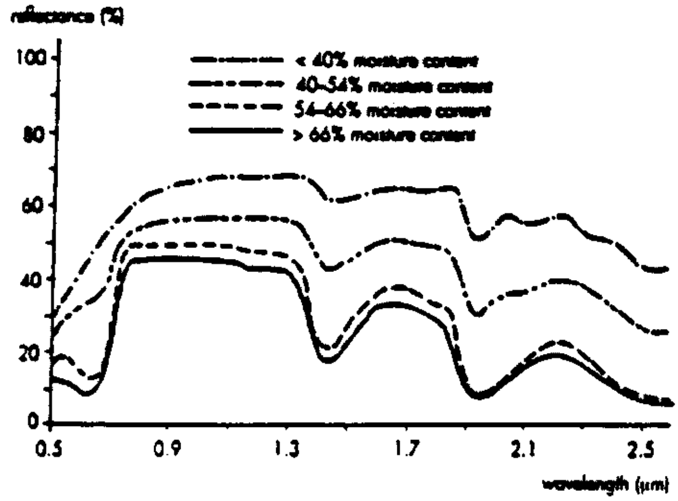

Figure 3.7, Influence of the moisture content of maize leaves on the spectral reflectance (Buiten 1993, p. 98)

From the preceding, it follows that the reflection in the visible range occurs mainly in the leaves directly in front of the sensor. Dependent on the characteristics of the fruit and the rest of the plant it might be possible to detect the fruit. This in contrast with the first part of the NIR range (0.7 to 1.3 μm) which may not give information about leaves directly in front of the sensor, but also behind these leaves. The following will make this clear.

The reflectance and the transmittance of a green leave in the visible range amounts to 10% or less each (see figure 3.4). This means the absorptance is at least 80%. If 10% of the incident radiation is reflected by the first leaf, the contribution to the total measured reflectance of a second leaf behind the first leaf would be approximately 1% of the reflectance of the first leaf (see figure 3.8). This implies that, in the visible range, the reflectance of only the first leaves would determine the total reflectance of a plant. In addition, visual observation of plants confirms this reasoning. On the other side, in the first part of the NIR range, the reflectance and transmittance of a green leaf amounts to approximately 50% each (see figure 3.4). A green leaf hardly absorbs any NIR radiation. Under these conditions, leaves behind the first ones contribute significantly to the total measured reflectance. In the simplest case of the reflectance and transmittance both amounting to 50%, the contribution of a second leaf would be about 15% of the incident radiation (see figure 3.8), which is not negligible. However, these considerations grossly simplify the reality, but they do explain the general concept.

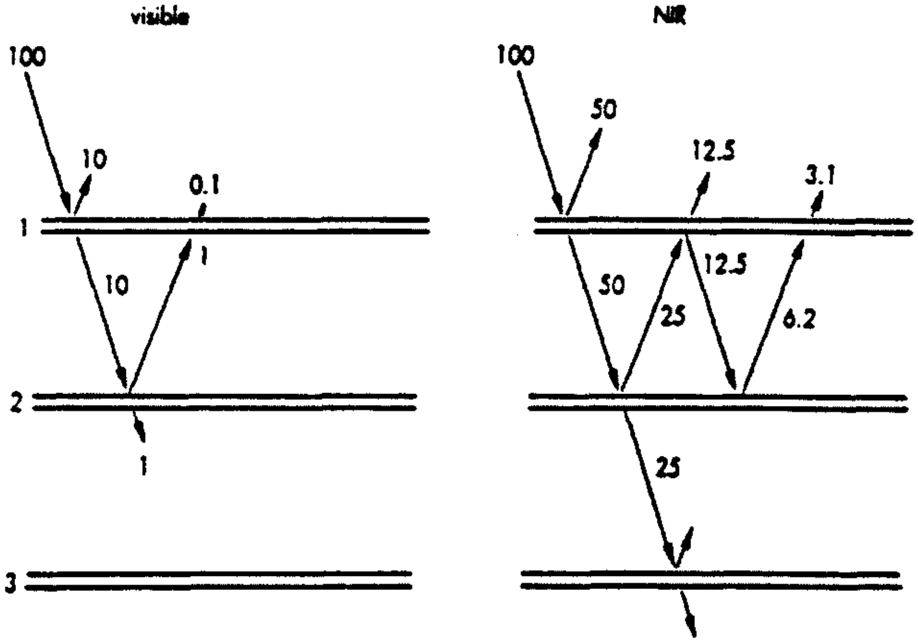

Figure 3.8, Schematic illustration of reflectance and transmittance of radiation through crop layers (leaf canopy) in the visible and NIR range, respectively (Buiten 1993, p. 189)

Using this concept and the possibility that the fruit and the rest of the plant react differently on the first part of the NIR radiation (because of their characteristics, for example moisture content) it might be suggested that the first part of the NIR should be capable of detecting some occluded fruits. However, fruits generally consist of a very large amount of water (Nelson, 1994) and because of the (weak) water absorption bands in the first part of the NIR only less information (most is absorbed) can be obtained about occluded fruits.

In view of what has been said about the changes of reflection in the second part of the NIR range (1.3 to 2.5 μm) by water in the cells and, as already mentioned, because fruits consist of a very large amount of water, this range may be useful for the detection of visible fruits. In addition, the water absorption bands in this part of the NIR are stronger than in the first part of the NIR. Moreover, because of the stronger absorption even less information can be obtained about occluded fruits in comparison with the first part of the NIR.

As seen each range might have some possibilities for the detection of fruits within their environment. The visible range for the detection of leaves and perhaps fruits which are not occluded, the first part of the NIR range for the detection of some hidden (and visible) fruits (when enough information can be gathered) and the second part of the NIR range for the detection of visible fruits. Let's now assume that all these three ranges can only be partly used, then for an optimal detection of fruits it can be thought to make use of a multispectral classification. This means that fruits and their environment are characterised by a special combination of frequencies in these ranges. Studies on fruit detection (Fujiura, 1992; Kondo, 1996; Moltó, 1992; Namikawa, 1988; et al.) already emphasise the use of different frequencies in the visible and near-infrared range. However, further and thoroughly research has to make clear which frequencies exactly should be used to make clustering possible.

In addition, polarization measurements in the visible and NIR range may have some interesting possibilities also (Brakke, 1994). For example in the visible range, the specular component of the reflected radiation yields information independent from the non-polarized diffuse radiation component. The latter is reflected by the interior of a leaf. The former (the specular component) is reflected and polarized by the interface between air and the surface of a leaf (it never enters the leaf) (Buiten 1993, p. 101). Thus, for detection applications, polarization data, can provide additional information.

Near-infrared

In agriculture, research on near-infrared reflectance and near-infrared transmission have mainly been directed to compositional analysis of agricultural objects (Bull, 1993 and Chen, 1991). Most of these studies have measured the integrated reflection or transmission response of the object with no spatial resolution. This is perhaps reasonable as the object is usually prepared in such a way as to ensure that it is homogenous and that the surface reflectance, or point transmission, is representative of the composition of the whole object. There are, however, applications in which there will be interest in the inhomogeneity of the object. For example, in monitoring of mixing and varying composition of a whole object. Research in this area suggested that '[...] in most cases it would be impractical to generate an image of the compositional changes across an object by measuring its reflection or transmission characteristics over a wide wavelength range, at a representative number of sampling points. Consequently, analysis techniques which quantify compositional changes by looking at changes in the shape of the reflection or transmission spectra are unlikely to be adopted in image analysis systems, especially when the acquisition and analysis of the image must be rapid. There is, however, some potential in obtaining a series of near-infrared images of the sample at selected wavelengths and then combining these images, in an appropriate manner, in order to obtain a calibrated image that shows spatial variation of the sample constituents [...]' (Bull, 1993). Using this concept, one may suggest that the use of some selected wavelengths might be interesting for the detection of fruits within their environment, because the agricultural scene can be considered as a varying composition of stems, fruits and leaves. This would strengthen the experience to use different frequencies already found in the paragraph above. However, fruits and the rest of the plants have to react differently on the NIR radiation first.

Another aspect of near-infrared reflection that has been exploited is its use for internal quality assessment (Kawano, 1994). It has been found that it may be the key to examining surface and near surface damage of agricultural objects. '[...] When material is deformed, its surface cell structure alters. Even if this is not accompanied by chemical changes, it should be possible to detect surface damage by the NIR reflection technique because of its sensitivity to the structure of the material [...]' (Bull, 1993). For example, there has been some research (Taylor, 1985) on imaging of a bruised apple at wavelengths up to 1.1 μm. '[...] A bruise in a fruit or vegetable results in massive cell rupture and redistribution of free water. Thus, a bruised region contains more free water per unit volume than the neighbouring region [...]' (Chen, 1989). However, the water absorption bands at 0.96 and 1.1 μm are weak so for greater sensitivity to structural damage it would be more sensible to use the stronger absorption wavelengths at 1.4 and 1.9 μm, as was concluded by Bellon et al. (1990) and Kawano et al. (1994). As a result of this and with the information that fruits generally consist of a very large amount of water (Nelson, 1994) these frequencies should be useful for detection of fruits.

From the above applications it follows, cautiously, that the use of a combination of some selected frequencies in the NIR (especially, the use of frequencies in the water absorption bands) might be a way to detect some visible fruit within their environment. This confirms the suggestions already made in the paragraph above. However, more research is needed to prove its capability of detecting occluded fruits.

In addition, near-infrared reflection has also been used in laser-ranging instruments (using the principle of time-of-flight (TOF)). However, these laser instruments tend to be very expensive, are somewhat fragile and require careful tuning and optical alignment (Dorf 1990, p. 874).

Visible range

In industry the measuring of reflectance of agricultural objects at a number of discrete wavelengths in the visible range in order to detect colour differences for inspection, sorting or grading operations is well established. Applications include, for example, colour sorting, as in sorting green and red tomatoes, detection of surface defects and contamination, such as defects on dried prunes and bruise on apples, separation of foreign materials, such as stones and dirt clods, from potatoes, onions or tomatoes, etc. (Chen, 1991). In contrast, there has been relatively very little research directed towards the application of colour image processing to agriculture.

'[...] By sight humans can use visible differences in the reflection of sunlight to recognize vegetation and fruit [...]' (Buiten 1993, p. 89). It is therefore sensible to take advantage of those differences. Two major imaging systems for colour representation of fruits within their environment have been reported (Sarig, 1993):

- A system of three monochromatic sources (R, G, B), where any colour is represented vectorially according to the luminous flux of the primary colours, red (R), green (G) and blue (B) in the three-dimensional space;
- A chromaticity system (r, g, b), where colour is described according to its hue and saturation. The components r, g and b are known as the chromaticity coordinates and are defined as the ratio between the luminance of one of the primary colours and the sum of all three (i.e. $r = R / (R + G + B)$).

Various tests (van Bree 1994, p. 20-37 and Searcy, 1989) have shown that the detection of coloured fruit, such as tomatoes, in each of the aforementioned systems can be done with only two components. This means that to detect tomatoes in the primary system (R, G, B), for example, only the red and the green components have to be used (the r and g components in the chromaticity system (r, g, b)).

However, '[...] the colour of an object is perceived differently depending upon the illumination, since colour can be difficult to distinguish in an image that is too dark or too bright [...]' (Sarig, 1993). Even in the case of ripe orange fruits, whose colour is very different from their leaves, the effects of a sunny weather cause a lot of erroneous or missing detections, due to shadowed areas and bright specular reflection spots on fruits and leaves (Rabatel, 1995). To overcome this problem it may be thought of using powerful photographic flashes (Rabatel, 1994). Moltó et al. (1992) have shown that the use of flashes improves substantially the quality of the image taken under daylight conditions and increases the percentage of fruits detected.

Once the lighting conditions are controlled, the method of colour segmentation may give good results when in the image the fruits and their environment have highly contrasting colours. For example, a classification model has been developed which could detect oranges within their environment using only colour information (Slaughter, 1989).

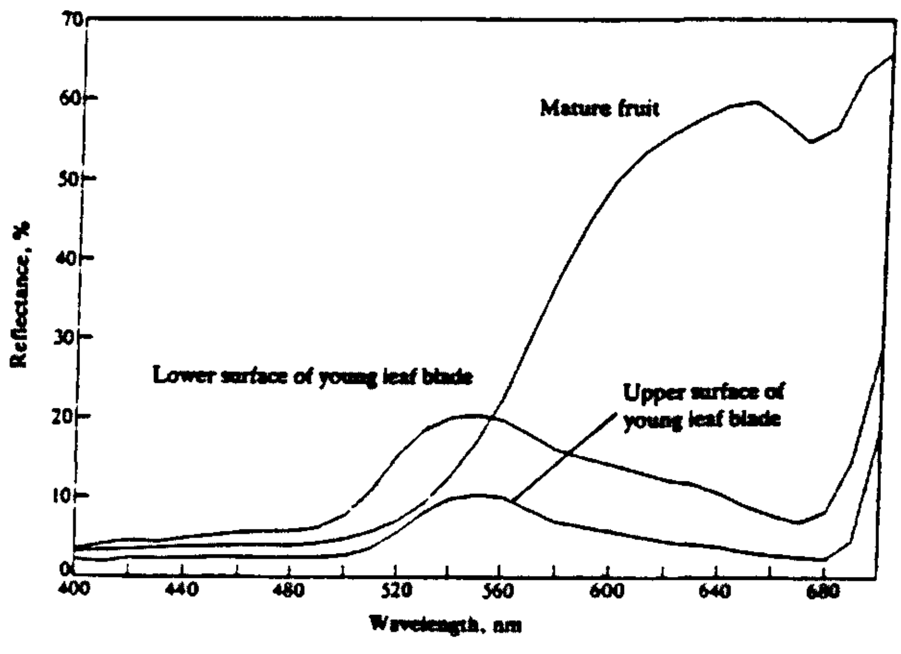

Figure 3.9. Difference between the spectra of mature fruits and young leaves (Moltó, 1990)

In another research (Moltó, 1992) the reflection spectrum in the visible range of the peel of citrus fruits and leaves have been conducted during the harvesting period. It was observed that during the whole season, the spectrum of the leaves was slightly variable and, in addition, the curves nearest to the citrus fruit are those of young leaves. This was also concluded by Edwards et al. (1988) which studied changes in spectral reflection of grapefruit leaves with age, air temperature and time of day. Figure 3.9 shows the percentage of reflectance and the wavelength of the mean of citrus fruits at full maturity and the upper and lower surfaces of young leaves, since these represent the most unfavourable conditions for detection. Two methods for the detection of the citrus fruits had been developed: one based on thresholding of an image taken with a red filter and the other using information from two images filtered in the red and green bands respectively. The latter proved capable of detecting the largest percentage of citrus fruit. However, early citrus varieties, which are usually very profitable to the grower, presented detection problems because of their green colour during the initial stages of maturation (their reflection spectrum is similar to that of leaves). It was concluded that the vision system of the harvesting robot cannot be based exclusively on partial data of colour of the citrus fruits, because this reduces the percentage of detection.

Further, detailed analysis in the visible and near-infrared range of fruits and leaves have been made for both apples and oranges (Rabatel, 1994). Promising results have been obtained even for fruits whose colour is very close to the colour of their leaves, such as 'Granny Smith' apples, by using a combination of visible and near-infrared wavelengths.

Thus, as already suggested, a combination of visible and near-infrared range might be a way to detect fruits within their environment. However, problems may arise with the detection of occluded fruits.

Structured lighting

Although the goal of lighting has primarily been the enhancement of contrast of particular object features, the goal of structured lighting is to yield direct three-dimensional information about the object. The basic approach with structured lighting is to project a known (structured) pattern of visible light onto an object and then use the distortions in this pattern in the reflected image to calculate the three-dimensional characteristics of the object's surface. This is, therefore, a form of ranging.

The application of this technique on a scene would result in a surface map which may be used for the detection of some objects (Bloemen, 1996 and Yang, 1993). As this lighting technique has two important advantages for detection applications. First, it uses a known pattern on the scene and disturbances of this pattern indicate the presence of an object, thus simplifying the object detection problem. Second, by analysing the way in which the light pattern is distorted, it is possible to gain insight into the three-dimensional characteristics of the object.

For the detection of fruits within their environment, it is first necessary that the three-dimensional shapes of the fruits are known. Using these shapes and the generated surface maps it should be possible to detect the fruits. However, in the agricultural environment fruits and their environment are complex and loosely structured so distortions of the light pattern would be very complex and difficult to detect (because of the variability of the fruits and the lack of controllability of the environment). In turn, this results in a very complicated scene analysis, especially in the case of (partly) occluded fruits.

Therefore, as a final note, the use of 'normal' lighting for the detection of fruits within their environment would be preferred to structured lighting (more controllability).

3.2.1.4 X-rays

In literature (Bull, 1993) it can be found that X-rays have short wavelengths (1 pm to 10^{-1}nm) but high energies which enable them to penetrate into most agricultural objects. The penetration of these rays depends mainly on the thickness of the object and other parameters such as structure, absorption coefficient and density of the material. Further, the depth of penetration depends also upon its energy. Consequently, low energy (or soft X-rays) are more suitable for agricultural objects which have relatively low densities and which may be sensitive to the destructive nature of high energy (or hard) X-rays (Chen, 1991).

There are a number of studies in which X-ray imaging has been used to evaluate the physical properties of agricultural objects. Examples are the detection of disorders in 'Alphonso' mango (Thomas, 1993), the detection of impact damage of sweet onions (Maw, 1995) and the detecting of bruises in apples (Rotz, 1978).

One of the problems with X-ray imaging is its complexity. The intensity at each point of the image is a function of the integrated absorption properties of the object between that point and the source. For example, a potato with an internal void will have the same absorption at its centre as an irregular shaped potato with a tapered centre. This ambiguity could be alleviated by a simultaneous determination of the object topology (Bull, 1993).

Another way to overcome this problem is the use of X-ray computed tomography (X-ray CT), where the object is reconstructed from multiple X-ray scans through it. Each point on a CT image represents a small volume in the plane scanned by the X-ray system, while a point on a normal X-ray image represents a volume average of many volume elements. This technique, which is commonly used in diagnostic radiography, has been used for damage assessment in fruits and vegetables (Tollner, 1992). It was concluded that internal differences in X-ray absorption within scans of fruit are largely associated with differences in volumetric water content. '[...] The lighter grey areas generally represent a more concentrated presence of water and the darker grey areas generally represent a more notable presence of air [...]' (Thomas, 1993). Thus, any process such as storage and associated moisture loss should cause changes in X-ray CT outputs.

Because fruits consist of a very large amount of water (Nelson, 1994) both X-ray techniques are likely to offer some opportunities for the detection of fruits. However, the use of multiple X-ray scans would result in more complicated measurements and, consequently, reducing the operation speed which would not be very practicable for a real-time detection of fruit. Thus, the use of only one X-ray scan would be preferred.

For an on-line detection of fruits the plants have to be scanned with a system, for example, similar to that used by airport security personnel to check baggage. The plants have to be moved in a single row between the two plates as if they were placed on a conveyer belt. Mostly, this is impossible in the used cultivation method or it results in very complicated measurements because of unavoidable large distances between the plates (more volume averaging).

Under these conditions, it follows that X-ray imaging would not be a very promising way to detect fruit within its environment. A solution would be to change the cultivation method, which probably makes the use of X-ray imaging more attractive.

3.2.2 Imaging techniques using thermal infrared radiation

In general, all objects with a temperature above absolute zero continuously emit thermal infrared radiation (TIR). The quantity of the emitted radiation depends on the temperature of the object. This property is expressed by means of the law of Stefan-Boltzmann for a blackbody (an ideal perfect radiator):

$$M = \sigma \cdot T^4, \qquad (F\ 3.1)$$

with

M = *total radiant exitance (in Wm^{-2}),*
σ = *Stefan-Boltzmann constant ($5.67 \cdot 10^{-8}\ Wm^{-2}K^{-4}$),*
T = *absolute temperature of the object (in K).*

Because real objects are not ideal blackbodies, they emit less energy than that corresponding with their temperature. The ratio (per unit of area) is determined by the emissivity ϵ ($\epsilon = 1$ for a blackbody) which is dependent on the physical properties of the object. For an opaque object $\epsilon = 1 - \rho$ (where ρ denotes the reflectance). Both ϵ and ρ are dependent on the wavelength. This means that in the TIR the reflected radiation must be taken into account, as each object receives and subsequently reflects radiation from the environment. This often complicates the determination of the objects temperature from the observed radiant temperature (Buiten 1993, p. 30-36).

Thermal imaging has been extensively used for missile tracking systems, remote temperature sensing, military and civilian surveillance and in medical applications such as tumour detection. However, applications within agriculture have been very limited (Bull, 1993).

Inoue et al. (1991) have used thermal imaging to measure physiological status in stressed and non-stressed maize and wheat canopies. It was found that thermal imaging is highly effective in detecting physiological depression or comparing various canopies in their physiological status on a remote and real-time bases. Further, a method has been presented for estimating leaf transpiration and stomatal resistance. As leaves have adjustable pores in the lower epidermis called stomata. The opening and closing of the stomata are determined by the plant taking up sufficient water, usually through the roots, to maintain the turgor. If there is sufficient moisture available there is a constant flow of water transpirating through the stomata. This withdraws thermal energy from the surface of the leaves, so that the plant temperature drops in respect of the surrounding air. The lower temperature can be measured and provide the possibility of tracing for example a shortage of water (Buiten 1993, p. 101-102). With regard to the detection of fruits within their environment, these measurements may suggest there is an open area for thermal imaging. As it can be assumed that differences in heat capacities of fruits and their environment have to cause different rates of heating and cooling (transpirating) and, consequently, temperature differentials which could be recorded by thermal imaging.

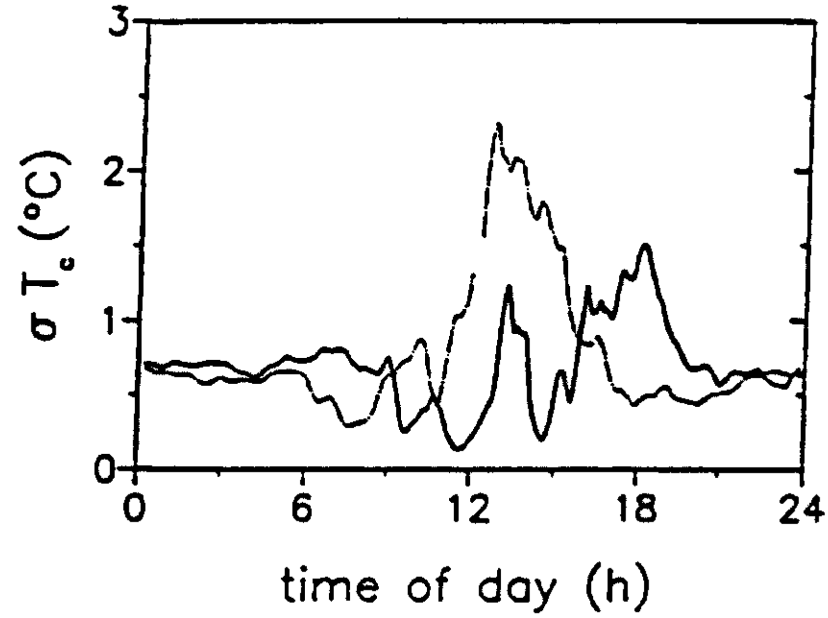

Figure 3.10, Daily course of standard deviation of measured leaf temperature at three levels and orientations in a tomato canopy for, respectively, a cloudy day and a LAI (leaf area index) of 3 (thick line) and a sunny day and a LAI of 1.5 (broken line)

However, measurements on leaf temperature of a glasshouse tomato plant at three levels in the plant and with various orientations (Jong de, 1996), have shown variation in standard deviation of the measured leaf temperature during the day, with an upper limit of 2.5°C (see figure 3.10). Let's now assume that the temperature distribution within the leaves would be normal and that 2.5°C would indeed be its standard deviation (in the worst case). Then, at any time, some 1% of the leaves would have a temperature differing by more than three standard deviations (7.5°C) from the mean. Then one can stipulate, that in order to ensure that all fruits can be detected, the difference in temperature between fruits and leaves has to be more than 7.5°C. In addition, stress in plants changes the leaf temperature even more (Inoue, 1991). Under these circumstances, the detection of fruits within their environment, based on difference in temperatures, might be complicated and more research in this area is needed.

However, as can be seen in figure 3.10, the standard deviation of the measured leaf temperature after sunset and in the early morning is rather constant and not so large (0.75°C). By using this part of the day more promising possibilities are created. This was also concluded in a recent study (Dobrusin, 1992) which detected melons in field using thermal infrared images. By analysing the images, it was found that the temperature differentials of melons, leaves and ground were considerably dependent on the time of day and reached maximum values after sunset. Furthermore, it was found that it is not particularly difficult to distinguish a melon from its leaves in the infrared spectrum and errors are only to be expected by the open ground patches which temperature is commensurable with that of melons. In turn, this favours the fruit detection.

Thus, in regard of the use of thermal imaging for the detection of fruits within their environment, care should be taken to avoid complication of the background, especially when sparse vegetation is being measured. Factors such as ambient air temperature, atmospheric influences, field of view and angle of incidence of the camera should be noted (Meyer, 1994). Under these conditions, thermal imaging can possibly be used as an imaging technique for the detection of fruits. However, a reasonable temperature difference between fruits and their environment has to be found first.

3.2.3 Imaging techniques using nuclear magnetic resonance (NMR)

'[...] Nuclear magnetic resonance imaging is a spectroscopic method used to noninvasively generate internal images based on the magnetic properties of nuclei. In particular, nuclear magnetic resonance (NMR) can detect the concentration and state of hydrogen nuclei within a sample. For standard nuclear magnetic resonance spectroscopy, a sample is placed in a large, homogeneous magnetic field. Nuclei which have a net magnetic moment precess when placed in an external magnetic field. The rate of precession is the Larmor frequency, defined by the following equation:

$$\nu = \gamma \cdot B / 2\pi, \qquad (F\ 3.2)$$

with

ν	=	*the frequency of precession,*
γ	=	*the magnetogyric ratio,*
B	=	*the external magnetic field strength.*

A pulse of radio frequency (RF) energy applied at the Larmor frequency excites the nuclear spin system. A radio frequency signal is given off by the sample as it returns to equilibrium. This signal is recorded and Fourier transformed to yield intensity versus frequency. This spectrum provides information concerning the chemical environment of the nuclei [...]' (Chen, 1989). However, the frequency spectrum of the sample will give no information about the spatial location of the nuclei. The extension of standard nuclear magnetic resonance to imaging begins by applying linear gradients in the external magnetic field. The Lamor frequency then becomes a function of the position.

NMR imaging is mainly used in medical field to detect tumours and other abnormalities in humans. Its use in agriculture is much more limited and NMR imaging studies have mainly been directed to internal quality evaluation of fruits and vegetables. Some experiments (Bellon, 1994 and Chen, 1989) have demonstrated that NMR imaging is suitable for detecting internal defects and various quality factors such as bruises, dry regions, worm damage, stage of ripeness and the presence of voids, seeds and pits. Further, it was found that by variation of experimental parameters, such as echo delay and resolution, specific internal features of the fruit can be enhanced. However, a higher resolution and longer echo delay require a longer time to scan.

However, one major drawback of this technique is that the magnetic field at any point in the imaging field has to be constant and well defined which emphasises the use of very costly magnets. This economical reason therefore tends to limit the size of the object which can be imaged, since the object must be smaller than the pole size of the magnet and the cost of a magnet increases with its size. At the moment, it can be concluded that NMR imaging for the use in detecting fruits within their environment is too limited (very big magnets have to be used).

3.2.4 Imaging techniques using ultrasonics

The high part of the ultrasonic frequency range (1 to 100 Mhz) has the ability to propagate through soft biological materials suffering only moderate attenuation. For this reason, it has been widely and successfully used for measurements and imaging in medicine and industry (Mizrach, 1991). '[...] The basis of the technique is that at an interface between two acoustically different types of tissue, ultrasound energy will be partly reflected and partly transmitted. The reflected energy can be collected and used as an indication of position of the interface by reference to the timebase, together with knowledge of the propagating velocity [...]' (Bull, 1993).

In spite of the wide use and success in medicine and industry, very little has been done to employ this technique in agriculture. Several researchers used methods and equipment that were available in medical and industrial applications for transmission and detection of ultrasonic waves in agriculture objects. Some of them indicated difficulties in the penetration of ultrasonic waves into fruits and vegetables. Others reported that the high attenuation of the signal does not allow satisfactory examination of the internal structure of the fruit. Upchurch et al. (1987) tried unsuccessfully to use 1 Mhz ultrasound to distinguish between damaged and undamaged apples, for example. It was concluded, because of the porous nature of fruits, high frequency ultrasound cannot penetrate deeply into fruits. Analysis of the results led to the conclusion that the difficulties caused by high attenuation may overcome by using lower frequencies (within the frequency range of 50 to 500 kHz) and by increasing the needed power of ultrasound, as long as it does not exceed the limit for fruit damage (Mizrach, 1989).

However, one of the primary problems of ultrasonic testing in the high frequency range, and certainly for the detection of fruits, is that the ultrasonic transducer and object need to be acoustically coupled (because of the high acoustic impedance between transmitter and air). This has tended to mean that ultrasonics in the high frequency range has mainly been used as a contact probe (Bull, 1993).

More interesting should be the use of the low frequency range of ultrasonics (<100 kHz) which can be used for (contactless) range measurements (using the principle of time-of-flight (TOF)) (because of the less attenuation of the signal due to atmospheric absorption at these frequencies). There have been several attempts to use this technique as the basis of a machine vision system (because of the low cost and simple construction of ultrasonic transducers). Surface maps have been generated using either a single transducer or a set of transducers (Bull, 1993). Using these surface maps and known three-dimensional shapes of objects it should be possible to detect objects (as in the case of the structured lighting technique). Furthermore, this technique has the possibility to distinguish between foreground and background objects (because of different TOF) which makes it interesting for the detection of partly occluded objects and, consequently, preferable to the structured lighting technique.

However, several problems are encountered in applying ultrasonics to dense ranging in support of three-dimensional scene analysis. First, simple ultrasonic transducers tend to have relative large solid angle beam spreads (in the vicinity of 30°) so that only very low spatial resolution can be provided. Narrowing the beam only partly increases the resolution. Moreover, ultrasonic waves reflected away from the transmitter/receiver pair when hitting a surface whose normal makes an angle with the ultrasonic axis of the imaging system. Further, ultrasonics is very sensitive to disturbances of the environment such as temperature changes, humidity, fluctuations in air, etc. (Dorf 1990, p. 874 and Lach, 1991). These problems make this technique less attractive for the detection of fruits.

Another technique, using the benefits of the low frequency range of ultrasonics, is to look at the (shape) features of reflected signals returned by objects when radiated with pulsed or bursted ultrasonic waves. The reflected signals show patterns that are characteristic for the object's shape and, therefore, might be useful for the detection of fruits. Moreover, many of the problems described above do not play a role when using this signature technique. '[...] With a fixed geometry and stable stimulus, the classification of an arbitrarily shaped object follows from a comparison between received echo pattern and a reference pattern. The comparison process may be performed either in the frequency domain or in the time domain. With this simple technique it is possible to distinguish between different objects whose shapes are quite different, or between orientation (normal versus upside-down position) [...]' (Regtien, 1995). Under certain conditions it is even possible to distinguish between both sides of a coin (Abreu, 1992). However, one of the main problems with this technique is its sensitivity to changes in the object's position. A slight change in the position may change the reflected signal to such a degree that correlation with the corresponding reference pattern is lost.

From the discussions above, it follows that ultrasonics (in the low frequency range) posses several attractive attributes for dense ranging and signature applications. However, their primary disadvantages of low resolution (the dense ranging technique) and large sensitivity to small changes in the object's position (the signature technique) make this imaging technique less attractive for the many uncertainties in the detection of variable fruits within its uncontrollable environment.

In addition, because ultrasonic systems use very little power, are relative simple and inexpensive and have the ability of range measurements (by using only one ultrasonic transducer) and, furthermore, the possibility of detecting partly occluded objects it can be thought to use this technique as an extra sensor which can give additional information.

3.2.5 Imaging techniques using luminescence

Many organic material, and some inorganic material, will emit radiant energy after they have first been exposed to radiation of some particular frequency. This behaviour is known as photoluminescence (Chen, 1991). If there is a measurable time delay between the absorption and re-emission of the energy, the effect is called phosphorescence. If there is no measurable time delay the effect is known as fluorescence (X-ray and chlorophyll). Because of this, the latter is more attractive for fruit detection (has to work in real-time).

In agriculture the X-ray fluorescence is mainly used in constituent analysis of agricultural objects. For example, it can be used to determine the concentration of various metals and vitamins within an object (Glidewell, 1993). '[...] As many plant and animal materials fluorescence, it is necessary to isolate the material carefully before making the fluorescent determination. In many procedures, the total fluorescence of a mixture is first determined. Then the desired substance is destroyed or converted to a non-fluorescing substance and the residual fluorescence is measured. The difference between the two fluorescence readings is taken as the amount due to the substance desired. Fluorescence is also strongly affected by the environment of the fluorescing material, for example pH, temperature and solvent [...]' (Bull, 1993). The quantitative use of X-ray fluorescence therefore requires careful object preparation. Consequently, most of the sensitivity and selectivity of the technique cannot be realised in non-destructive measurements, as is essential for fruit detection.

'[...] Many of the chlorophyll fluorescence techniques relate to the induction kinetics or initial rise (±200 ms) and subsequent decay (±5 min) of fluorescence from a pre-darked object which has been subjected to a pulse of light (for instance a laser or flash light) [...]' (Bull, 1993). The chlorophyll fluorescence technique has already shown its potential as a field sensor of stress related factors (Miranda, 1995). However, because of the requirement to pre-darken the leaves this technique has only been used to monitor isolated leaves of a plant. In order to control the agricultural process, one would require a measurement over the whole or a large representative part of the field. As will be needed in fruit detection. The possibility of making measurements at night should be considered although the long measurement times would still preclude rapid sensing and, therefore, its use for the detection of fruits. More promising techniques can be found by using the other imaging techniques described in the previous paragraphs.

In addition, a possible application of fluorescence techniques is to monitor the application of sprays on fruits by mixing herbicides or pesticide with a fluorescent dye. Although it would be desirable to monitor spray deposits on fruits as part of the detection within their environment, it is unlikely that the fluorescence technique could be used unless a biological safe dye could be used and the practice is acceptable to the consumer.

3.3 Selection and testing of desired fruit features

The importance of knowing which imaging technique has to be used in order to develop a harvesting system has been discussed in the paragraphs above. For clarity, the main features of the different imaging techniques and their potential for fruit detection have been summarised in appendix C.

With choosing an imaging technique, desired fruit features have to be selected and tested so that the harvesting task can be performed. In order to select and test the fruit features the following steps have to be carried out:

- Selection of desired fruit features which have to be measured for the harvesting task;
  A fruit feature is a characteristic of a fruit measured by the imaging technique. These features are used to detect fruits within their environment. A method to select desired fruit features is to study literature about the imaging technique in combination with the character of the fruit of interest within its environment.
- Testing to see whether the desired fruit features are measurable in the image;
  After having chosen a fruit feature, a check has to be done whether the feature can be measured.
- Testing the quantitative properties of the fruit feature;
  The quantitative properties of a fruit feature describe its reproducibility, called 'consistency', its range (has to be large enough in comparison with its environment) and its relationship to the actual value of the feature.

- Testing the qualitative properties of the fruit feature;
  The qualitative properties of a fruit feature describe its relation to the Harvesting System Detection Output (HSDO). The better the relation of the feature to the HSDO, the higher its quality as fruit feature.
- Testing the performance of the fruit feature in combination with a decision model.
  After the qualitative properties of a fruit feature have been determined, its performance is tested in decision models.

In figure 3.11, the overall selection and testing of desired fruit features in combination with an imaging technique is shown.

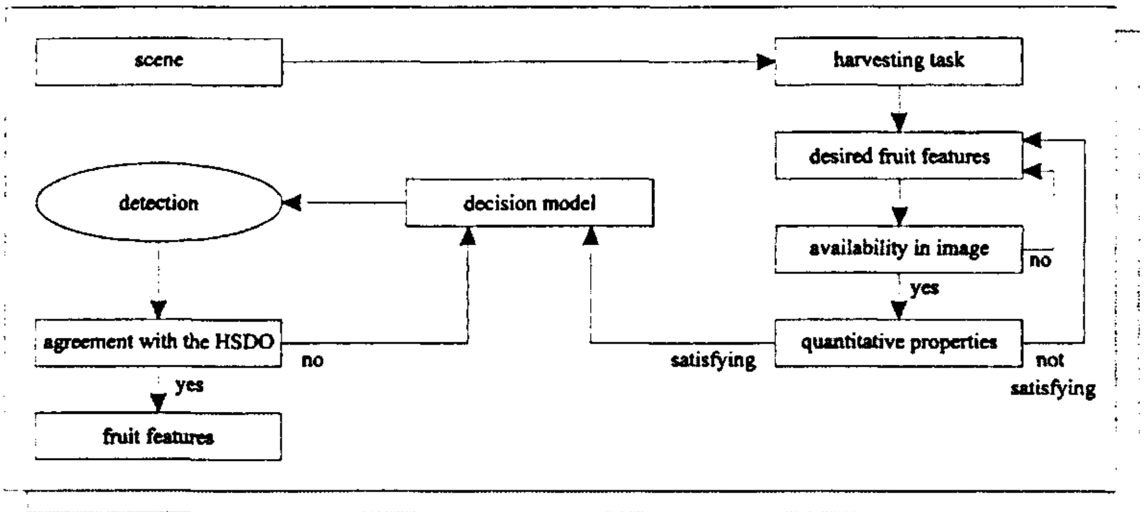

Figure 3.11. The selection and testing of desired fruit features

3.4 Conclusions and discussion

In this chapter various imaging techniques have been reviewed and their potential for the detection of fruits within their environment have been discussed. Clearly, the most appropriate imaging technique depends on the character of the fruit of interest, its interaction with its environment (such as changing illumination conditions, shadows and occluding by leaves) and other practical restrictions such as imaging time (real-time).

Up to now, much of the research on the detection of fruits within their environment have been directed towards images obtained in the visible range. Although this range has given acceptable results, it does not include the possibility of detecting fruits which have a colour close to that of the rest of the plant or which are occluded. This review has shown there are other imaging techniques such as the use of microwaves, a combination of some selected frequencies in the near-infrared and visible range and thermal infrared radiation which might be capable of detecting fruits within their environment. However, problems may still arise with the detection of occluded fruits. But, as microwaves and near-infrared are able to penetrate into objects (leaves) these imaging techniques are likely to offer the most promising opportunities for those problems. Further, a combination with polarization data might improve the performance of the detection of (occluded) fruits within their environment. At the moment, the potential of the other imaging techniques such as X-rays, nuclear magnetic resonance and fluorescence are too restricted. However, some imaging techniques have received little attention in which there is a potential as an additional sensor for ranging such as ultrasonics and lasers (near-infrared).

Further, the selection and testing of desired fruit features for their quantitative and qualitative properties and their performances in a harvesting system were discussed. The quality of a feature is determined by the strength of its correlation with the HSDO. The quantitative properties of a feature also influence the qualitative properties. As low consistency and a small range weaken the correlation.

In general, features for detection applications can be measured more accurately in industry than in agriculture. As the definition of the objects is much better in industry than in agriculture and, consequently, the measurements can be performed more accurately. However, the consequences of false detection in agriculture are, in general, not so serious as in industry because of the relatively low prices of the objects and the low penalty cost.

4 DETECTION OF THE CUCUMBER WITHIN ITS ENVIRONMENT

Detecting and locating the position of a fruit are essential for robotic harvesting. In most of former studies, the difference in colours or brightness between fruits and the other parts of the plant has been used to detect the fruits within their environment or to determine the positions of the fruits. However, it is difficult to apply the same procedure to plants whose fruits have a colour close to that of their leaves and stems (Amaha, 1989).

As cucumbers have a colour close to that of their leaves and stems and may be (partly) hidden by their big leaves, the detection of cucumbers within their environment will be a complex task. Furthermore, the variability of the fruit and influences of the unpredictable changing environment complicate the detection process even more. Consequently, under these circumstances, it is necessary that an imaging technique be capable of detecting cucumbers within their environment which has undetermined features different from the cucumbers to be detected should be found.

4.1 Detection of the cucumber

Cucumbers (*Cucumis sativus L.*) are delicate and fresh soft fruits. They grow rapidly and their locations are randomly scattered within the plant. The main visual characteristics of cucumbers are:

- Shape;
  The shape of a cucumber is like a column (which may be curved a bit) and usually has a short neck on the stem end.
- Size;
  The mature cucumber length is variety dependent and varies from 300 to 500 mm. The width is fairly uniform throughout the length and varies from 50 to 100 mm.
- Colour;
  The cucumber colour changes from green at the early stages of growth to uniformly dark green at the mature stages.
- Texture.
  Mature cucumbers have a slightly wrinkled surface and are slightly ridged lengthwise.

Cucumbers do not ripen at the same time and, consequently, every cucumber has to be detected separately and evaluated for ripeness prior to harvesting.

Most of the work in fruit detection has lead to implicit colour detection (use of interferometric filters) or explicit colour detection (image processing using RGB (red, green and blue) or IHS (intensity, hue and saturation)). However, cucumbers have a colour close to that of their leaves and stems and may be (partly) occluded by their big leaves. As a result of this, an imaging technique has to be found which would be capable of detecting cucumbers based on features different from their environment. In chapter three it has been shown that there are other imaging techniques which might be capable of detecting fruits within their environment, namely the use of microwaves, a combination of some selected frequencies in the near-infrared and visible range and thermal infrared radiation. Before reviewing these imaging techniques for their use in cucumber detection it has sense to expose some cucumber features in more detail first.

Generally, fruit production, and so cucumber production, is the result of a complex system of interacting processes with both short term and long term responses (see figure 4.1). Photosynthesis (the absorptance of irradiation in the PAR (Photosynthetic Active Radiation) range, 400-700 nm) is often considered as the driving force for fruit production. The assimilates or dry matter, produced by photosynthesis, can be stored or partitioned among the different plant components. For optimal fruit production, just sufficient dry matter should be partitioned into the vegetative plant parts to realise and maintain a high production capacity, while the remaining dry matter is partitioned into the fruits. In the case of cucumbers, the dry matter percentage (% of fresh weight) changes during their development. Initially the dry matter percentage decreases rapidly (from about 10%). This decrease then slowed down and finally becomes nearly constant (about 3.2%) (Marcelis 1994, p. 58-59). Consequently, a (mature) cucumber has a high moisture content (about 96%) (Nelson, 1994 and Boersma, 1995). In addition, the dry matter percentage of the (thin) skin of a cucumber (about 4.5%) is a bit higher than the flesh of a cucumber. Further, the skin of a cucumber is liked to be waxed to prevent the cucumber from moisture loss.

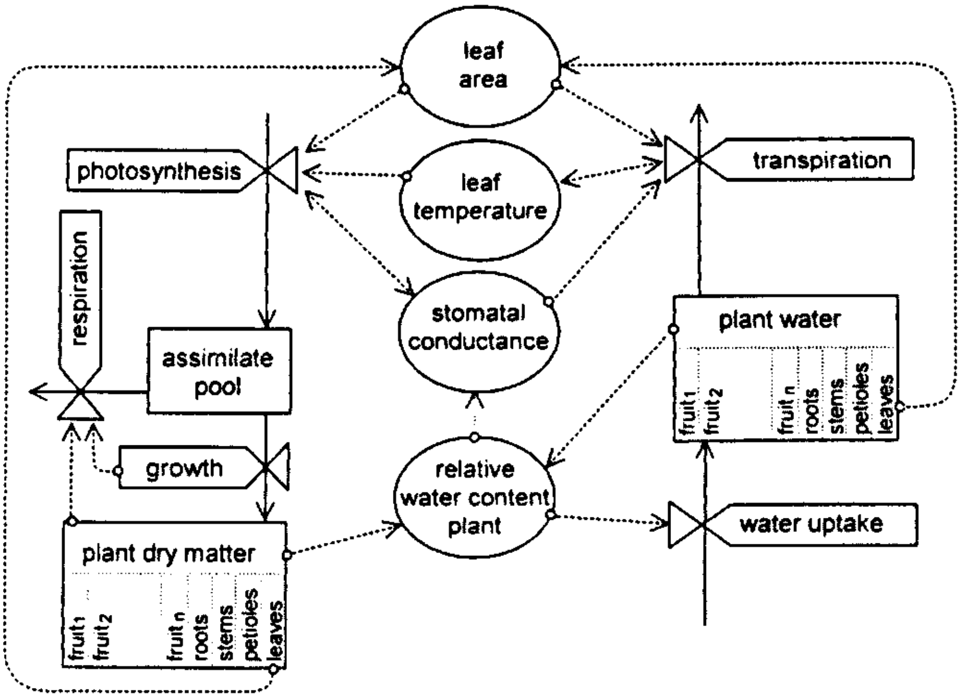

Figure 4.1. A simplified relation diagram of fruit production, such as cucumbers (Marcelis 1994, p. 2)

Plant growth and development is not only a function of the production and partioning of dry matter (left side of figure 4.1), but also of the plant water relations (right side of figure 4.1). Water and dry matter relations interact with each other, for example via leaf temperature, stomatal conductance, relative water content of the plant (ratio of actual to maximum water content) and leaf area (Marcelis 1994, p. 1-5). In turn, these relations will have their impact on the imaging technique which should be selected (based on different responses (features) of cucumbers in comparison with their environment).

4.2 *Detection of the cucumber using microwaves*

As already mentioned in paragraph 3.2.1.2, in fruits the dielectric properties (which determine the nature of interaction with the electromagnetic energy at microwave frequencies) are highly correlated with moisture content, because the permittivity of water greatly exceeds that of the dry matter of fruits. More specific, the behaviour of the dielectric constant is more regular than that of the loss factor with respect to changes in moisture content and the frequency (Nelson, 1994). In cucumbers the dry matter percentage is about 3.2% and, consequently, the dielectric properties of a cucumber, and so the attenuation of microwaves, should be influenced by its moisture content. Thus, if there would be a difference in moisture content between cucumbers and their environment a difference in microwave reflectance might be detected.

However, a simple (idealised) assessment (Whalley, 1991) of microwave reflectance as a technique for estimating volumetric water content pointed out some general statements:

- Reflectance measurements have to be taken over a large range of frequencies (for example from 1 to 10 GHz);

- When the difference in water content is small the magnitude of the frequency dependent effects in reflectance are small too;
- Calibrating microwave reflectance is complex.

Combining these statements with the changing moisture content of cucumbers and leaves during the day (Graaf de, 1992), the scattering of microwave reflectance due to among others surface roughness and the known information that moisture content is a dominant variable that influences the permittivity value, but there are also other sources of variation (Nelson, 1994 and paragraph 3.2.1.2) it can be concluded that microwave reflectance would not be a promising imaging technique for the detection of cucumbers within their environment. Especially, because of the complexity of the agricultural environment in combination with the dependency of this imaging technique on different and very complex parameters.

In addition, '[...] active radar studies are by no means perfect. Even less is understood about the interaction of microwaves with soil and vegetation than is the case in the visible waveband [...]' (Holmes, 1990).

4.3 Detection of the cucumber using near-infrared and visible range

When colour or spectral reflectance of an object is different from those of others, detection might be possible by using R, G, B (red, green and blue) signals from a colour camera or by using optical filters. For example, tomatoes and leaves can be detected by comparing the R (red) signal with the G (green) signal (Searcy, 1989). As cucumbers have a colour close to that of the rest of the plant their detection can not be based exclusively on data obtain from the visible range. However, in literature (Fujiura, 1992; Kondo, 1993; Kondo, 1996 and Namikawa, 1988) it can be found that cucumbers have different reflectance as compared to their leaves and stems reflectance in the near-infrared range. Thus, it can be assumed that cucumbers might be detectable within their environment by using some interference filters in the near-infrared range.

Measurements by Czarnowski (1994) of optical properties of single cucumber leaves showed that they are characterised by high absorptance (75-80%) of irradiation in the PAR range (400-700 nm). The highest PAR absorptance occurred in the blue and red ranges, while a small decrease in absorptance was observed in the green one. The maximum reflectance and transmittance within the PAR range occurred at wavelengths from 540 to 560 nm (particularly by young leaves). Conversely, in the near-infrared range very low absorptance (6-8%), high reflectance (about 45%) and high transmittance (about 45%) did occur. This protects the leaves from overheating and also from inhibition of the process of photosynthesis. Basic optical properties (reflectance, transmittance and absorptance) of single cucumbers were not found in literature (by the author). It is, therefore, difficult to select some frequencies in the near-infrared range which might be effective for the detection of cucumbers within their environment. In general, the water absorption band such as 970 nm and 1170 nm, the chlorophyll absorption band and the 850 nm wavelength band are especially effective for detection purpose (Fujiura, 1992; Kondo, 1996 and Namikawa, 1988).

Nevertheless, because of the experience found in literature (and paragraph 3.2.1.3) on difference in reflectance of cucumbers and their leaves and stems it can be concluded that the imaging technique of using some selected frequencies in the near-infrared range might be capable of detecting cucumbers within their environment. However, to make a proper selection of some interference filters it would be sensible to execute some experiments in laboratory first to study the reflection properties of a single cucumber. After which, the imaging technique can be tried in a greenhouse (to criticise its dependency on external factors).

4.3.1 The reflection properties of a single cucumber

To study the reflection properties of a single cucumber, samples of cucumbers (and also of some cucumber leaves) were collected (bought in a normal greengrocery). In general, to measure the reflectance of a sample different methods can be applied. In this experiment it was chosen to illuminate the samples (the cucumbers and the two sides of the cucumber leaves) diffusely (using a fenced 150 Watt halogen lamp) and to measure the reflected light perpendicular on each sample. To carry out such an experiment a 'Ball of Ulbricht' had been used, which was painted white inside. The samples were placed on a circular transparent opening, with a diameter of 30 mm, in the ball (which has an inner diameter of 85 mm itself). The resulting reflected light of the sample was sent to a monochromator (Jobin-Yvon, model HR320) via an opening in the ball, a rotatable mirror and two lenses with a diafragma between them. The output of the monochromator was connected to a Peltier cooled detector, a Hamamatsu photomultiplier model R636, which in turn was connected to a computer. The input and output of the monochromator had a setup of $\Delta\lambda$ = 3 nm and measured the reflectance in the range of 350 to 1650 nm with intervals of 5 nm.

As reflection standard was chosen for a white standard: $BaSO_4$ (Merck, norm DIN 5033). This because the area of the sample opening was not negligible in comparison with the area of the ball and additional measurements had to be done, namely the reflection measurement of the sample, the reflection measurement of the innerside of the ball with the sample on the sample opening, the reflection measurement of the white standard and the reflection measurement of the innerside of the ball with the white standard on the sample opening. The reflection factor (ρ) of the sample can then be expressed as:

$$\rho_{sample}(\lambda) = \frac{I_{sample}(\lambda)}{I_{standard}(\lambda)} \cdot \frac{I_{innerside\ of\ ball\ with\ standard}(\lambda)}{I_{innerside\ of\ ball\ with\ sample}(\lambda)} \cdot \rho_{standard}(\lambda) \qquad (F\ 4.1)$$

with

I = *photomultiplier current (in mA).*

Finally, this resulted into the reflection properties of the sample. Figure 4.2 shows the average percentage of reflected light of the samples of cucumbers and the upper surface of cucumber leaves (as these represent the most unfavourable conditions for detection) and the wavelength. Single measurements of the cucumbers and the two sides of cucumber leaves can be found in appendix D.

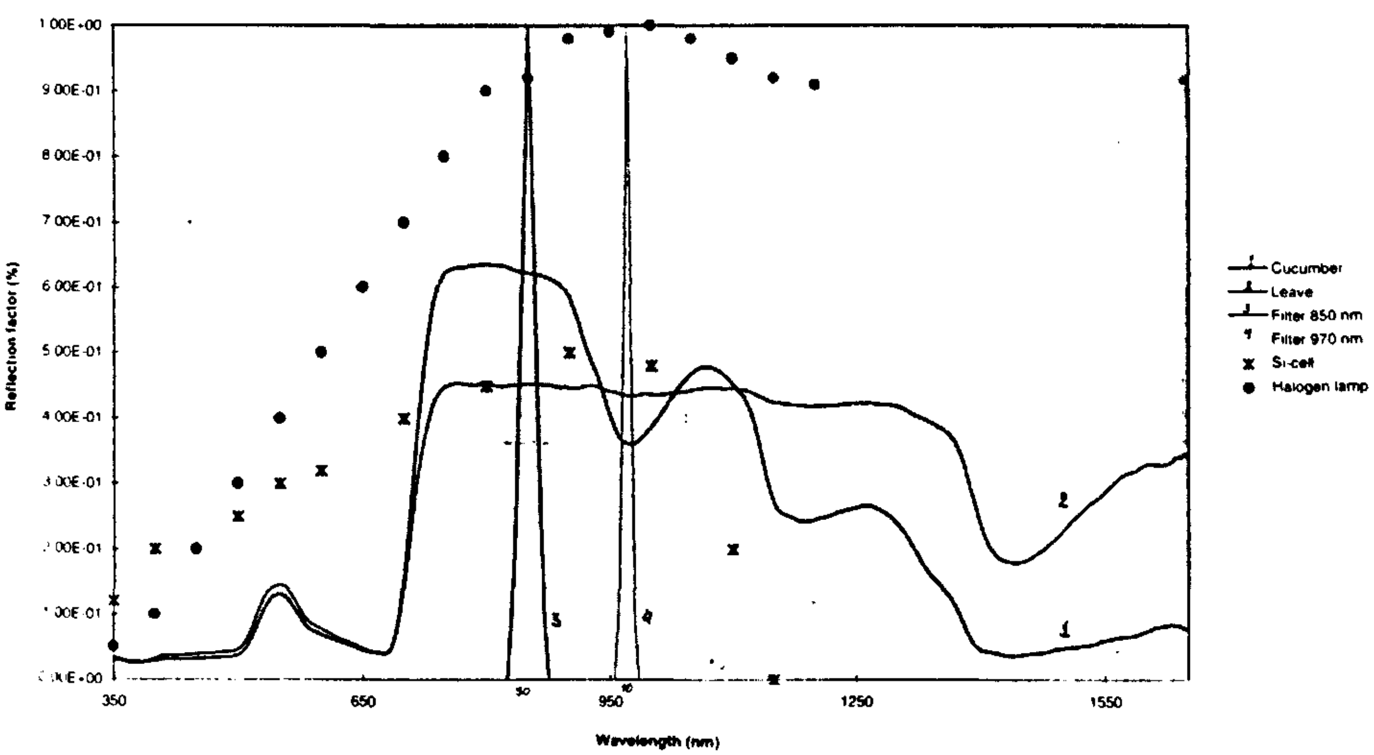

Figure 4.2. The average percentage of reflected light of samples of cucumbers and the upper surface of cucumber leaves and the wavelength

From the results it can be observed that in the PAR range the reflection properties of a cucumber is approximately the same as the reflection properties of a cucumber leaf (using literature and the results of the experiment). Further, the cucumbers showed in the near-infrared range that they are characterised by a successively high (about 63%) and low reflectance (about 35%). The high reflectance within the near-infrared range occurred at wavelengths from 750 to 900 nm and the low reflectance occurred at wavelengths from 950 to 1000 nm. This in contrast with the upper surface of cucumber leaves which showed in the near-infrared range a nearly constant reflectance (about 45%).

As a result of this small experiment (only five cucumbers and five leaves had been measured) it can be concluded cautiously that in the near-infrared range a difference in reflection properties between cucumbers and cucumber leaves exist (which is in agreement with literature). The largest difference between the spectra can be found between 750 and 900 nm and a smaller one between 950 and 1000 nm. Consequently, in these ranges some frequencies should be selected which might be capable of detecting cucumbers within their environment (as was also suggested in literature).

4.4 Detection of the cucumber using thermal infrared radiation

Thermal imaging allows to obtain a simultaneous measurement of different temperatures (infrared radiation) within a scene (a 'thermal map'). Further, as it can be assumed that cucumbers and their environment (leaves and stems) have a difference in heat capacity this would result in different rates of heating and cooling (transpirating) (Dobrusin, 1992). In turn, these temperature differentials could be recorded by thermal imaging and used for the detection of cucumbers.

However, cucumbers have big leaves so it can be expected that the temperature distribution within a single leaf will be different (and probably relatively large). Especially, between the middle and the side of a leaf. As in the latter the temperature increases or decreases more rapidly (Lefebvre, 1993). Besides, mutual shading of leaves (and cucumbers) and their various orientations and positions within the canopy cause an additional variation in their temperatures. Furthermore, as already noted in paragraph 3.2.2, care should be taken to avoid complication of the background. As factors such as air temperature, weather conditions, time of the day, time of the year, position in the greenhouse, field of view and angle of the camera, etc. will have their influence on the measurement temperatures.

From the above discussion (and paragraph 3.2.2), it can be concluded that it is not yet clear whether or not this imaging technique is feasible for the detection of cucumbers within their environment. As it is still not known if the temperature difference between cucumbers and their environment will be reasonable enough to detect the cucumbers. First, various complex issues have to be solved, such as the dependency of the background, the time of the day, the time of the year and a lot more factors influencing the temperature measurements. Further, and also important, the expense of the equipment (tend to be very expensive) has to be evaluated and accounted. Consequently, because of this and the many uncertainties, the use of thermal infrared radiation for the detection of cucumbers within their environment is no longer investigated in this research.

4.5 Conclusions and discussion

In this chapter selected imaging techniques have been reviewed for their use in cucumber detection. As cucumbers have a colour close to that of their leaves and stems the most appropriate imaging technique should be based on different responses (features) of cucumbers in comparison with their environment.

This review has shown that the imaging technique of using some selected frequencies in the near-infrared range might be the most promising imaging technique capable of detecting cucumbers within their environment. In agreement with literature, it has been found (by experiment) that the reflectance of cucumbers in the near-infrared range is different in comparison with their leaves. The largest difference between the spectra can be found between 750 and 900 nm and a smaller one between 950 and 1000 nm. Consequently, in these ranges some frequencies (the interference filters) should be selected which might be capable of detecting cucumbers within their environment.

The potential of the other imaging techniques for their use in cucumber detection are doubtfully. The imaging technique of using microwaves is dependent on different and complex parameters. Furthermore, the reflection measurements have to be taken over a large range of frequencies while their effects will probably be only small and unpredictable. In the case of thermal infrared radiation it is still not known if the temperature difference between cucumbers and their environment will be reasonable enough. As there are too many factors influencing the temperature measurements which have to be solved first. Further, and also important, the equipment tend to be very expensive.

At the moment, problems may still arise with the detection of occluded cucumbers. However, as near-infrared is able to penetrate into leaves this technique might offer some opportunities and more research in this area is needed first.

5 NEAR-INFRARED REFLECTANCE OF THE CUCUMBER IN COMPARISON WITH ITS ENVIRONMENT

In the previous chapter it has been shown that the near-infrared reflectance of a single cucumber is different in comparison with a single cucumber leaf. This difference can yield useful information for the detection of cucumbers within their environment. Especially, when some frequencies in the near-infrared range are selected which combination will be characteristic for a cucumber within its environment (its leaves).

However, radiation reflected by a tall plant, as in the case of cucumbers, in a greenhouse cannot in practice, be related straightforwardly to single reflection measurements made under laboratory conditions or even made in a greenhouse, due to the many factors influencing the reflection and the large variations from place to place of the reflected radiation (Stanghellini 1987, p. 62-74).

5.1 Some selected frequencies in the near-infrared range

Near-infrared reflectance of single cucumbers are characterised by a successively high (because of a rise of the reflectance) and low (because of a decline of the reflectance) reflectance, which occur respectively at wavelengths from 750 to 900 nm and from 950 to 1000 nm. On the contrary, single cucumber leaves show a nearly constant reflectance in the near-infrared range (see paragraph 4.3.1 and figure 4.2). Using this information, it follows that a combination of the reflection of only two frequencies will be sufficient to distinguish between a cucumber and a cucumber leaf (this by using the minimal reflectance caused by water and the maximum reflectance in the adjacent region of the curve). However, this would be the case of measurements made under laboratory conditions and further experiments in a greenhouse have to prove its use for the detection of cucumbers within their environment. Therefore, two interference filters of the following characteristics (see also figure 4.2 and appendix E) have been chosen:

- 850 ± 3.5 nm interference filter;
  Band width of 25 ± 3.5 nm and 45% minimum peak transmittance.
- 970 ± 2 nm interference filter.
  Band width of 11 ± 2 nm and 45% minimum peak transmittance.

By expressing the resulting data of these filters as a ratio, the variation caused by difference in total irradiance of the spectral data at the time of collection is minimised (Edwards, 1988). This spectral ratio (SR) is defined as the reflection intensity value at 850 nm with respect to the reflection intensity value at 970 nm.

As a result, in the case of a cucumber the SR value should be larger than one and in the case of a cucumber leaf about one. But, experiments in a greenhouse have to make this clear first. At the same time, this is the objective of this chapter too. It has to be determined if spectral reflectance at the selected frequencies in the near-infrared range of a cucumber is different from a cucumber leaf during the time of only one day at a fixed place in a greenhouse. Besides, this experiment has to be seen as a basis to decide if the imaging technique of using near-infrared reflection should be a way of detecting cucumbers within their unpredictable changing environment.

5.2 Radiation in a greenhouse

In general, reflection of radiation by a plant in a greenhouse occurs by either the components of the plant or the underlying soil surface. Further, it can be assumed that the reflectance of a component of a plant, in this case a cucumber or its leaf, in a greenhouse will be smaller than the single reflection measurements of the same component made under laboratory conditions. Since mutual shading and multiple scattering within the plant result in a sort of 'cavity' effect, which causes an additional absorption of radiation (Stanghellini 1987, p. 66).

Besides, it can be found that the radiation at the upper surface of the plants is by no means isotropic and it is disturbed further as it penetrates into the plants. The incoming radiation at the upper surface of the plants depends among others on the transmissity of the greenhouse, which in turn is dependent on the nature of light (amount of direct and diffuse light, atmospherical circumstances, weather conditions, etc.), the time of the day, time of the year, position and construction of the greenhouse, position in the greenhouse, etc. (Bakker, 1985; Elgersma, 1985 and Middendorp, 1985).

How a component of a plant will interact with the incoming radiation depends on the kind of component and its production (growth). As seen in paragraph 4.1, in the case of cucumbers the latter is the result of complex water and dry matter relations which interact with each other. In turn, these relations will have their impact on the amount of reflection. Since the reflection in the near-infrared range depends on leaf area index (LAI, the total one-sided area of the leaves per unit of ground area), (air) temperature, transpiration and water absorption (humidity), age, time of the day, etc. (Czarnowski, 1994; Edwards, 1988 and Graaf de, 1992).

From above it follows that the resulting 'wild scattering' of radiation at different places is, in fact, a common problem with greenhouse experiments and, therefore, should be kept in mind. In addition, '[...] an exhaustive theoretical description of the radiative exchanges of a canopy is made almost impossible [...]' (Stanghellini 1987, p. 62).

5.3 Experimental setup

The experimental determination of the spectral reflection at the selected frequencies, 850 nm and 970 nm, have to be performed for a cucumber and a cucumber leaf growing in a greenhouse. The latter is a single-glass, Venlo-type, East-West orientated one. The cucumbers are produced by a high-wire cultivation method (see appendix B). The plants grow on rockwool mats and both soil and rockwool are covered with white plastic sheets so that no evaporation can take place and to increase the radiation available for the plants (a fairly common practice in The Netherlands).

Incoming radiation has to be measured, by means of a solarimeter, where the spectral reflection measurements have to take place. This measurement is needed because the spectral reflection is dependent on the amount of incoming radiation (which is position dependent). In fact, it is worthwhile pointing out once more that the reflection measurements will be influenced by many factors. In other words, for a correct measurement a large number of additional measurements, to determine the influence of each factor, have to be carried out at several places. However, in this experiment only a possible difference in spectral reflectance has to be detected (and not determinated precisely). Therefore, it is sufficient to capture only those factors which have to be known to provide an indication of the circumstances under which has been measured. So, at least, temperature and humidity in the greenhouse have to be known.

As the measurements have to be carried out at only one fixed place in the greenhouse (because of lack of time) an appropriate place has to be chosen. Since this experiment has to be seen as a basis, it has sense to choose for a favourable place: the middle of the greenhouse under a ridge (because of the more steady conditions there).

Further, to improve the quality of the images acquired under conditions of natural illumination an additional light can be used. One of the first considerations in selecting an illumination source is the spectral distribution required by the application (see paragraph 2.3.1). '[...] You should choose a lamp with high output in your desired spectral region and low output at wavelengths that could cause stray light or other problems [...]' (Burke 1996, p. 128-129). Here, the spectral reflection in the near-infrared range has to be measured, so it would be preferred to use an illumination source which contains this spectral range, for instance a halogen lamp (see figure 4.2).

In addition to considerations as the radiance of a light source, also attention has to be given to the setup of the scene illumination (see paragraph 2.3.1). In this case frontlighting should be chosen to enhance the spectral features. However, it can be thought to illuminate the scene not only from the front but also from the left or the right or from both sides as has been done by Amaha et al. (1989) to reduce the noise from leaves by comparing two images of the same area.

5.4 Results

The reflection measurements in the greenhouse were carried out, from early in the morning (5.30h) on 14 th of May (at a rainy day), by means of a digital CCD black and white camera (Spindler & Hoyer, 280 SW-D/C) with adjustable exposure time (needed to measure in the near-infrared range) and a computer interface. All camera parameters were computer adjustable (it was also possible to optimise the image at the moment of acquisition by using a lower and upper limit to adjust the digitalisation range and so reducing, for instance, the background noise) and the image captured by the camera was transferred directly into the main memory where it could be manipulated by the running image processing program SCIL-Image (see appendix F and figure 2.1)). A chosen (mature) cucumber and neighbour cucumber leave were recorded repeatedly (in the same image) by the camera (using the two interference filters) in the middle of the greenhouse at a height of 90 cm and a distance of 80 cm from the camera.

Unfortunately, it seemed that with a spectral irradiance of about 24 W/m^2 (measured in the morning with a Kipp 18, 1271 solarimeter), it was impossible to create a visible image of the scene when using the 970 nm interference filter. Even when the exposure time was increased to 21.51 min (the 850 nm interference filter needed only an exposure time of 1.22 min) and it was decided to use an additional light source: a 1000 Watt halogen-U-lamp. Consequently, the exposure time could be reduced to less than 6 min to create an image of the scene. However, a disturbing circular darkened border around the image was formed now (see figure 5.1). It seemed that this was caused by the used lens (TV lens, Emitec of Denmark with f = 8 mm and 1:1.3) which was subjected to spherical aberration.

Figure 5.1. Recorded scene using the 970 nm interference filter and an additional light source (exposure time = 5.28 min)

In addition, generally, because of the spherical nature of the lens (the ideal lens is actually aspherical), the center point of an image may be in focus while its edges are out of focus. This is called spherical aberration or SA and is mainly be found in cheap or large-aperture lenses. '[...] Spherical aberrations arise from the use of spherical surfaces. The required degree of refraction is not constant but varies in each concentric annular zone of a spherical surface [...]' (Burke 1996, p. 356). For a converging lens with spherical surfaces, the outer rays come to a focus to soon (between the lens vertex and the focal point instead of at the focal point). Likewise, for a diverging lens the outer rays tend to intersect after the central focal point. The degree of SA is the percentage distance the focal point is displaced for outer versus central rays.

A simple method to minimise SA is to use only the central portion of the lens and avoid the outer edges. The degree of SA thus varies with the aperture of the lens (it is less for a small aperture). In addition, stopping down the aperture reduces SA, but this also greatly reduces brightness. Further, a more difficult solution to decrease SA is to manipulate the lens shape.

It follows that in this experiment the aperture of the used lens should have been kept small to obtain less distorted images. Further, only the middle part of the images should have been used to reduce this distortion even more. However, more experiments in laboratory (see appendix G) found that the used lens was also subjected to chromatic aberration (the lens seemed to be susceptible to this kind of aberration).

which results from the fact that the index of refraction of the lens material varies with the frequency. Different frequencies have different refractive indices and are, therefore, focused at different points.

In fact, the stated focal length of the used lens was not correct for the near-infrared measurements. Because of this, the gray scale variations in the obtained images in the near-infrared range were not correct (the images were out of focus), which precluded them to be used in the possible detection of cucumbers within their environment. Generally, the true focal length of a lens increases with increasing frequency into the near-infrared range. Thus, a possible remedy to this problem should have been the use of an extension tube. However, more experiments in laboratory have to prove this first. In addition, to expect any lens to focus the entire 400 to 2000 nm range (the visible and near-infrared range) simultaneously is unrealistic.

Regrettably, the above problems were noticed too late and future (more) correct measurements in the greenhouse were not possible anymore (because of lack of time) and only measurements made in laboratory could be evaluated. In these measurements also spherical and chromatic aberration occurred, but these could be more controlled because of the smaller exposure times and only a small aperture had to be used (in comparison with the measurements made in the greenhouse). It is worthwhile pointing out once more that the significance of nearly all aberrations increases with increasing aperture. Further, as a general rule any optics that work in the visible range will work satisfactory in the near-infrared range, but a few precautions have to be taken. For example, the stated focal length of the lens is often not correct for the near-infrared range (Burke 1996, p. 521).

5.4.1 Results of measurements made in laboratory

First, in order to determine the amount of distortions (the incorrect gray scale variations) caused by the aberrations (using a small aperture) as good as possible reflection calibration standards were used (see appendix I). Because of this, the measurements of both interference filters could be better understood and, therefore, correct conclusions could be drawn.

The standards were recorded, successively, with and without the two interference filters at a distance of 74 cm from the camera and with the use of an additional light source (a 1000 Watt halogen-U-lamp). Further, the aberrations were reduced as good as possible by stopping down the aperture. The results (the different reflections) are shown in figure 5.2 and table 5.1.

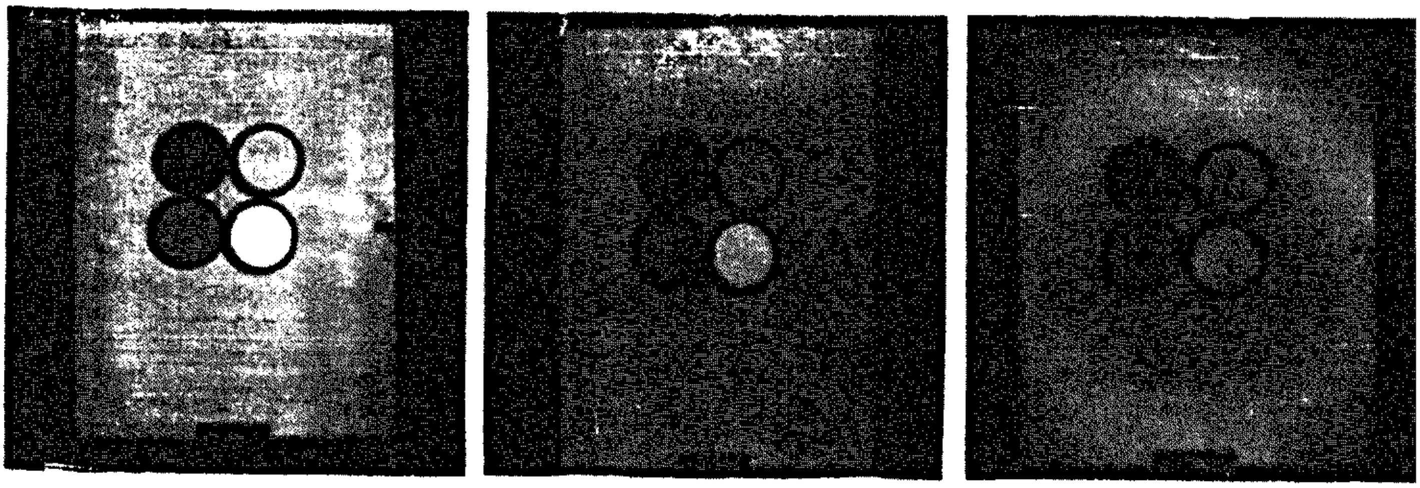

Figure 5.2. The standards recorded, successively, without and with the 850 nm and 970 nm interference filter (exposure time (respectively) = 100 µs, 10.24 s and 20.48 s and distance = 74 cm)

Certified reflectance factor values of the calibration standards [-]	**Without an interference filter** [gray value]	**With an 850 nm interference filter** [gray value]	**With a 970 nm interference filter** [gray value]
0.02	24 - 25	38 - 40	35 - 37
0.52	125 - 130	106 - 109	93 - 96
0.76	187 - 193	139 - 142	138 - 142
0.99	239 - 245	172 - 175	151 - 153

Table 5.1, The measured reflectance values of the standards with and without the use of the interference filters

From the results it could be seen that the mutual ratios between the calibration standards for the measurements without an interference filter and with the 850 nm interference filter were (on average) in agreement with the mutual ratios between the certified reflectance factor values. In addition, it could also be seen that the camera was contaminated with an offset. From this, it followed that the amount of distortions under those circumstances and with or without the 850 nm interference filter could be considered as almost negligible (the results had a linear relation). However, measurements with the 970 nm interference filter showed a deviant result. The mutual ratios at this frequency were not in agreement with the certified reflectance factor values anymore. Especially, in the reflectance range between 0.52 and 0.99. At the same time, this is also the range where the reflection properties of the cucumbers (and cucumber leaves) are approximately situated (see figure 4.2). Consequently, the images obtained at this frequency would not have been correct, which precluded them to be used in future measurements with cucumbers and cucumber leaves (at this frequency distortions (incorrect gray scale variations) played an important part in the measurements). It followed that only the 850 nm interference filter could be used for future (correct) measurements.

Anyhow, to determine a possible reflectance difference between a cucumber and cucumber leaf it was decided to use only the 850 nm interference filter. For this purpose a single cucumber leaf was sticked to a board against which a cucumber was hold. This scene was recorded with the 850 nm interference filter, under the same circumstances as described above. Then, from the obtained image the gray values of the pixels at different chosen lines were depicted on different graphs (using the written algorithm in appendix H) (see figure 5.3).

From these graphs it could be seen that the reflectance of the cucumber was always higher than its surrounding leaf (the hole in the graph was caused by the shadow of the cucumber). Unfortunately, because of a different exposure time (in comparison with the standards) nothing could be said about the amount of reflection (there was no reference). The only thing that could be said more is that the ratio between the reflectance of the cucumber and the cucumber leaf was a bit lower in comparison with the ratio of the corresponding values in figure 4.2.

In addition, although the images obtained with the 970 nm interference filter were not correct, nevertheless, little attention had been given to these measurements. Some graphs had been depicted and, furthermore, some corresponding SR values had been determined (by using different thresholds) (see appendix J). However, because of preciseness only little attention should be given to these results and more research is needed first.

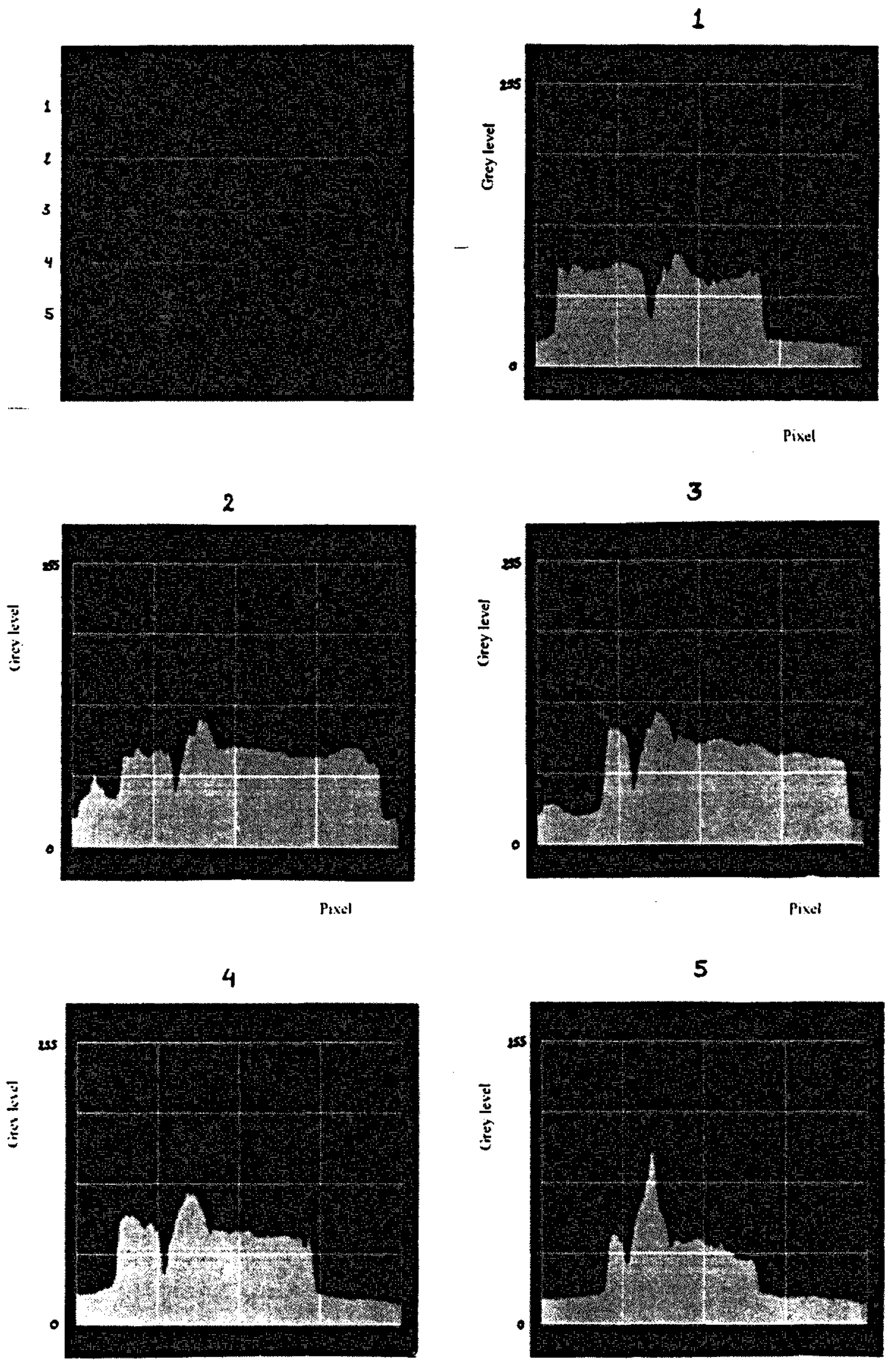

Figure 5.3. Recorded scene using the 850 nm interference filter and the corresponding line histograms (exposure time = 8.12 s and distance = 0.74 cm)

5.5 Conclusions and discussion

In this chapter the near-infrared reflectance of cucumbers in comparison with their environment have been discussed. It was found that the discrimination between the cucumber and its leaf is considered to be possible by the value of the spectral ration (SR). However, this would be the case of measurements made under laboratory conditions.

Unfortunately, experiments in a greenhouse could not take place because the used lens was subjected to several aberrations (spherical and chromatic aberration). In practice, altering the aperture is the main tool to control these distortions. However, the use of calibration standards showed that the images obtained with the 970 nm interference filter were not correct (suffer from incorrect gray scale variations). Consequently, measurements in laboratory could only be carried out with the 850 nm interference filter and showed a reflectance difference between a cucumber and a cucumber leaf (their ratio is larger than one) at this frequency.

However, these measurements cannot in practice be related straightforwardly to measurements made in a greenhouse due to the many factors influencing the reflection and its large variation from place to place there. The interaction of radiation with a plant in a greenhouse is actually the interaction with a huge amount of (different) components of that plant. Generally, the resulting 'wild scattering' of radiation at different places is, in fact, a common problem with greenhouse experiments. Consequently, it cannot be proved practically that the imaging technique of using near-infrared reflection is the way of detecting cucumbers within their environment. In fact, correct measurements (without distortions) in a greenhouse are needed first.

Further, it follows that the used camera was not an appropriate choice for near-infrared measurements in a greenhouse. As changing lighting (weather) conditions during the large exposure times (needed for near-infrared measurements) can influence the measurements badly. However, the use of an additional light source can reduce the exposure time significantly.

In addition, near-infrared images look blurry because of among others residual aberrations (including SA), reduced modulation transfer function (MTF) of the lens at longer wavelengths and influences of the anti-reflection coating of the lens in the near-infrared range.

6 CLASSIFY THE CUCUMBER WITHIN ITS ENVIRONMENT

As already mentioned, cucumbers do not ripen at the same time and, consequently, every cucumber has to be evaluated for ripeness (classified) prior to harvesting. Thus, another important harvesting task of the harvesting system is to determine the maturity stage of the cucumbers.

In general, '[...] the principles which dictate at which stage of maturity fruits should be harvested is crucial to their subsequent storage and marketable life and quality. These may be defined in terms of either their physiological maturity or their horticultural maturity, and are based on the measurement of various qualitative and quantitative factors [...]' (Thompson 1996, p. 26).

6.1 Harvest maturity

There are certain guiding principles to be followed when selecting fruit to be harvested. Harvest maturity should (Thompson 1996, p. 26):

- Be at a stage which will allow it to be at its peak condition when it reaches the consumer;
- Be at a maturity that allows it to develop an acceptable flavour or appearance;
- Be at a size required by the market;
- Have an adequate shelf life.

The methods used to determine the maturity of fruits may be based on the subjective estimate of people carrying out the harvesting task. To achieve this, sight, touch, smell, morphological changes and resonance may be used. However, the goal of this project is the development of a harvesting robot of soft fruits. Furthermore, especially the use of computer vision as the major sensing technique has to be evaluated. Thus, under these circumstances, appropriate features have to be used in the harvesting system to determine the maturity of fruits. In addition, this results in a more objective and perhaps more consistent determination of the maturity of fruits.

Image analysis systems have already been widely applied during the last years in the inspection and classification of fruits for their use in automatic sorting and grading machines (Chen, 1991). Different quality features have been studied, using different image analysis techniques (use of a solid-state TV camera, line-scan camera, X-ray scanning, ultrasonic scanning, NMR imaging, etc.), like size, shape, colour (for both maturity estimation and detection of irregular fruits) and external damages (bruises, blemished or rotten fruits). However, these systems cannot simply be applied to the agricultural environment (in which the maturity of fruits have to be determined) because of such problems as occlusion of fruits and influences of the unpredictable changing environment (sun illumination, shadows, etc.). Basic techniques developed for automatic sorting and grading can be applied. However, modifications are necessary in order to make them suitable for the determination of the maturity of fruits within their (variable) environment.

6.2 Harvest maturity of cucumbers

In practice, the main criterion to determine when a cucumber should be harvested is the size of the cucumber (400-600 g fresh weight). Generally, changes in size of a fruit as it is growing are frequently used as the main criterion for its harvest. In fruits this may simply be related to the market requirement. Nevertheless, a cucumber is harvested at a larger size when its average growth rate increases and, therefore, the harvest size changes during the season (400 g fresh weight in spring, 500-600 g fresh weight in summer and 300 g fresh weight in autumn). In addition, the harvest date may also depend on shape of the cucumber, number of cucumbers growing on the plant, price of the cucumber, availability of labour and the personal view of the grower. Further, besides size there are other parameters which determine the quality of the cucumber: ratio between length and thickness (determines to a great extent its shape), curvature, taste, shelf life, firmness, etc. (Marcelis, 1994 and Marcelis 1994, p. 55-63).

At harvest, cucumbers are not physiologically mature. They could keep on growing for a long period. Some are harvested even before they reach the maximum growth rate, while others are harvested when they are more than twice as old. When the growth rates of the cucumbers are high they are harvested at an earlier development stage, which has important implications for the quality of the cucumber. The average growth rate of a cucumber depends primarily on the net assimilation rate, the competition from other cucumbers for the available assimilates and the temperature. With increasing temperature the age at harvest (days from anthesis until harvest) decreases, but not necessarily the development stage. When cucumbers are harvested at an early development stage they are more susceptible to the incidence of rubber necks (low firmness and shrivelled skin). On the contrary, when cucumbers are harvested at a later development stage they soon start to yellow (overripe) (Haghuis, 1991; Marcelis 1994, p. 55-63 and Roest van der, 1991).

6.3 *Determination of the cucumbers maturity*

In automatic sorting and grading machines colour is commonly used as a decisive factor in the determination of the maturity of fruits, where the colour of the fruit changes as the fruit matures (Moltó, 1996). However, in the case of cucumbers there is no perceptible colour change during maturation. Therefore, global or average colour cannot be used as an indicator of maturity for cucumbers.

On the contrary, as already mentioned in the above paragraph, cucumber fresh weight can be considered as the major parameter for maturity determination of cucumbers. Thus, to determine the maturity of cucumbers an accurate nondestructive method for estimating the fresh weight of cucumbers has to be found. Literature showed that this can be done by measuring the volume of a fruit, as has been reported for tomato (Marcelis 1994, p. 62), pear (Mitchell, 1986) and eggplant fruit (Barbieri, 1990) where relationships have been described that relate fruit size (fresh weight) to volume by converting diameter or circumference (X) to volume (Y) by means of logarithmic transformation $Y = aX^b$.

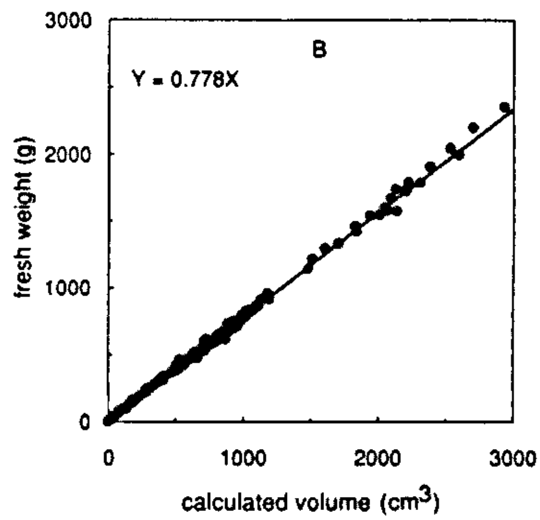

Figure 6.1. Cucumber fresh weight as a function of volume calculated from length and circumference (average of circumference at a quarter, half and three quarters of the cucumber length). Each symbol represents one cucumber from plants with one or seven cucumbers, grown at 20, 25 or 30°C and 75 or 135 Wm^{-2} PAR. The cucumbers were harvested between 0 and 40 days after flowering

Assuming a cucumber to be cylindrical, its volume can be estimated from its length and circumference. Although this would result in an overestimation of the volume, research by Marcelis (1994, p. 55-63) showed that the fresh weight will be proportional to the calculated volume independent of cucumber age, cucumber size or temperature (see figure 6.1). Furthermore, it was found that the best relationship between calculated volume and fresh weight was obtained when circumference was measured at three places along the length of a cucumber, but measuring the circumference only halfway along the cucumber also yielded a close linear relationship.

It follows to determine the maturity of cucumbers by a harvesting robot the harvesting system should be capable of measuring the volume of a cucumber. Because normally the output of the sensing is a two-dimensional image the volume of the cucumber has to be estimated from its length and diameter (at one or more places). However, the agricultural environment has a three-dimensional nature. The plants have volume that is filled by stems, leaves and cucumbers, which may obstruct the cucumber of interest, disturbing evaluation of size (respectively volume). Further, the cucumber may be distorted by occlusion so that sometimes it cannot be recognized at all. Needed analysis of the complex images and reconstruction of the cucumber from an occluded image demand, however, for sophisticated processing techniques that are time consuming and make them less attractive for their use in robotic (real-time) harvesting. As a result of this, the robotic harvesting of mature cucumbers calls for three-dimensional information to avoid obstacles (occlusion). Although, the above method, based on a two-dimensional image, can be suitable in the case of clearly visible cucumbers. However, it should be kept in mind that errors can possibly be introduced in measuring the length and diameter of the cucumber in the two-dimensional image because of such problems as insufficient resolution, too large variation in distance between imaging sensor and cucumber, threshold results are not consistent because of shading, etc.

Another possible method to determine the maturity of cucumbers is to compute the time between flowering and cucumber being ready for harvesting. Marcelis (1994, p. 55-63) found that length, circumference and fresh weight of cucumbers followed sigmoid curves from which the cumulative growth and growth rates of the cucumbers can be described accurately. However, as with most fruit it is difficult to utilize this consistency in practice. Forecasting harvest fruit size requires knowledge of the reaction of the fruits to different environmental factors (Welte, 1990).

Before using one of the above (sophisticated) methods it is important to remind that this research is limited to applications to the high-wire cultivation method. In this cultivation method most mature fruits can be found at a height of 1200-1250 mm to 1750-2000 mm, certainly in period of maximum possible output from halfway of February till end of October (see appendix B). Furthermore, and also important, at these heights the cucumbers are very uniform in length and fresh weight. So it would be preferable to harvest all cucumbers, which are detected by the harvesting system, at these heights. As the consequences of false determination of maturity are, in general, not so serious because of the relatively low prices of cucumbers and the low penalty cost and the large probability of detecting uniformly mature cucumbers at these heights.

6.4 Conclusions and discussion

In this chapter the determination of the maturity of cucumbers has been discussed. Because the maturity estimation has to be carried out by the harvesting robot appropriate features in the harvesting system have to be used. The strength of using image analysis in the determination of the maturity of cucumbers is its ability to measure maturity in an objective way.

The evaluation of cucumbers within their environment is a complex task, due to the three-dimensional nature (possible occlusion of cucumbers) and influences of the unpredictable changing agricultural environment. Consequently, the robotic harvesting of mature cucumbers calls for three-dimensional information to avoid obstacles (occlusion). Although, in the case of clearly visible cucumbers the maturity of a cucumber can be estimated from its volume by measuring its length and diameter (at one or more places) based on a two-dimensional image. However, errors can possibly be introduced in these measurements.

Another possible method to determine the maturity of cucumbers is to compute the time between flowering and cucumber being ready for harvesting. However, as with most fruit it is difficult to utilize this consistency in practice.

Because of the use of the high-wire cultivation method in this research most mature cucumbers can be found at a height of 1200-1250 mm to 1750-2000 mm. Furthermore, at these heights the cucumbers are very uniform in length and fresh weight. As a result of this, the easiest way to determine the maturity of cucumbers is to harvest all cucumbers, which are detected by the harvesting system, at these heights.

Furthermore, the consequences of false determination of maturity are, in general, not so serious because of the relatively low prices of cucumbers and the low penalty cost.

7 PRECISE LOCATING THE CUCUMBER WITHIN ITS ENVIRONMENT

'[...] Fruits are not isolated objects. They are scattered in a three-dimensional space among vegetation. To reach them human pickers use an arm with many joints and 3-D vision [...]' (Rabatel, 1994). In the same way, the harvesting robot requires a sensing system to precisely locate the cucumbers and a mechanical arm, also called the manipulator, to reach and harvest them.

Due to the three-dimensional nature of the agricultural environment, which may obstruct the cucumber of interest, robotic harvesting calls for three-dimensional information to direct the harvesting device and to avoid obstacles in the unpredictable changing agricultural environment.

7.1 Precise locating the cucumber

As shown in previous chapters, computer vision plays a privileged role in robotic harvesting. Using this approach, cucumbers have to be localised by means of an imaging sensor placed in front of the plants, in order to control the motion of a harvesting device that will harvest the cucumbers one by one. However, this localisation is not a simple task. The agricultural environment is fairly complex to deal with, because cucumbers have to be localised among a lot of variable objects presented in a greenhouse (like stems, leaves, wires, pipes, sky, etc.) which may obstruct or even occlude the cucumber of interest. Therefore, three-dimensional information is needed to locate the cucumber and to direct the harvesting device to it.

Although most of the computer vision techniques appear quite sophisticated, they are inherently two-dimensional (the output is a two-dimensional image) and are strictly speaking not suited for dynamic robot guidance. However, once a cucumber has been detected (partly or fully), an efficient way of linking detection and finally harvesting is to use the straight line between the imaging sensor and each visible cucumber as a trajectory for the harvesting device to reach the cucumber, because this line is guaranteed to be free of obstacles (otherwise it would not be (partly) visible). Then, only the latitude and longitude coordinates of the harvesting device trajectory have to be determined. But, because these are directly related to the coordinates in the two-dimensional image, the localisation of the cucumber in this image is sufficient to determine the angular orientation of the harvesting device trajectory and to start its motion (see figure 7.1). The cucumber distance remains unknown, but the harvesting device motion can be stopped by means of a local sensor when the cucumber is reached (Rabatel, 1991 and Rabatel, 1994). This results in a very simple way of locating cucumbers within their environment.

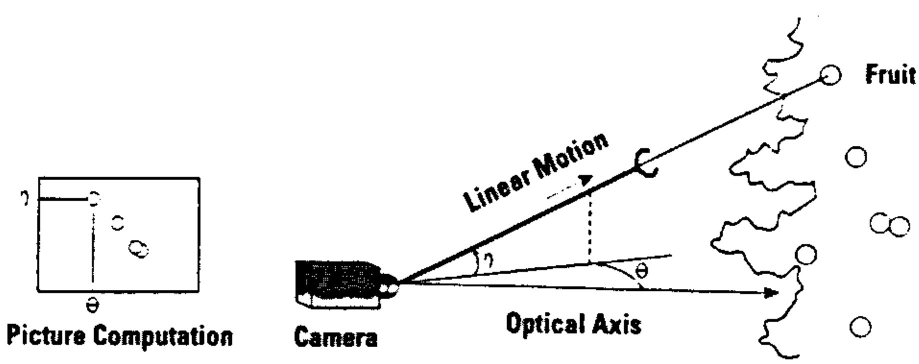

Figure 7.1. Detection and motion principle (Rabatel, 1994)

In addition, obviously the task of the harvesting robot is to locate every cucumber within the plant that is visible from the imaging sensor. However, it does not mean that every cucumber in the plant will be located. This depends on how many cucumbers can be detected by the imaging sensor, which in turn will be related to the amount of occlusion (the plant structure) and the possibility of the imaging sensor to detect these occluded cucumbers.

7.1.1 Ranging techniques

This paragraph is essentially a brief survey of techniques that can be used for distance measurements which may additionally support the localisation mentioned above. Since the third dimension is not known until the cucumber is reached, these techniques can be used to obtain spatial (3D) information of the agricultural scene beforehand and might so be useful, for example, to guide a harvesting device towards (fully) occluded cucumbers (if detected) by a roundabout way, while avoiding collisions with obstacles. Some potential ranging techniques are given below:

- Stereo vision;
  If two images of a scene taken from different known positions (laterally displaced along a defined baseline) are obtained and the two image points corresponding to a given scene point P can be detected, then the position of the point in space (its distance) can be calculated by triangulation (similar to the function of human eyes). In the case that the imaging sensor is attached to the end of a manipulator, the sensor is moved into the scene and the sequence of images (taken at predetermined motion intervals) provides the data for distance measurements. As the number of pixels representing a given scene point (object) increases when the manipulator moves into the scene.
  The main difficulties with both types of stereo ranging techniques are that corresponding pairs of image points are not easy to detect, the diminishing accuracy with distance and both are computational intensive (slow and expensive). On the contrary, the most obvious advantage is their wide applicability without the need for special lighting and the simplicity of combining range with image intensity data. A less obvious strength is that they correspondence with human visual process permitting advantage to be taken of what is known about that process to improve the technique (Dorf 1990, p. 871).

- Structured lighting;
  The basic approach with structured lighting is to project a known (structured) pattern of light on a three-dimensional scene and to use the distortions in this pattern to retrieve the three-dimensional information of the scene (see also paragraph 3.2.1.3). Absolute ranging data can be derived using simple triangulation geometry of the projector and imaging sensor positions relative to the scene and optical parameters.
  However, this technique is restricted in application to those situations where structured lighting is possible and acceptable. Further, it is computational expensive.

- Ultrasonics;
  Ultrasonic range sensors are based on the time-of-flight (TOF) principle. A narrow-band pulse of ultrasound is transmitted into the scene by a transducer that can act both as a transmitter and a receiver. The time it takes for the pulse to travel to the object of interest and back is proportional to the range (see also paragraph 3.2.4).
  Ultrasonic systems use very little power, are relatively simple and inexpensive and can be compactly packaged into robust modules. Thus, at first sight ultrasonics seems to offer an ideal technique for ranging.

- Laser systems.
  Laser range instruments are also based on the TOF principle. It measures the transit time of a very short laser pulse to and from the object of interest. However, laser instruments tend to be very expensive, are somewhat fragile and require careful tuning and optical alignment. They also tend to be bulky (Dorf 1990, p. 874).
  A better method which uses the same principle but is much cheaper and relatively simple is the use of a photoelectric sensor (Fujiura, 1992).

7.2 Conclusions and discussion

In this chapter the precise locating of the cucumber within its environment has been discussed. A difficulty in developing a robot to selectively harvest cucumbers is the localisation of individual cucumbers. This specification is basic prerequisite to guide a harvesting device towards a cucumber, while avoiding collisions with obstacles.

While three coordinates are normally required to describe the position of a cucumber within the plant, it has been shown that the output of an imaging sensor, a two-dimensional image, is sufficient to define the location of the cucumber. The third dimension is not known until the cucumber is reached and sensed by a local sensor. This seemed to be the easiest way to locate the cucumber within its environment.

However, in the case of (fully) occluded cucumbers the localisation depends on the possibility of the imaging sensor to detect these occluded cucumbers and the use of a ranging technique, such as stereo vision, structured lighting, ultrasonics and laser systems, to guide the harvesting device towards the occluded cucumbers, while avoiding collisions with obstacles.

In general, accuracy, resolution speed, range of applicability, reliability and cost are the crucial parameters of any ranging techniques. In fact, these five measures will determine the feasibility of using a ranging technique for any particular application. In this case, ultrasonics and the use of a photoelectric sensor have the most promising possibilities in the given unpredictable changing agricultural environment, because they are relatively simple, inexpensive and, furthermore, very accurate and very fast (in comparison with the other methods).

8 CONCLUSIONS AND FURTHER RESEARCH

The goal of this research was to derive a possible imaging technique(s) which should be capable of detecting mature cucumbers within their environment for its use in a harvesting robot. Finally, this has to result in a harvesting system which should have to encompass the sensing and the processing tasks, detection and classification of the cucumber after which the cucumber can be located. However, the accent of this research has mainly been addressed to the detection problem and to a lesser degree to the other ones.

8.1 Results and conclusions

In this research a first step towards the development of a harvesting robot of cucumber fruits has been made. This has to be done from the very beginning due to the variability of cucumbers and the difficulty in interpretation of the uncontrollable agricultural environment (like changing illumination conditions, shadows and occluding cucumbers). Therefore, various imaging techniques were reviewed and, finally, some were proposed for their use in a harvesting robot. These are:

- the use of microwaves;
- the use of a combination of some selected frequencies in the near-infrared and visible range;
- the use of thermal infrared radiation.

In addition, the strength of using image analysis in the harvesting of cucumbers is its ability to measure many cucumber features in an objective way. Further, knowledge and cucumber features (like length and diameter) seemed to be required to meet the detection of mature cucumbers.

After more research and a study on reflection properties of cucumbers and cucumber leaves, it was shown that the imaging technique of using some selected frequencies in the near-infrared range is the most promising imaging technique capable of detecting cucumbers within their environment. The potential of the other imaging techniques for their use in cucumber detection are doubtfully. In agreement with literature, it was found that reflectance of cucumbers in the near-infrared range is different in comparison with their leaves. This difference can yield useful information for the detection of cucumbers within their environment and was considered to be possible by the value of the spectral ratio (SR). However, this would have been the case of measurements made under laboratory conditions.

Unfortunately, experiments in a greenhouse could not take place and only measurements with the 850 nm interference filter could be carried out in laboratory. These measurements showed a reflectance difference between a cucumber and a cucumber leaf at this frequency. However, these measurements cannot in practice be related straightforwardly to measurements made in a greenhouse due to the many factors influencing the reflection and its large variation from place to place there. Generally, the 'wild scattering' of radiation at different places is, in fact, a common problem with greenhouse experiments. Consequently, it cannot be proved practically that the imaging technique of using near-infrared reflection is the way of detecting cucumbers within their environment. However, considering the results obtained by literature and measurements made in laboratory, on the contrary, suggested there is an opportunity for this imaging technique and, in fact, only correct measurements in a greenhouse are needed to prove its feasibility.

Further, an also important harvesting task of the harvesting system is to determine the maturity stage of cucumbers. This is needed because cucumbers do not ripen at the same time and, consequently, every cucumber has to be evaluated for ripeness prior to harvesting. The evaluation of cucumbers within their environment was seen to be a complex task. However, because of the use of the high-wire cultivation method in this research most mature cucumbers can be found at a height of 1200-1250 mm to 1750-2000 mm. Furthermore, at these heights the cucumbers are very uniform in length and fresh weight. As a result of this, the easiest way to determine the maturity of cucumbers is to harvest all cucumbers, which are detected by the harvesting system, at these heights.

Another difficulty in developing a robot to selectively harvest cucumbers is to locate the individual cucumbers. While three coordinates are normally required to describe the position of a cucumber within the plant, it was shown that the output of an imaging sensor, a two-dimensional image, is sufficient to define the location of the cucumber. The third dimension is not known until the cucumber is reached and sensed by a local sensor. However, in the case of (fully) occlusion the use of an additional ranging technique, such as ultrasonics or the use of a photoelectric sensor, is needed to guide the harvesting device towards the occluded cucumber by a roundabout way while avoiding obstacles.

Obviously, the task of the harvesting system is to locate every cucumber within the plant that is visible from the imaging sensor. However, it does not mean that every cucumber in the plant will be located. This depends on how many cucumbers can be detected by the imaging sensor, which in turn will be related to the amount of occlusion and the possibility of the imaging sensor to detect these occluded cucumbers. At the moment, problems may still arise with the detection of occluded cucumbers. However, as near-infrared is able to penetrate into leaves this technique might offer some opportunities and more research in this area is needed.

In addition, there are more aspects where the image analysis system can be helpful in improving the harvesting system. One example is the harvesting procedure management. Which cucumber has to be picked first? Or how should the harvesting device motion be adapted for cucumbers which are very close to the main stem (difficult to grasp and cut)? Should the cucumber be harvested now or wait for better visibility? All these aspects (and more) require the image analysis to go further than a simple evaluation of location coordinates.

In conclusion, many problems have to be solved in finding or in later extending the reliable cucumber detection algorithm(s) (including the imaging technique) to a really efficient harvesting system. Some of these problems have already been solved, while others are still being studied. In all cases, this requires specific image processing developments, but, above all, a lot of in field experiments and strong links with the design of the other components of the robot.

8.2 Further research

In general, there is no consensus on the viability of the robotic harvesting system as an alternative method for the current manual harvesting. While all will agree that no commercial cost-effective product is yet available on the market, some will argue that it is only a matter of time and money required for further research and development before robots will replace manual harvesting. Others, however, still maintain that robotic harvesting will never be economically practical. These diverse and contradictory opinions, are the result of the uncertainty in solving successfully the various problems still associated with the implementation of the harvesting robot.

While in this research some progress has been made with the detection, classification and localisation of the cucumber under laboratory conditions, still correct and validating measurements in a greenhouse have to be carried out to prove, for example, that the imaging technique of using near-infrared reflection is the way of detecting cucumbers within their environment. More (correct) research in this area is needed and, perhaps, the other imaging techniques have to be considered again.

Besides, variability in lighting conditions and occlusion of cucumbers require further research. Artificial lighting and shading effects have to be studied and, in the case of occlusion, some 'look through' experiments (using backlighting) have to be carried out to possibly improve the detection results. Further, the use of an air blower has to be considered to blow away the cucumber leaves and expose the cucumbers which are normally occluded by them.

In addition, the rate at which the robot will function may very well determine its economic viability, it is crucial to minimise the time required for the harvesting cycle and thus increase its productivity, to make the harvesting robot competitive with manual harvesting. An attempt to minimise the harvesting cycle time can possibly be achieved by preplanning the sequence of the robot (harvesting device) motions before beginning the harvesting process. According to this approach, cucumbers should be recorded prior to harvesting. However, these locations might have to be updated at a very high sampling rate to account for changes in cucumber positions due to growth or neighbour cucumber detachment for example.

In conclusion, although under current conditions a harvesting robot is not justifiable, it is by no means a hopeless situation. The increasing costs of labour and decreasing costs of computers, vision systems and robotic equipment may pave the way for its future commercial implementation. However, much more research is needed first.

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APPENDIXES

APPENDIX A, SPECIFICATIONS

A SPECIFICATIONS

Although a decision to start a new technological development is sometimes influenced by political motives such as prestige or future technological developments, in general it is necessary to determine beforehand the justification for investment in a complex project such as the harvesting robot of cucumber fruits.

A.1 Robot specifications and economical analysis

For the harvesting robot the following specifications have been made (see table A.1 and A.2):

Harvesting rate [s/cucumber]	**Sorting rate** [s/cucumber]
2.94	0.96
	Total rate: 3.9 [s/cucumber]

Table A.1. Harvesting and sorting rate under the present situation

No.	**Handling**	**Rate** [s/cucumber]
1	Robot displacement (every 60 cm)	2 - 2.5
2	Detection of the cucumber (far locate, classify and precise locate the cucumber)	5 - 8 (aimed at 2)
3	Reaching, handling and cutting the cucumber by the manipulator/end-effector	1 - 2.5
4	Put the cucumber in the right crate	1 - 3
5	Manipulator/end-effector back to start position	to 0.5
		Total rate: 9 - 16.5 [s/cucumber]

Table A.2. Harvesting and sorting rate with robotic harvesting

Further, the robot should work up to 12 hours a day (the cucumbers should be harvested before afternoon), regularly during the whole harvesting season. Under these assumptions, the cost of the robot should be less than FL 150.000,-. In addition, this will not justify the cost of development. Thus, from the point of view of the manufacturer, it would not be an economic investment.

However, with a proper design of the robot, the future robot will classify the cucumbers better and more uniform and, besides, it will handle the cucumbers more gently, resulting in higher cucumber quality than that obtained with manual harvesting. Hence, a dominant factor in the robotic harvesting will be the overall cucumber quality.

APPENDIX B, HIGH-WIRE CULTIVATION METHOD

B HIGH-WIRE CULTIVATION METHOD

More and more cucumber growers use or will use in the future the high-wire cultivation method. Therefore, it will be obvious to limit the development of a harvesting robot of cucumbers to applications to this cultivation method, which has almost no curved and bruised (deviating) cucumbers (and so a high quality) and, furthermore, it has been proved to give a high production.

B.1 Basic principle

In the high-wire cultivation method every plant is tied (screwed) to a wire, which is stretched at about 4 m height by rolling the wire up at a spool and fixing it to the cropwire (one of the parallel horizontal wires at about 4 m height) (see figure B.1). When the top of the plant reaches the cropwire the wire is rolled off and the top of the plant hangs again approximately 500 mm under the cropwire. At the same time, every spool on the cropwire is simultaneously displaced horizontally. Consequently, after some time the top of the plant will not be straight above its roots.

Before lowering the plant, first all leaves at the bottom of the plant are removed (nearby the main stem to prevent mycosis). In addition, the average growth of the plant is about 450 mm a week (often a bit less in summer).

B.2 Handling and harvesting

Cucumbers are harvested from January until November for fresh market consumption. These cucumbers are produced by one crop or by two or three subsequent crops per year. In this cultivation method only cucumbers on the main stem are harvested (all side shoots are removed manually). The cucumbers are formed in the axils of the leaves. In principle, more than one cucumber can be formed in each axil, but this is manually restricted to one cucumber per two axils. Some other (intensive) manual handlings are: screwing of the plants into the wires, removing of the lowermost leaves and lowering of the wires.

In this cultivation method most mature cucumbers can be found at heights of 1200-1250 mm to 1750-2000 mm, certainly in period of maximum possible output from halfway of February till end of October (initially they hang lower in the plant) (see figure B.1). At these heights the cucumbers are very uniform in length and fresh weight (400 g in spring, 500-600 g in summer and 300 g in autumn). Moreover, in this cultivation method there are almost no curved or bruised (deviating) cucumbers (only approximately 1% of the crop) and it can be said that the cucumbers of this cultivation method are of high quality.

The cucumbers are harvested two till three times a week. The yield per square metre of greenhouse vegetables varies between 0.5 and 4 cucumbers/m^2 and it has been proved that this cultivation method results in a high production.

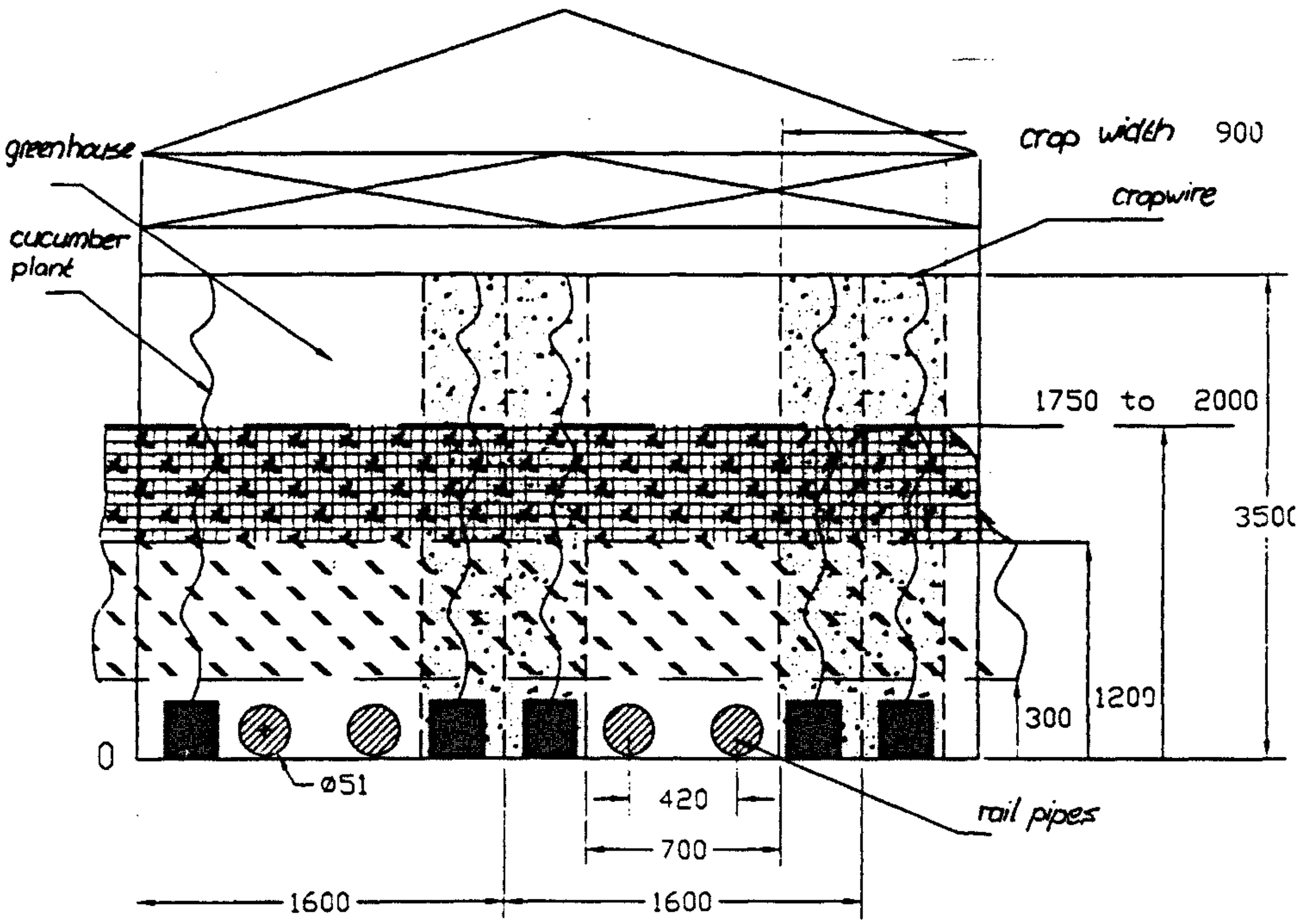

Figure B.1, Sketch of a greenhouse with the high-wire cultivation method (not a scale drawing)

APPENDIX C, MAIN FEATURES OF THE DIFFERENT IMAGING TECHNIQUES

C MAIN FEATURES OF THE DIFFERENT IMAGING TECHNIQUES

Imaging technique	Main features	Potential for the use in the fruit detection
Radio wave detection and ranging (radar)	(i) The reflected energy is a function of the frequency, polarization, incidence angle and object properties. (ii) The object features which determine the reflected energy to a large extend are the geometric and electric properties of the object. (iii) The reflected energy from different objects become more distinct by using frequencies that span the natural electromagnetic resonance of these objects.	The influence of the wavelength range of radio waves in combination with the small size of fruits on the radar sensitivity strongly limits its use for detection. As radar also operates at lower wavelengths, the microwave range, more promising opportunities may be found in using this range.
Microwaves	(i) Same main features as radio waves. (ii) Its able to penetrate into an object.	The use of microwaves might be a way to detect fruits. However, research on using microwave reflection as an imaging technique of soil moisture content has shown that this technique can be highly problematic as the microwave reflection depends on different and very complex parameters.
Near-infrared and visible range (with respect to vegetation)	(i) In the visible range various pigments in vegetation influence the reflection. (ii) The first part of the NIR is mainly determined by the absence of absorption (by pigments). (iii) In the second part of the NIR a great part of energy is absorbed by water in the cells. (iv) The first part of the NIR may not give information about leaves directly in front of the sensor only, but also behind these leaves	Each range might have some possibilities for the detection of fruits. The visible range for the detection of leaves and perhaps fruits which are not occluded, the first part of the NIR for the detection of some hidden (and visible) fruits and the second part of the NIR for the detection of visible fruits. Promising results might be obtained by using a combination of some selected frequencies in the NIR and visible range.
Near-infrared	(i) Sensitive to absorption by the CH, NH and OH bonds. (ii) To determine the mixing and varying composition of an object the reflected image at a number of discreet NIR wavelengths can be measured.	For the detection the use of some selected frequencies in the NIR might be very interesting. Especially, the use of the frequencies in the water absorption bands.

Imaging technique	Main features	Potential for the use in the fruit detection
Visible range	(i) Highly contrasting colours between object and background improves segmentation. (ii) The colour of an object is perceived differently depending on the illumination.	A combination of visible and near-infrared range might be a way to detect fruits.
X-rays	(i)The penetration of these rays depends mainly on the thickness of the object and other parameters such as structure, absorption coefficient and density of the object. (ii) Gives a two-dimensional image integrated along the third axis, although X-ray computed tomography can be used to obtain a three-dimensional image. (iii) The X-ray technique has to be combined with surface topography measurements to remove the ambiguities in the integrated two-dimensional X-ray images	Because of the complexity of this technique if applied in the used cultivation method (more volume averaging) X-ray imaging would not be a very promising way to detect fruit. However, changing the cultivation method would probably make the use of X-ray imaging more attractive.
Thermal infrared radiation	(i) All objects with a temperature above absolute zero continuously emit thermal radiation. (ii) Care should be taken to avoid complication of the background.	Under the condition that factors influencing the radiation have been taken into account thermal imaging can possibly be used as an imaging technique for the detection. However, a reasonable temperature difference between the fruits and their environment has to be existed first.
Nuclear magnetic resonance (NMR)	(i) Can detect the concentration and state of hydrogen within an object. (ii) The equipment is expensive and this has implications on the maximum size of an object which can be scanned.	There might be opportunities for the use of NMR imaging in detection applications. However, in the near future the cost is likely to be prohibitive to its use in the fruit detection.
Ultrasonics (in the high frequency range)	(i) It has the ability to propagate through soft biological materials suffering only moderate attenuation. (ii) The transducer and object need to be acoustically coupled because of the high acoustic impedance between transmitter and air.	Because the ultrasonics in this range has been predominantly used as a contact probe it has no opportunities for the detection.

Imaging technique	Main features	Potential for the use in the fruit detection
Ultrasonics (in the low frequency range)	(i) Posses several attractive attributes for dense ranging and signature applications (because of less attenuation of the signal at these frequencies). (ii) Can distinguish between objects in the foreground and background.	Their primary disadvantages of low resolution and large sensitivity to small changes in the object's position make this imaging technique less attractive for detection. Because ultrasonic systems use very little power, are relative simple and inexpensive and have the ability of range measurements and, furthermore, the possibility of detecting partly occluded objects it can be thought to use this technique as an extra sensor.
Luminescence	(i) Many biological materials fluorescence. (ii) Quantitative use of X-ray fluorescence requires careful object preparation and a controlled environment. (iii) Measurements of chlorophyll fluorescence have to be made on pre-darkened objects which are subjected to a pulse of light.	Because most fluorescence measurements cannot be realised in non-destructive measurements or have to be made by physical contact the use of this technique is very limited. The possibility of making measurements at night should be considered although the long measurement time preclude rapid sensing and, therefore, its use for detection.

APPENDIX D, SINGLE REFLECTION MEASUREMENTS

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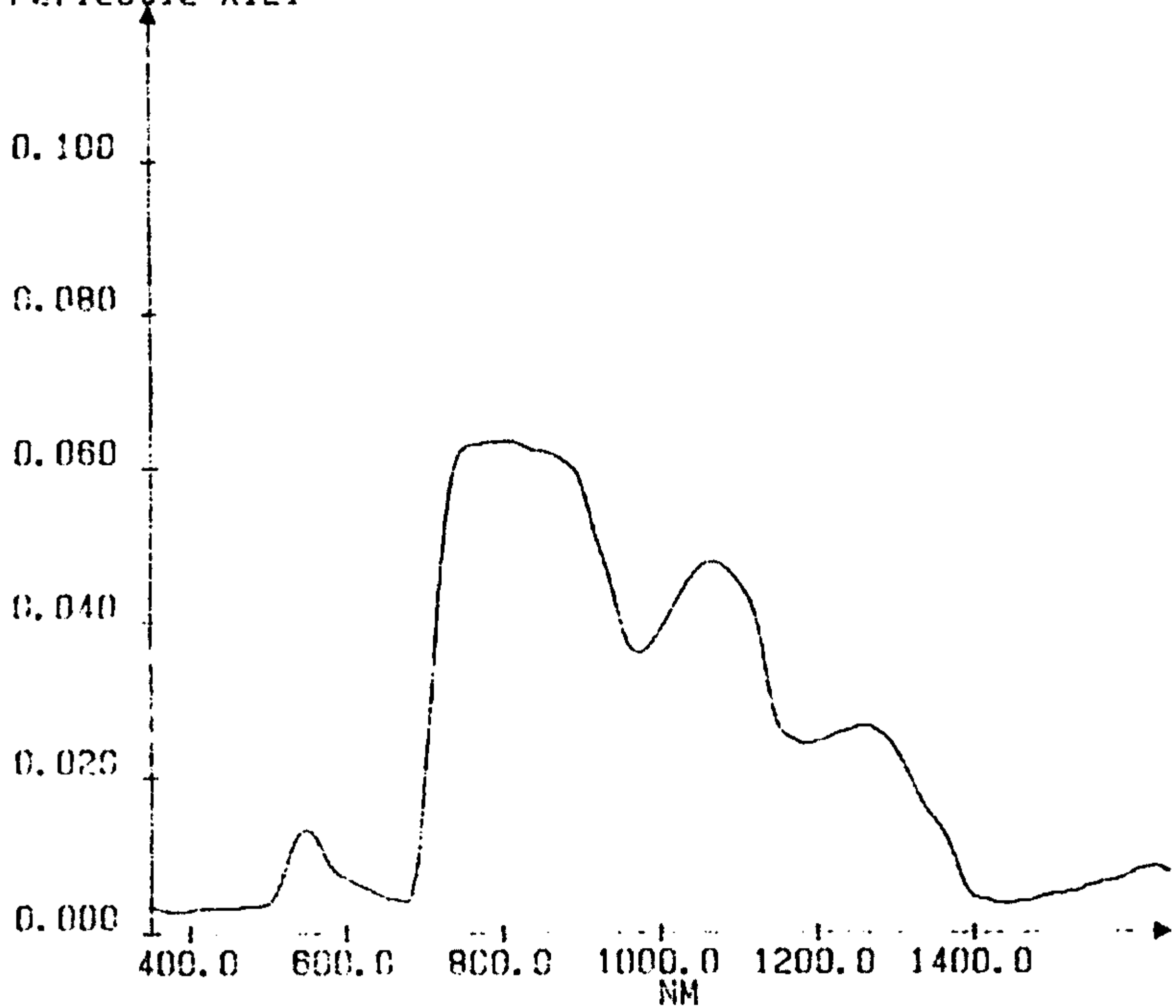

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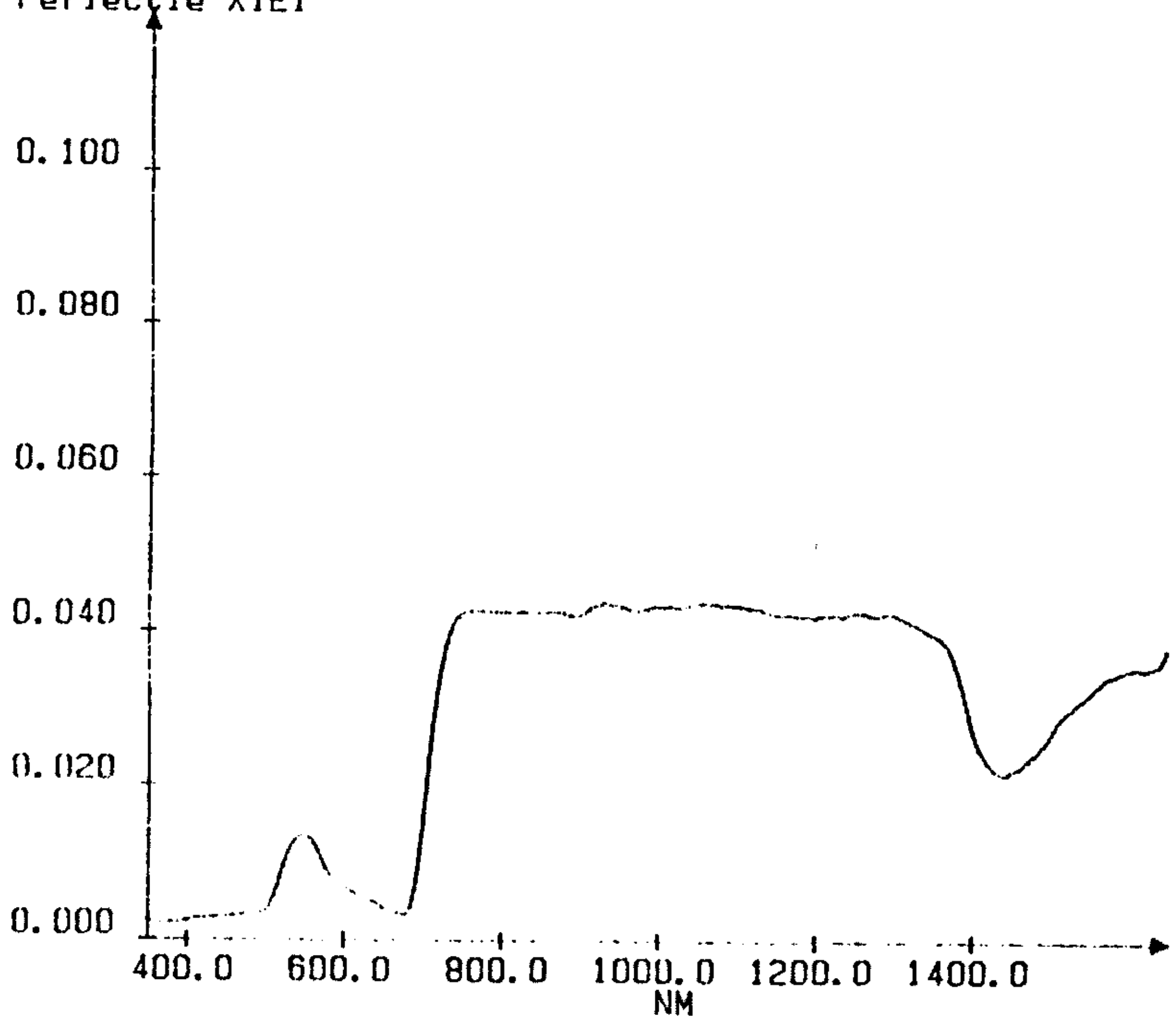

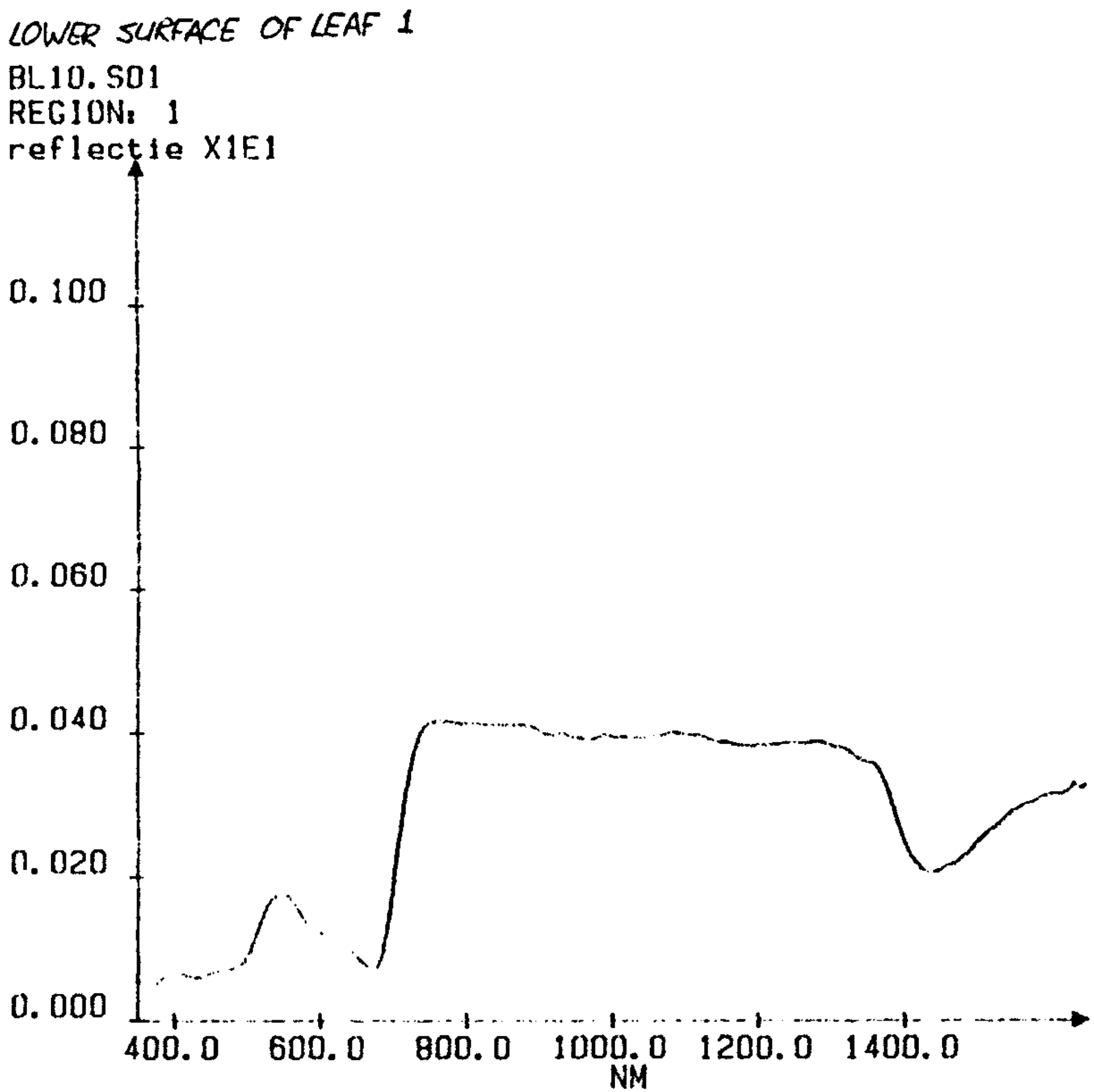
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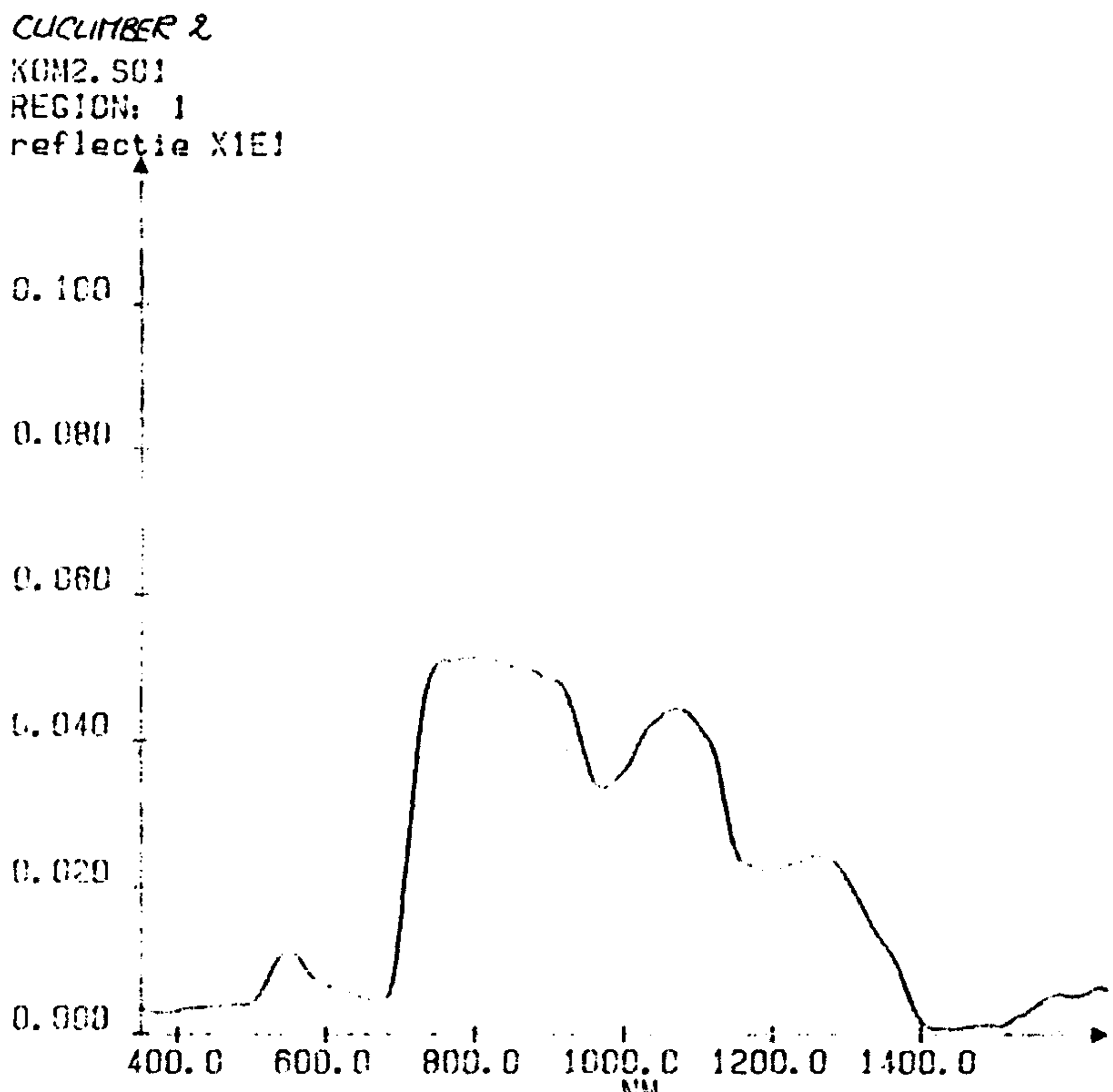

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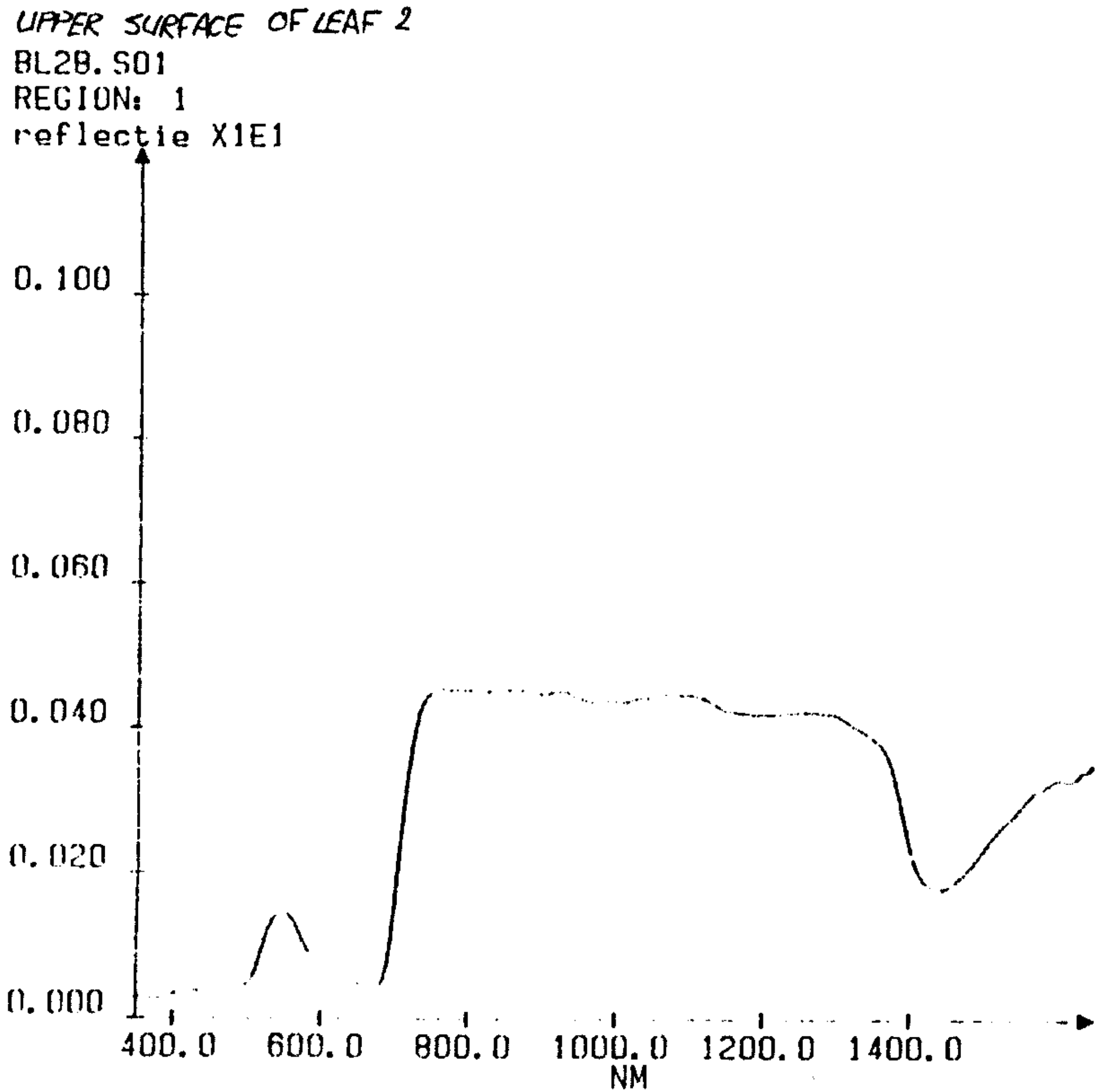
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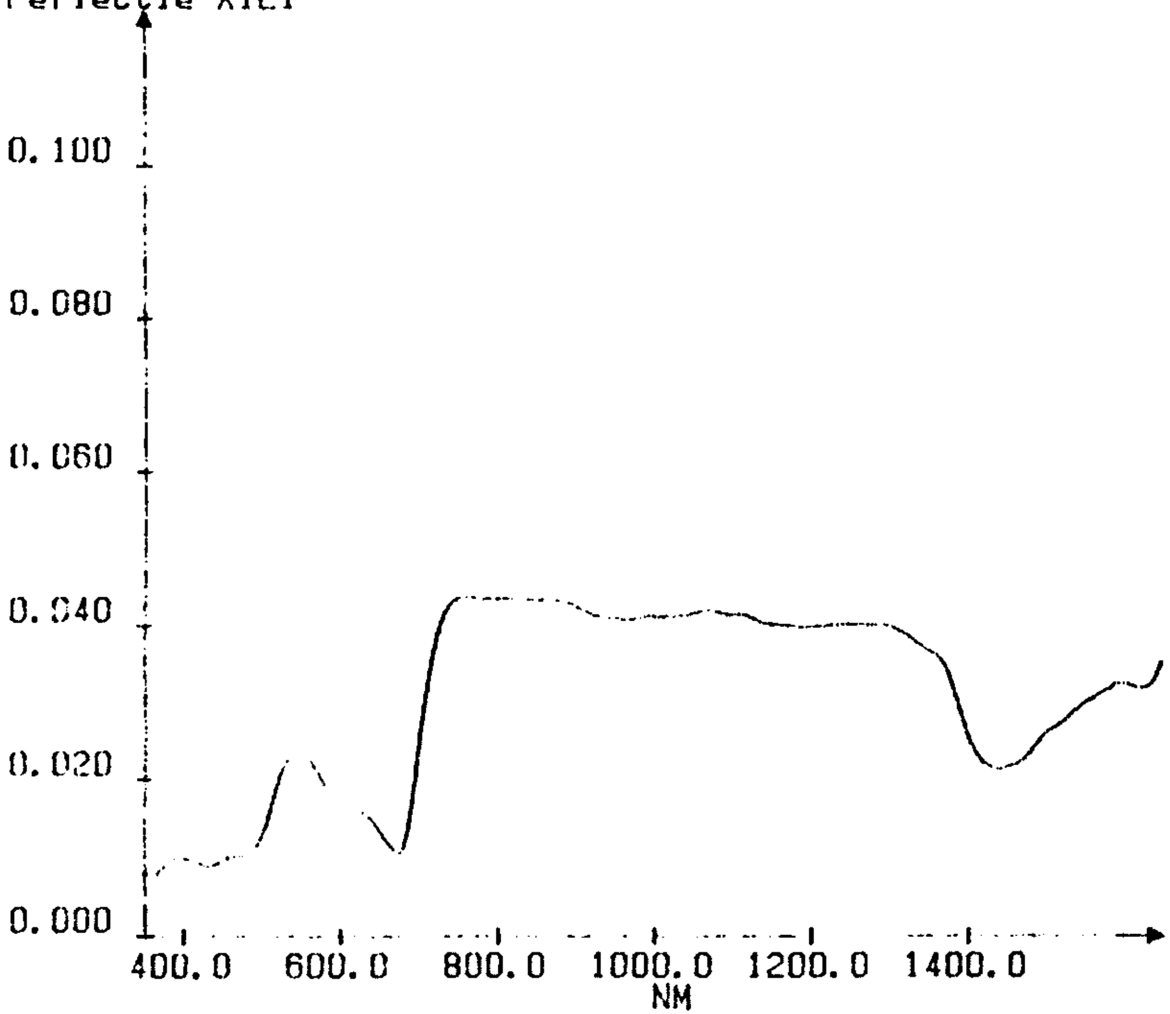

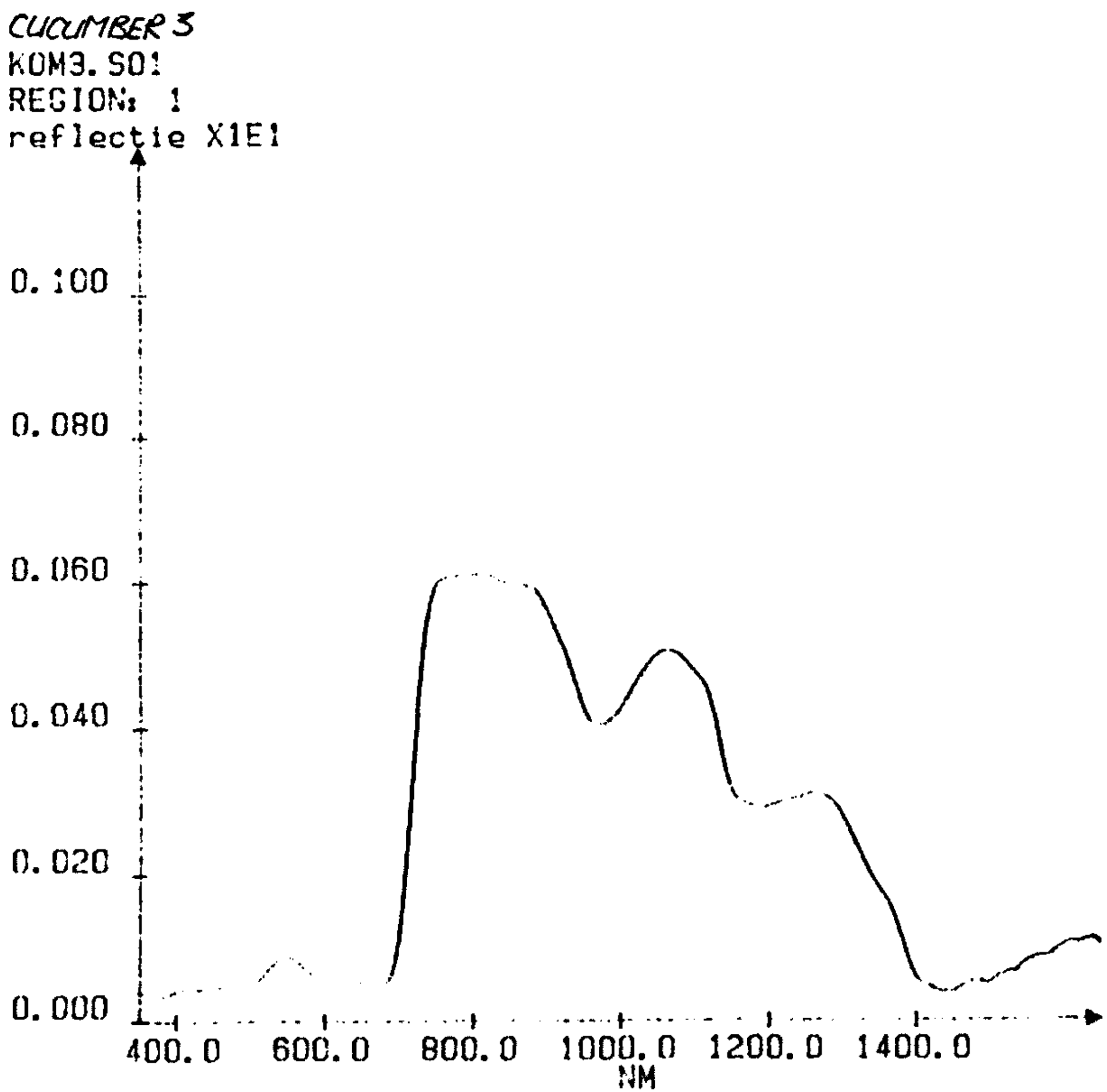

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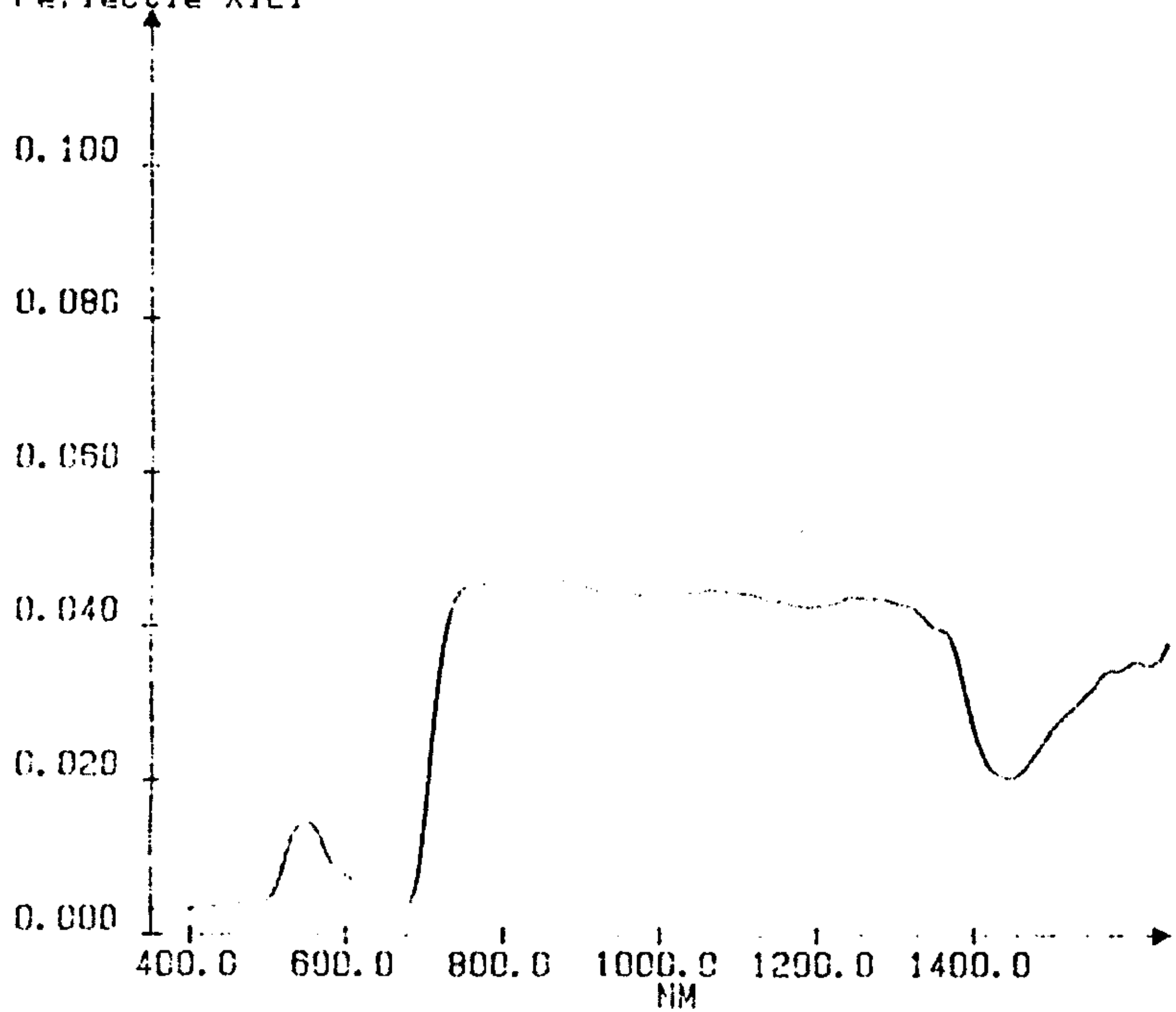

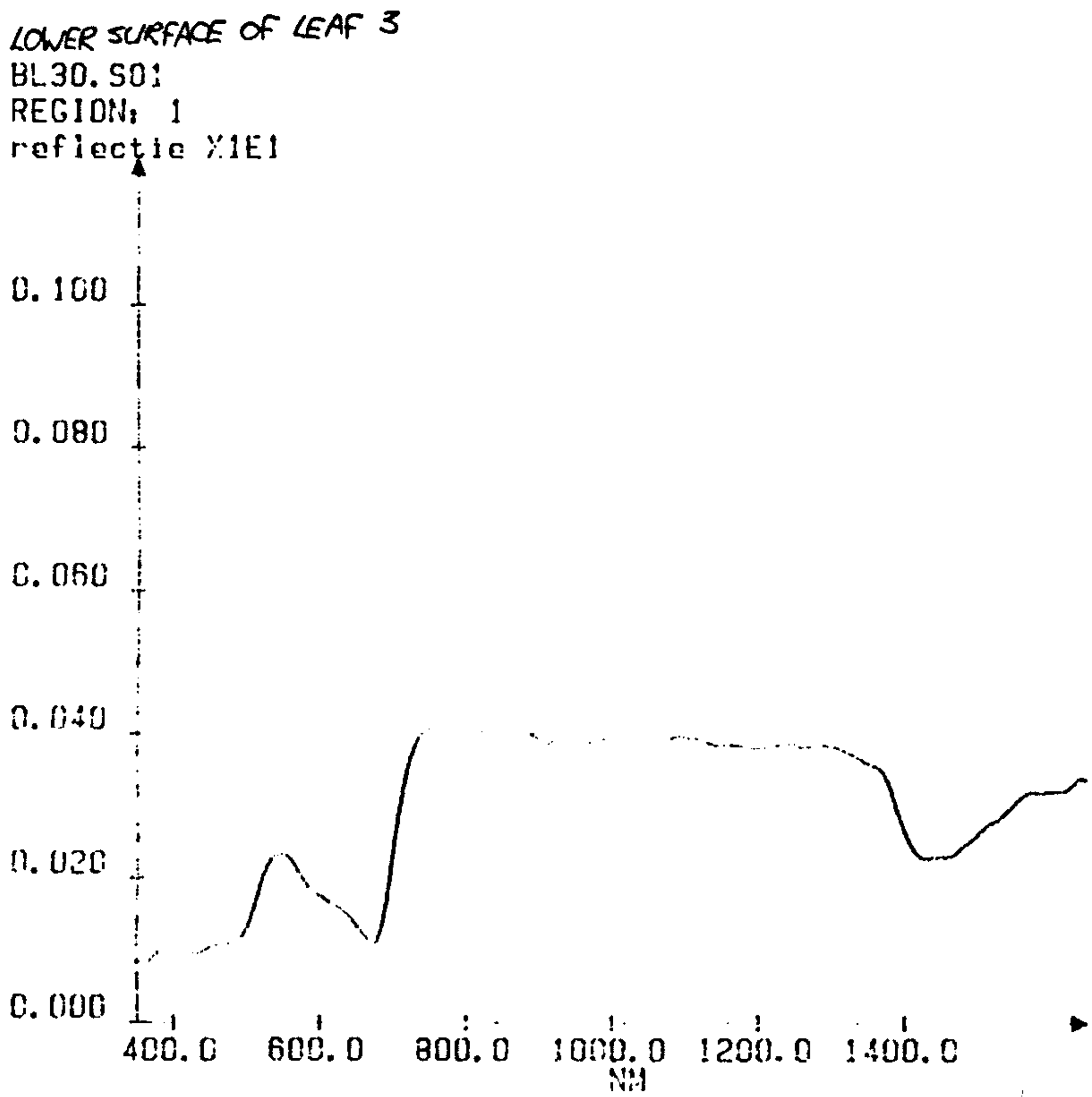

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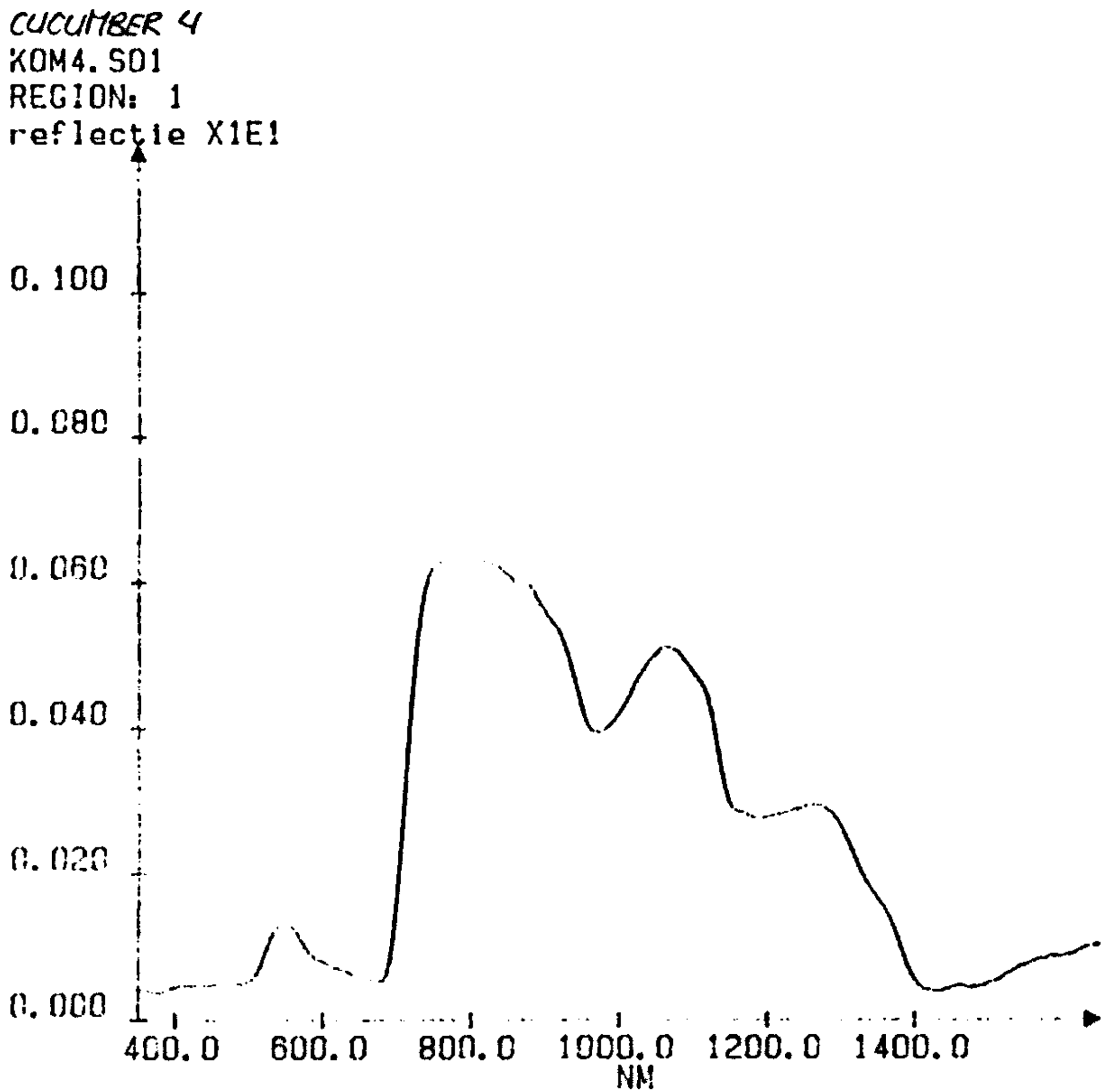

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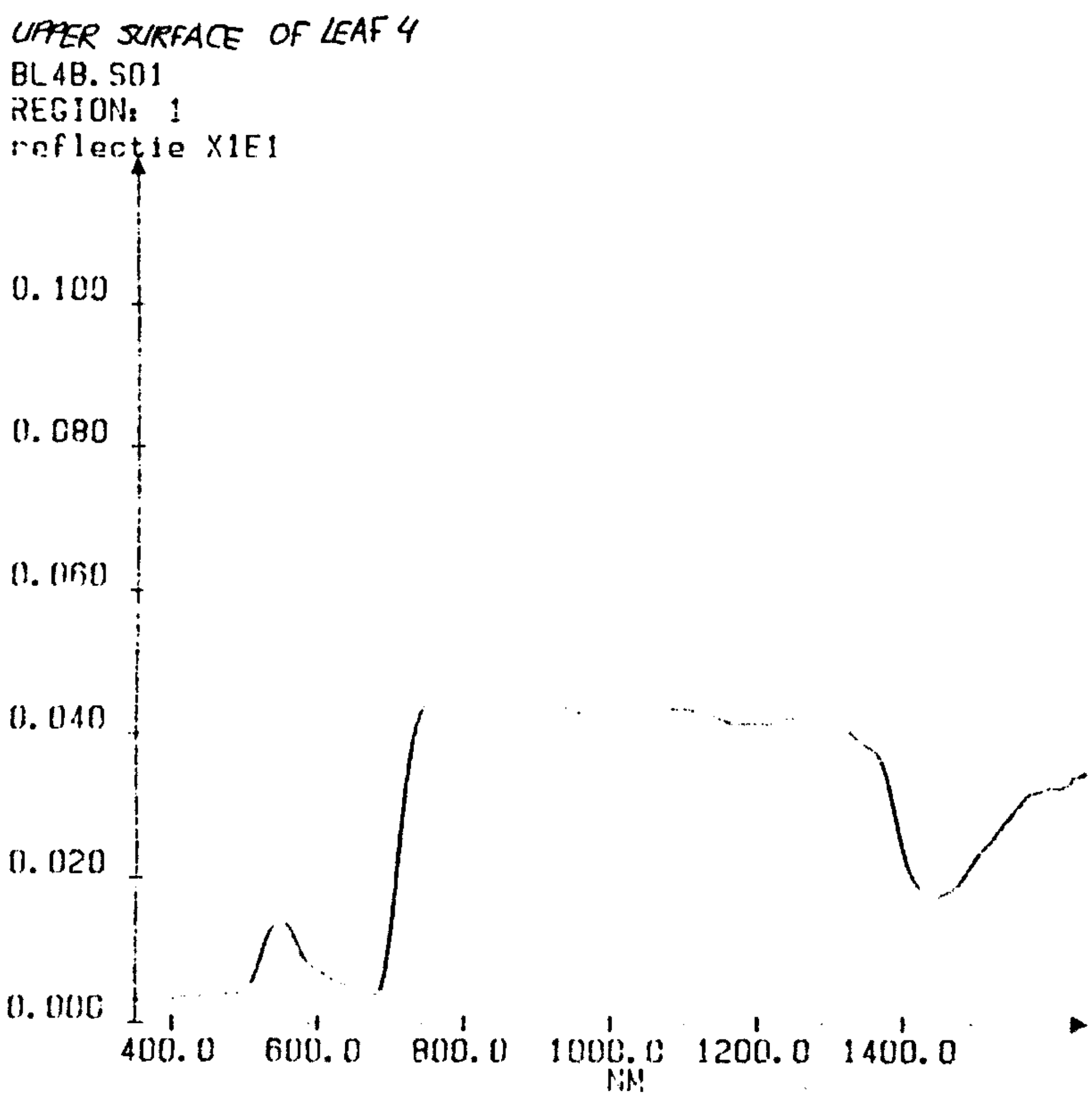

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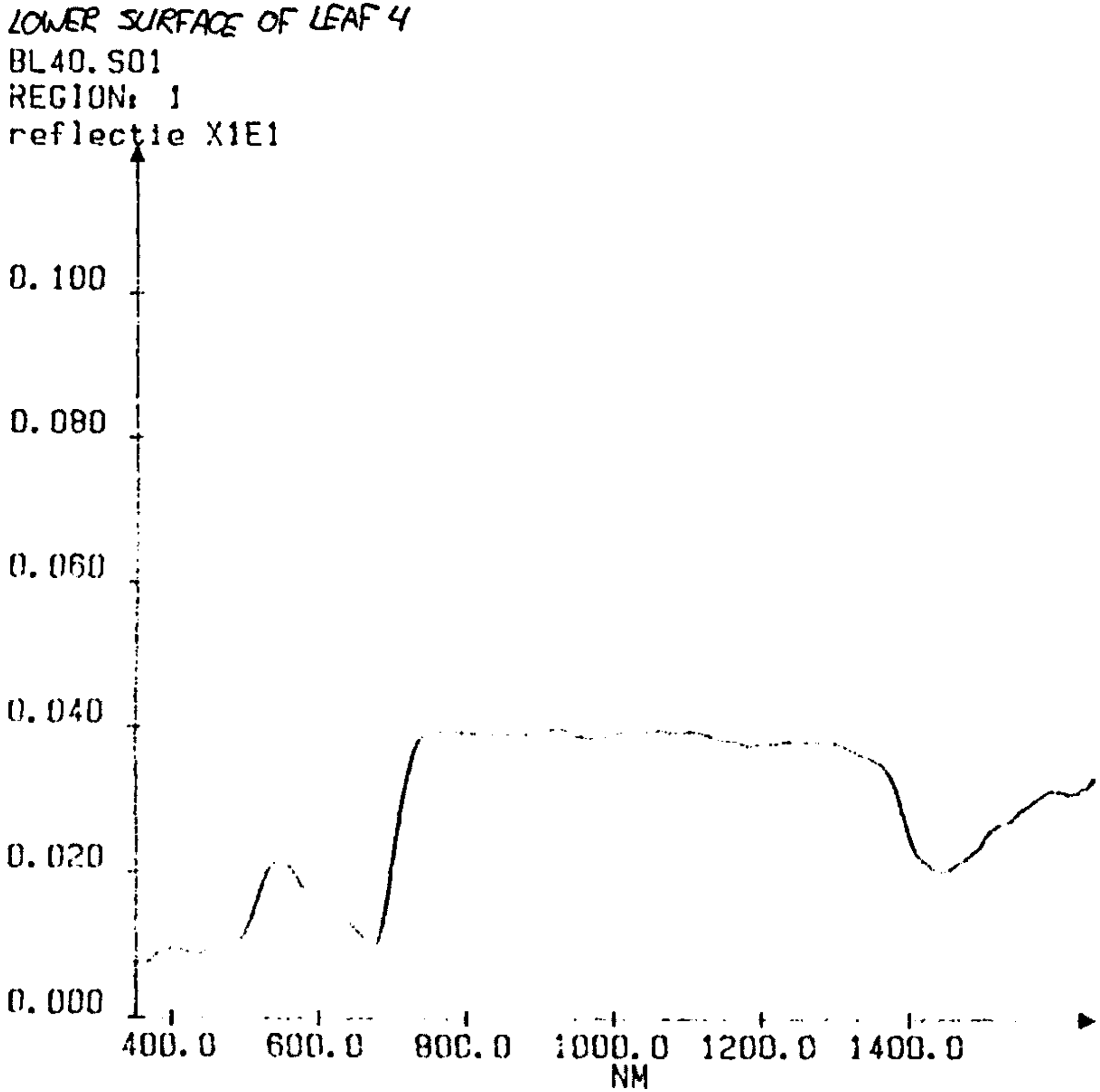

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NM

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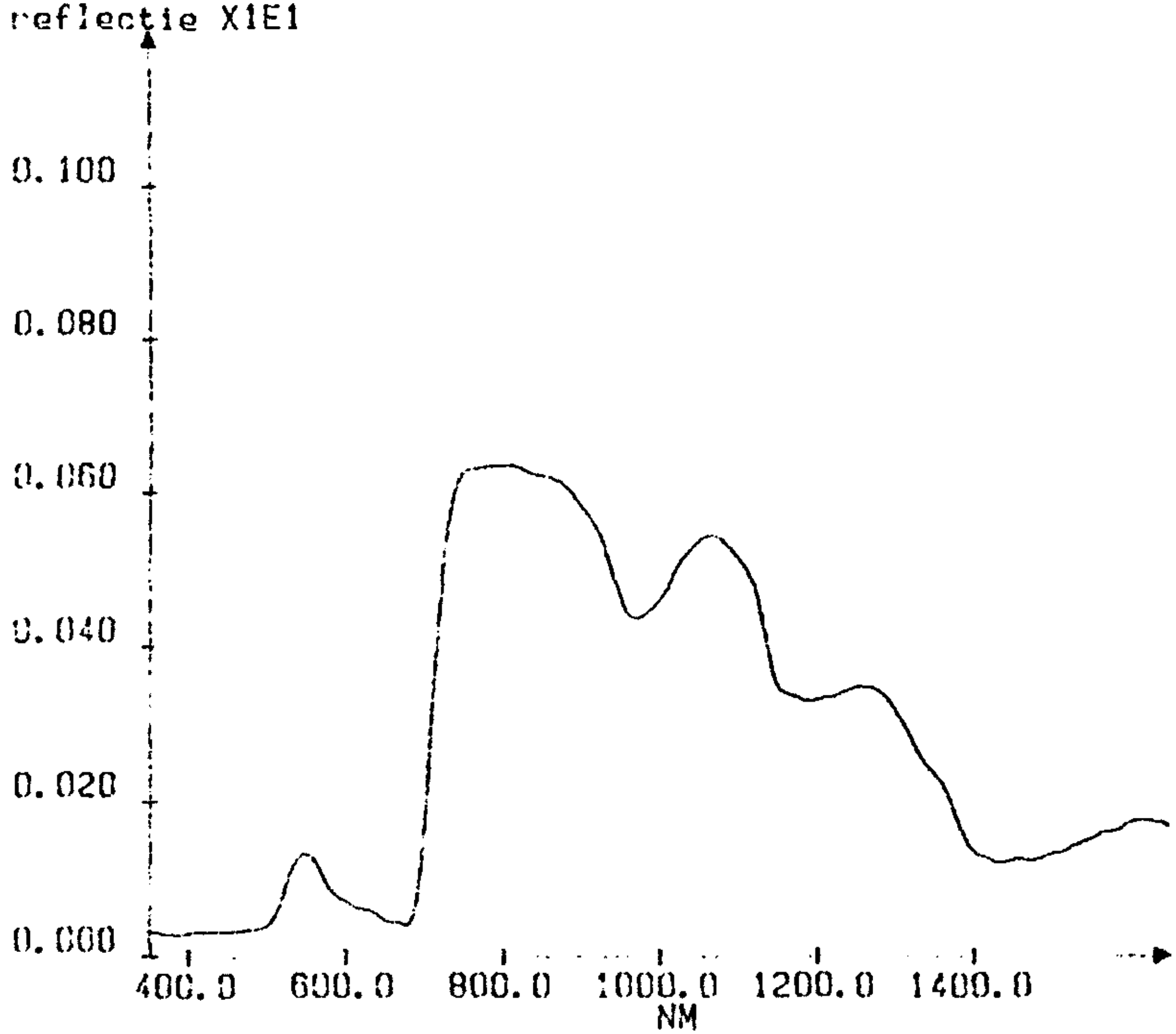

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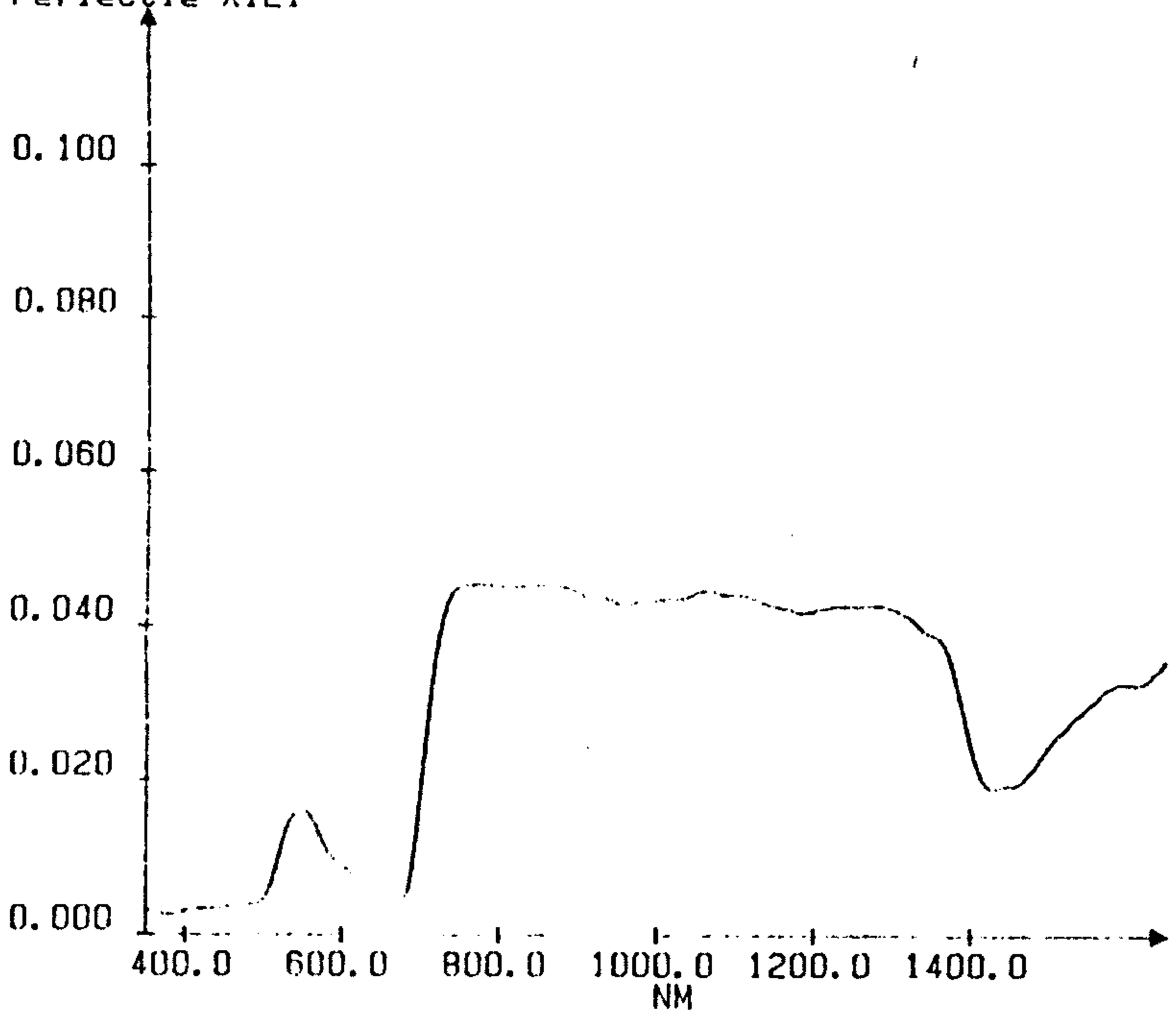

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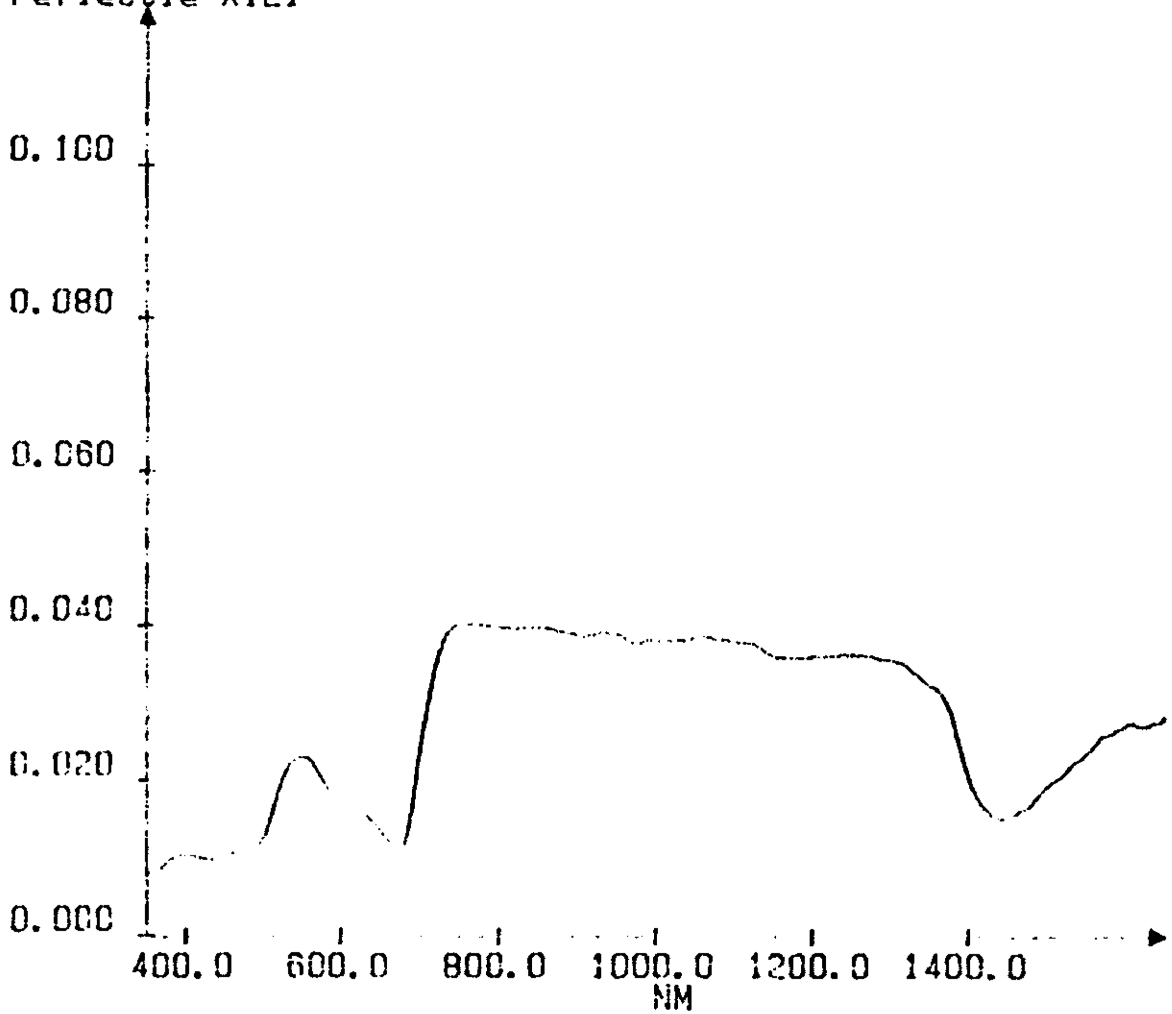


APPENDIX E, CHARACTERISTICS OF THE INTERFERENCE FILTERS

BANDPASS FILTERS

	λ_o Center Wavelength (nm)	Band Width FWHM (nm)	T_{pk} Minimum Peak Transmittance (%)	Data Curve Number (see pgs. 69-77 except as noted)	Part Number Prefix	Size Suffix 12.7mm	18.0mm	25.4mm	50.8mm	50.8mm SQ
	800 ± 6	40 ± 8	45%	21	S40-800-	A	—	F	R	S
	800 ± 10	70 ± 30	60%	22	P70-800-	A	—	F	R	S
	810 ± 2	12 ± 2	45%	16	S10-810-	A	—	F	R	S
	820 ± 2	12 ± 2	45%	16	S10-820-	A	—	F	R	S
	830 ± 2	12 ± 2	45%	16	S10-830-	A	—	F	R	S
	840 ± 2	13 ± 2	45%	16	S10-840-	A	—	F	R	S
Laser Diode	850 ± 2	13 ± 2	45%	16	S10-850-	A	—	F	R	S
	850 ± 3.5	25 ± 3.5	45%	20	S25-850-	A	—	F	R	S
Laser Diode	850 ± 6	40 ± 8	45%	21	S40-850-	A	—	F	R	S
	850 ± 10	70 ± 30	60%	22	P70-850-	A	—	F	R	S
	860 ± 2	13 ± 2	45%	16	S10-860-	A	—	F	R	S
Laser Diode	870 ± 6	40 ± 8	45%	21	S40-870-	A	—	F	R	S
Laser Diode	870 ± 2	13 ± 2	45%	16	S10-870-	A	—	F	R	S
	880 ± 2	14 ± 2	45%	16	S10-880-	A	—	F	R	S
	890 ± 2	14 ± 2	45%	16	S10-890-	A	—	F	R	S
	900 ± 2	10 ± 2	45%	16	S10-900-	A	—	F	R	S
	900 ± 3.5	25 ± 3.5	45%	20	S25-900-	A	—	F	R	S
	900 ± 6	40 ± 8	45%	21	S40-900-	A	—	F	R	S
	900 ± 10	70 ± 25	60%	22	P70-900-	A	—	F	R	S
Ga As Laser	905 ± 2	10 ± 2	65%	23	SD10-905-	A	—	F	R	S
Ga As Laser	905 ± 3.5	25 ± 3.5	75%	24	SD25-905-	A	—	F	R	S
	910 ± 2	10 ± 2	45%	16	S10-910-	A	—	F	R	S
	920 ± 2	10 ± 2	45%	16	S10-920-	A	—	F	R	S
	930 ± 2	10 ± 2	45%	16	S10-930-	A	—	F	R	S
	940 ± 2	10 ± 2	45%	16	S10-940-	A	—	F	R	S
	950 ± 2	11 ± 2	45%	16	S10-950-	A	—	F	R	S
	950 ± 3.5	25 ± 3.5	45%	20	S25-950-	A	—	F	R	S
	950 ± 6	40 ± 8	45%	21	S40-950-	A	—	F	R	S
	950 ± 10	70 ± 30	60%	22	P70-950-	A	—	F	R	S
	960 ± 2	11 ± 2	45%	16	S10-960-	A	—	F	R	S
	970 ± 2	11 ± 2	45%	16	S10-970-	A	—	F	R	S
	980 ± 2	11 ± 2	45%	16	S10-980-	A	—	F	R	S
	990 ± 2	11 ± 2	45%	16	S10-990-	A	—	F	R	S
	1000 ± 2	12 ± 2	45%	16	S10-1000-	A	—	F	R	S
	1000 ± 3.5	25 ± 3.5	45%	20	S25-1000-	A	—	F	R	S
	1000 ± 6	40 ± 8	45%	21	S40-1000-	A	—	F	R	S
	1000 ± 10	70 ± 30	60%	22	P70-1000-	A	—	F	R	S
	1050 ± 2	13 ± 2	45%	16	S10-1050-	A	—	F	R	S
	1060 ± 2	13 ± 2	45%	16	S10-1060-	A	—	F	R	S
[illegible]	1064 + 0.5, -0	4 ± 0.5	50%	23	SD4-1064-	—	—	F	R	—
[illegible]	1064 ± 2	10 ± 2	65%	23	SD10-1064-	A	—	F	R	S

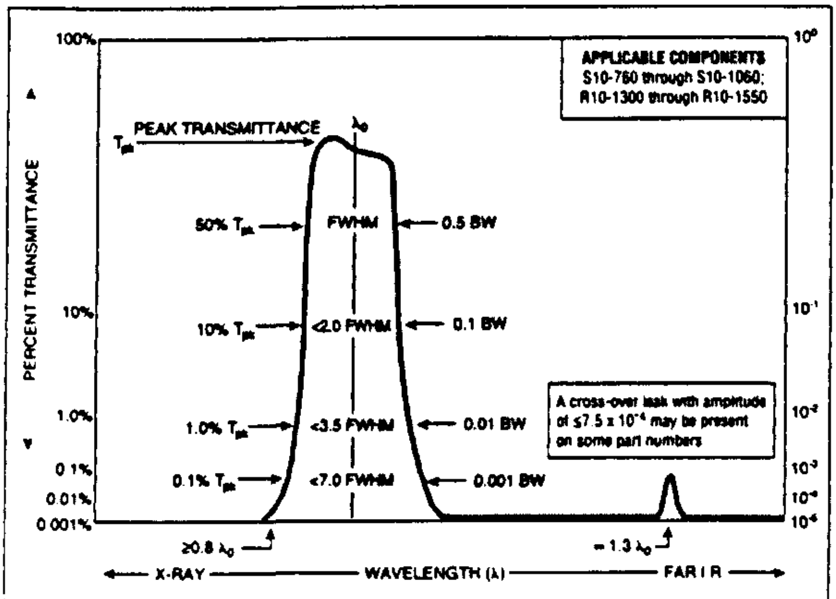
Components shaded in red have been designed for use with silicon photodetector systems requiring signal-to-noise ratios in excess of 1000/1. They may also be used with photomultiplier systems.

* Thickness range (7.7mm - 9.2mm)

UNBLOCKED FILTER SEE DATA CURVE NO. 25

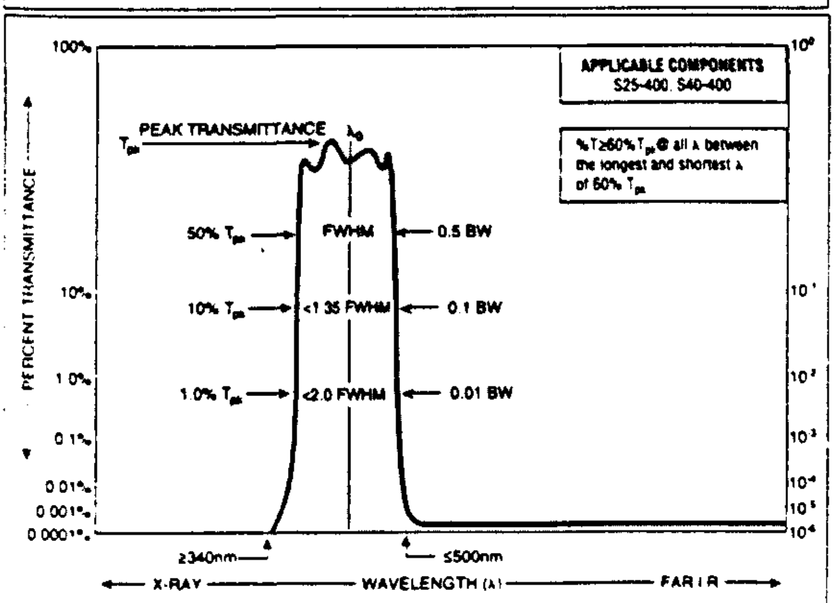
Custom filters and sizes available upon request. Refer to page 106 for filter sets.

BANDPASS FILTERS



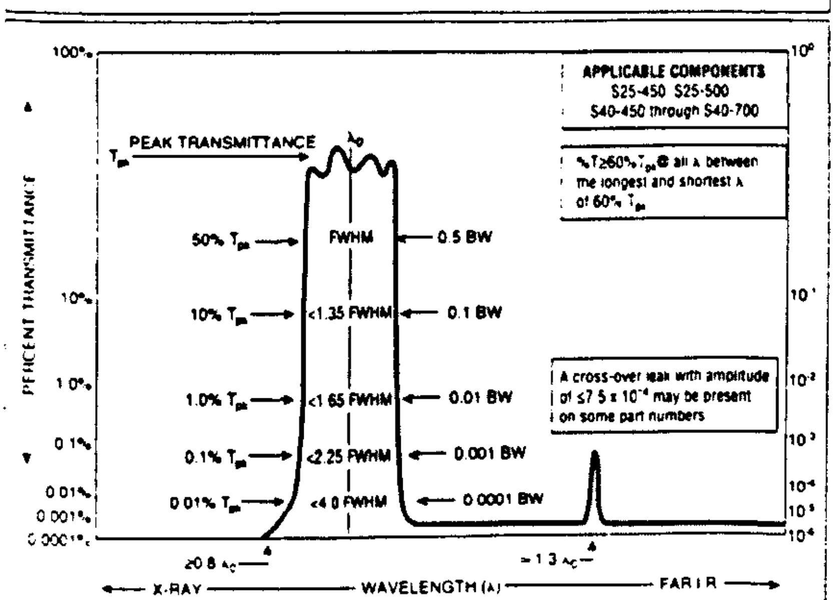
DATA CURVE NO. 16

- **Rejection (Spectral)** - Design Goal
  Range: X-ray to Far I.R.
  Degree: ≤0.01% T or $\leq 10^{-4}$
- **Rejection (Signal/Noise)** - Design Goal
  Radiant source: Tungsten at 2800°K;
  Detector: Silicon
  S/N ≥1000/1 or ≥3.0 O.D.
- **Effective Index:** $n_e = 1.47$
- $\Delta\lambda_0/\Delta C° = 0.02$nm/°C
- **Operating Temperature Limits:** -50°C to +100°C
- **Humidity:** Per MIL-STD-810E, Method 507.3 Procedure III, Modified to 7 cycles



DATA CURVE NO. 17

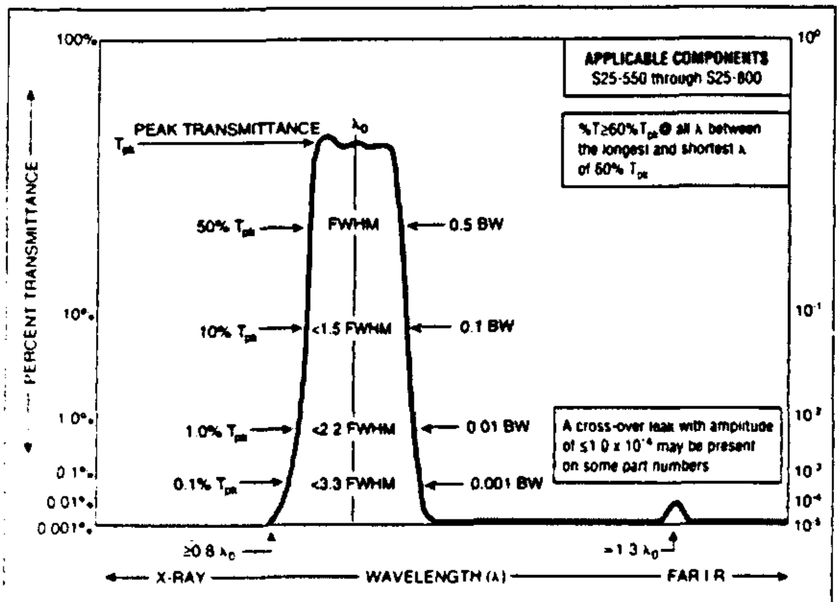
- **Rejection (Spectral)** - Design Goal
  Range: X-ray to Far I.R.
  Degree: ≤0.01% T or $\leq 10^{-4}$
- **Rejection (Signal/Noise)** - Design Goal
  Radiant source: Tungsten at 2800°K;
  Detector: Silicon
  S/N ≥1000/1 or ≥3.0 O.D.
- **Effective Index:** $n_e = 1.55$
- $\Delta\lambda_0/\Delta C° = 0.01$nm/°C
- **Operating Temperature Limits:** -50°C to +80°C
- **Humidity:** Per MIL-STD-810E, Method 507.3 Procedure III, Modified to 7 cycles



DATA CURVE NO. 18

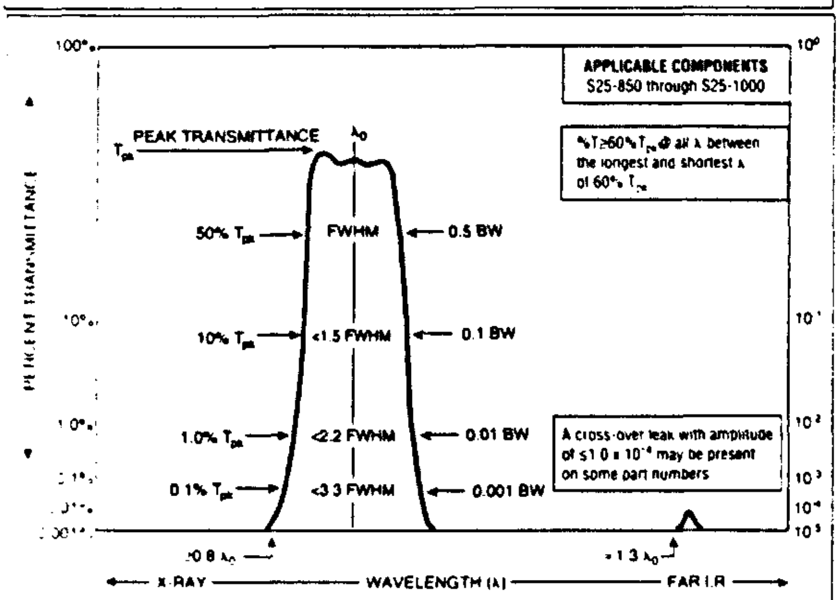
- **Rejection (Spectral)** - Design Goal
  Range: X-ray to Far I.R.
  Degree: ≤0.01% T or $\leq 10^{-4}$
- **Rejection (Signal/Noise)** - Design Goal
  Radiant source: Tungsten at 2800°K;
  Detector: Silicon
  S/N ≥1000/1 or ≥3.0 O.D.
- **Effective Index:** $n_e = 2.0$
- $\Delta\lambda_0/\Delta C° = 0.018$nm/°C
- **Operating Temperature Limits:** -50°C to +100°C
- **Humidity:** Per MIL-STD-810E, Method 507.3 Procedure III, Modified to 7 cycles

BANDPASS FILTERS



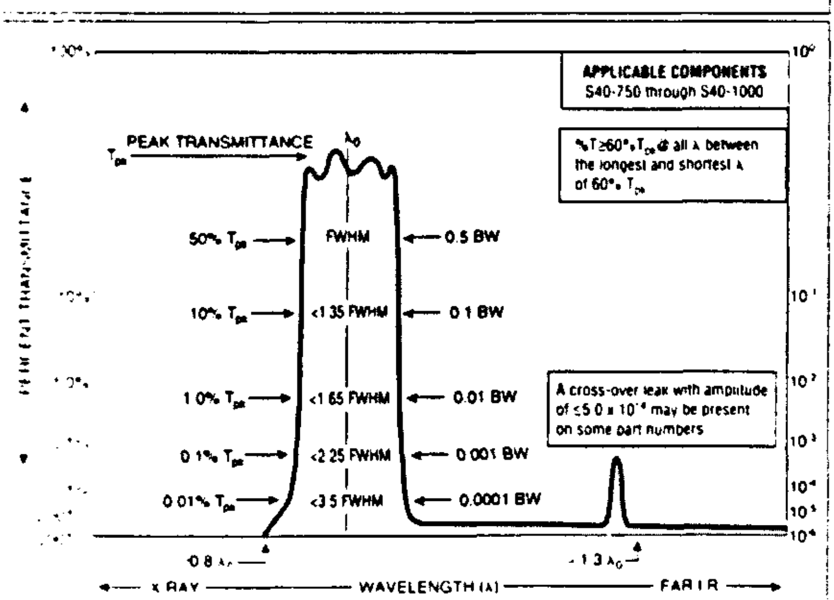
DATA CURVE NO. 19

- **Rejection (Spectral)** - Design Goal
  Range: X-ray to Far I.R.
  Degree: ≤0.01% T or ≤10^{-4}
- **Rejection (Signal/Noise)** - Design Goal
  Radiant source: Tungsten at 2800°K;
  Detector: Silicon
  S/N ≥1000/1 or ≥3.0 O.D.
- **Effective Index:** n_e = 1.5
- $\Delta\lambda_0/\Delta C°$ = 0.015nm/°C
- **Operating Temperature Limits:** -50°C to +100°C
- **Humidity:** Per MIL-STD-810E, Method 507 Procedure III, Modified to 7 cycles



DATA CURVE NO. 20

- **Rejection (Spectral)** - Design Goal
  Range: X-ray to Far I.R.
  Degree: ≤0.01% T or ≤10^{-4}
- **Rejection (Signal/Noise)** - Design Goal
  Radiant source: Tungsten at 2800°K;
  Detector: Silicon
  S/N ≥1000/1 or ≥3.0 O.D.
- **Effective Index:** n_e = 1.9
- $\Delta\lambda_0/\Delta C°$ = 0.022nm/°C
- **Operating Temperature Limits:** -50°C to +100°C
- **Humidity:** Per MIL-STD-810E, Method 507. Procedure III, Modified to 7 cycles



DATA CURVE NO. 21

- **Rejection (Spectral)** - Design Goal
  Range: X-ray to Far I.R.
  Degree: ≤0.01% T or ≤10^{-4}
- **Rejection (Signal/Noise)** - Design Goal
  Radiant source: Tungsten at 2800°K;
  Detector: Silicon
  S/N ≥1000/1 or ≥3.0 O.D.
- **Effective Index:** n_e = 1.47
- $\Delta\lambda_0/\Delta C°$ = 0.002nm/°C
- **Operating Temperature Limits:** -50°C to +100°C
- **Humidity:** Per MIL-STD-810E. Method 507. Procedure III. Modified to 7 cycles

APPENDIX F, SPECIFICATIONS OF THE CAMERA

SPINDLER & HOYER

Digital CCD Black and White Cameras *NEW*

The CCD 280 is a fully digital video camera with a computer interface. All camera parameters are computer adjustable and the image captured by the camera is transferred directly into the main memory. This creates ideal conditions for solving high grade image processing tasks. The images can be printed on a laser or inkjet printer.

The camera can be precisely adjusted to optimize the image at the moment of acquisition. This is particularly useful when dealing with low contrast samples in microscopy. Chromosome images, which do not have a good contrast, can be rendered with full contrast. Irrelevant gray values can be suppressed with the analog-to-digital converter.

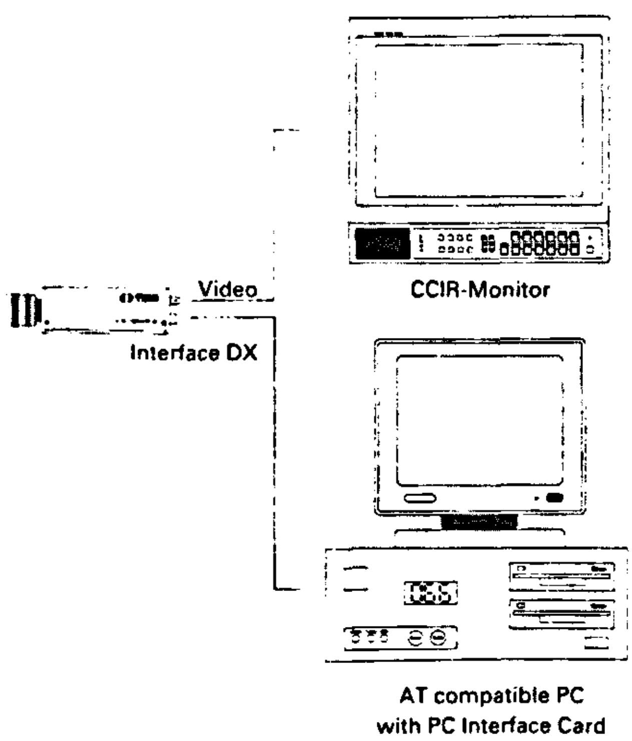
The camera is ideal for applications in automation and measurement technology. The precise digitization guarantees a high geometric stability.

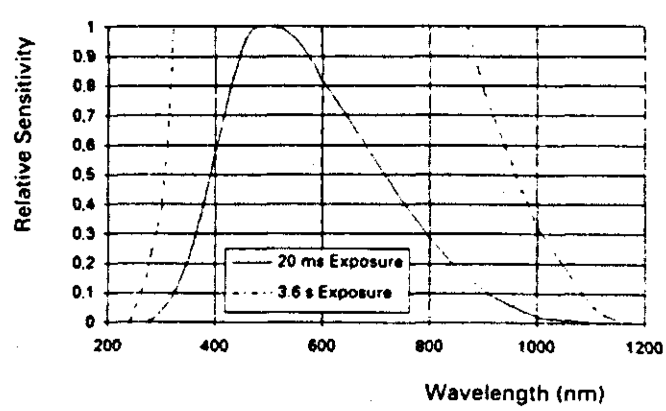
Digital and Analog Video Output
The digital and analog output is used to transfer information to various devices. The digital output transfers the image into a computer; the analog output allows you to simultaneously record the image on a video recorder or video printer. The analog output is also used to display the image on a monitor so adjustments can be made before the image is stored in the computer.

Exceptionally High Resolution
The actual resolution is 752 by 582 at high MTF values and at the resolution limit for a single chip camera.

Exact, Pixel Synchronous Digitization
The CCD signal is pixel synchronously stored in real time. This means that the camera digitizes the signal exactly at a point when the analog signal of one pixel is "true".

Wide Spectral Range
The spectral response of the camera is from the ultraviolet to the near infrared. Images can be captured at about 250 nm.

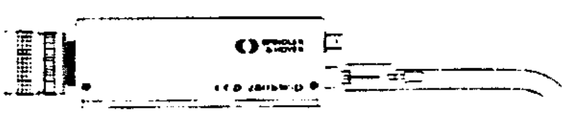


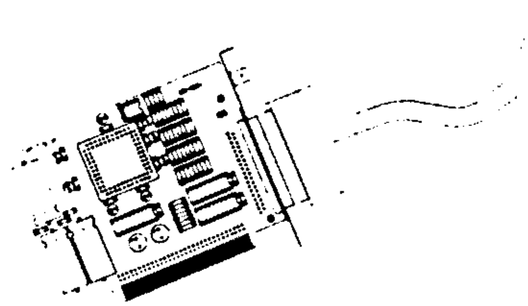


High Dynamic Range
The CCD chip can have a higher dynamic range than the usual 8 bits. This is accomplished by capturing the same scene twice with different parameter settings of the A/D converter.

Exposure Time
The exposure time may be controlled over a wide range. At ambient temperatures the upper limit is ten seconds with a resulting sensitivity of 5 x 10^{-4} lux. Extending the exposure beyond this time will show dark current artifacts. By cooling the CCD camera to -9 °C, we can achieve exposure times up to 15 minutes and achieve a sensitivity of 5 x 10^{-6} lux.

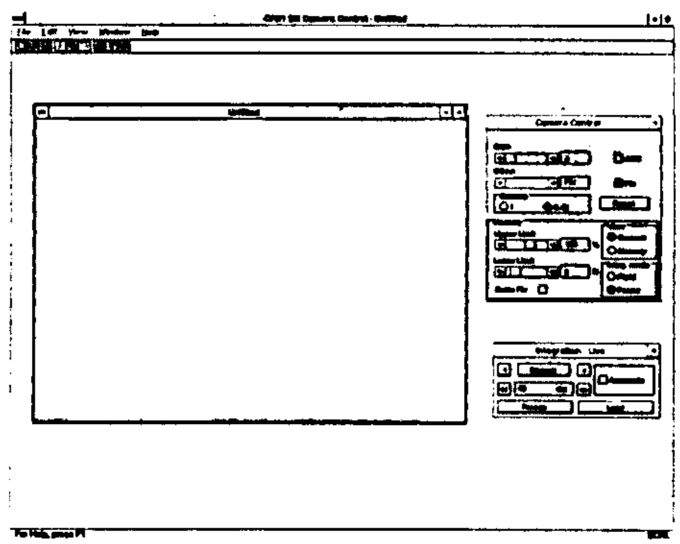
Software and Interface Card
The application package includes the camera, ISA card, a cable to connect the two units and application software which runs under Windows™ . The software records images as DIB or as TIF files that can be processed in other image processing or analysis programs

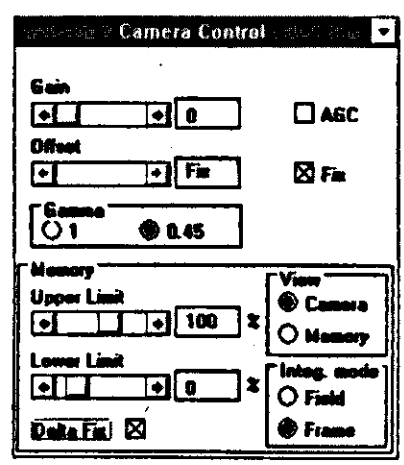


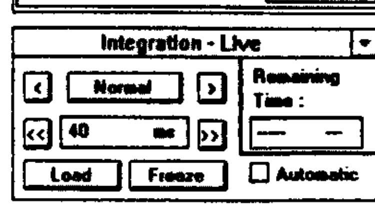


We provide the pin-out of all interfaces and information of their logic function. This will give users with computer knowledge the opportunity to develop their own hardware or software.

Simple Operation under Windows™
Inexperienced users can control the camera parameters intuitively. A Windows DLL, included in the package, provides the opportunity to tie the camera function into your own program.



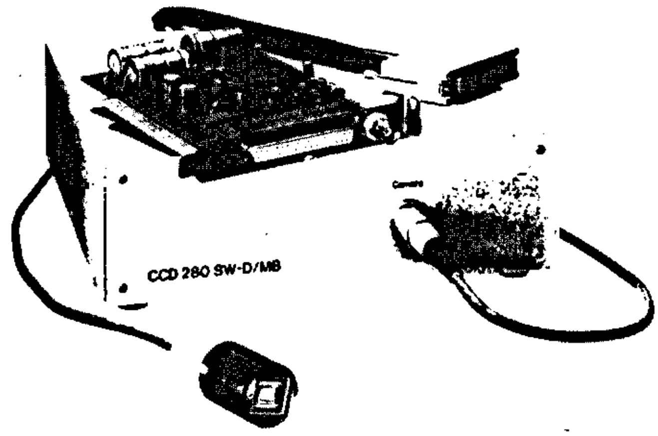




SPINDLER & HOYER

Digital Black and White CCD-Cameras

- CCD camera with a PC interface
- full digital image transfer from CCD to PC
- all camera parameters controlled from your PC
- easy to use Windows™ software
- 100 µs to 15 min exposure times (up to 3 hours, on request)
- display live or stored images



CCD 280 SW-D/MB

Technical Data	**CCD 280 SW**
Video standard	CCIR, 2:1 interlaced
Integration mode	Field / Frame, adjustable
Image sensor	1/2" Interline Transfer CCD with microlenses
Image sensor area	6.4 mm (H) x 4.8 mm (V); equivalent to 1/2"
Number of pixels	752 (H) x 582 (V) effective / 768 (H) x 494 (V) effective, EIA RS 170
Pixel size	8.6 µm (H) x 8.3 µm (V) / 8.4 µm (H) x 9.8 µm (V) EIA
Resolution	752 TV Lines
Synchronization	internal
Video output	BAS 1 Vpp
Signal output	8 Bit parallel
Responsivity	0.12 lux (without IR filter, 41 dB S/N)
Min. responsivity	5×10^{-6} lux, 15 minute exposure (cooled version)
Gain	manual / automatic / fixed
Offset for analog output	manually adjustable / fixed
A/D converter levels	fixed / manually adjustable
Gamma correction	0.45 or 1, switch selectable
Exposure time	100 µs to 15 minutes
Exposure time regulation	automatic, from 100 µs to 20 ms
Voltage supply	12 V DC, 800 mA from PC or external supply
Operating temperature	-10 °C to + 50 °C

The digital CCD camera 280 SW is available in three models:

CCD 280 SW-D	43 0022
CCD 280 SW-D/MB	43 0023
CCD 280 SW-D/C	43 0025

Digital CCD-Camera, 280 SW-D

The CCD 280 SW-D is the most basic digital camera in the series. It consists of a compact camera, a connecting cable, a PC card and Windows™ software for driving, controlling and selecting digital images. The control electronics are in the camera.

Technical Data	CCD 280 SW-D
Minimum Sensitivity	5 x 10^{-4} lux with 10 s exposure
Camera Size	70 mm (W) x 61.5 mm (H) x 170 mm (L)
Connecting Cable	37 pin, 2 m long
Objective Mount	C-Mount (1" x 32 TPI)
Mount to Array Distance	17.526 mm
Part No.	**43 0022**

Digital CCD-Camera, 280 SW-D/MB

For Microbench applications, using the CCD 280 SW-D/MB, the control electronics are separate from the camera head. This results in an extremely small camera head with a 25 mm outside diameter. The CCD 280-D/MB consists of camera head, separate control electronics, connecting cable, a PC card and Windows™ software for driving, controlling and selecting digital images.

Technical Data	CCD 280 SW-D/MB
Minimum sensitivity	5 x 10^{-4} lux with 10 s exposure
Camera head, size	Ø 25 mm x 35 mm
Camera head, weight	< 80 g
Control electronics, size	210 mm (W) x 75 mm (H) x 245 mm (L)
Connecting cable, camera head	2m long
Connecting cable, control electronics	37 pin, 2 m long
Objective mount	25.4 mm outside external thread
Mount to array distance	17.526 mm
Part No.	**43 0023**

Digital CCD-Camera, 280 SW-D/C

The CCD 280 SW-D/C is the cooled version in the camera series. The camera is air cooled and can achieve exposure times up to 15 minutes. The camera consists of a compact camera, and power supply for the cooling unit, connecting cable, a PC card and Windows™ software for driving, controlling and selecting digital images. The control electronics and cooling unit are in the camera head.

Technical Data	CCD 280 SW-D/C
Minimum sensitivity	5 x 10^{-6} lux with15 minutes exposure
Camera size	70 mm (W) x 61.5 mm (H) x 190 mm (L)
Connecting cable	37 pin, 2 m long
Objective mount	C-Mount (1" x 32 TPI)
Mount to array distance	17.526 mm
Power supply, size	210 mm (W) x 75 mm (H) x 245 mm (L)
Part No.	**43 0025**

The cameras can be equipped with optional water cooling. This provides a response down to 10^{-7} lux with an exposure time up to 3 hours.

APPENDIX G, CHROMATIC ABERRATION

G CHROMATIC ABERRATION

It is theoretically impossible to make a perfect lens. Therefore, most lenses are subjected to various types of distortions or aberrations. One such a class of aberrations is the chromatic aberration, which results from the fact that the index of refraction of the lens material varies with the frequency.

G.1 Chromatic aberration

In literature (Burke 1996, p. 289) it can be found that the index of refraction of glass (n_g) is a function of the frequency. Moreover, it can be found that the focal length F of a lens is critically dependent on n (index of refraction). Therefore, the focal length F will vary with the frequency.

The used (glass) lens in this research is susceptible to this kind of aberration. As will be shown by the following experiment. First, in laboratory a white board at a distance of 59 cm from the camera is recorded (with a small aperture to reduce spherical aberration) without an interference filter and with the use of an additional light source (a halogen lamp). Then, successively, different interference filters are chosen (403 nm, 577 nm, 692 nm, 747 nm, 850 nm and 970 nm) and used to record the white board again (also with a small aperture). Finally, from each obtained image of the white board the gray values of the pixels at a chosen line (the horizontal line) are depicted on a graph (using the written algorithm in appendix H) (see figure G.1 till figure G.7).

It can be seen that only the interference filter of 692 nm gives approximately the same graph as the graph without an interference filter. Further, a decrease or increase of the frequency of the interference filter at this frequency will deteriorate the graph more and more. In addition, the digitalisation range has been adjusted with a high lower limit which caused the quite straight sides of the graphs. Because of this dispersion phenomenon, the focal length of the lens is not constant but varies for the different frequencies. This causes differing frequencies to focus at different distances (see also figure G.8 and G.9).

In fact, it follows that the stated focal length in this lens is not correct for measurements in the near-infrared range. Generally, the true focal length of a lens increases with increasing frequency into the near-infrared range. Therefore, a possible remedy to this problem should be the use an extension tube.

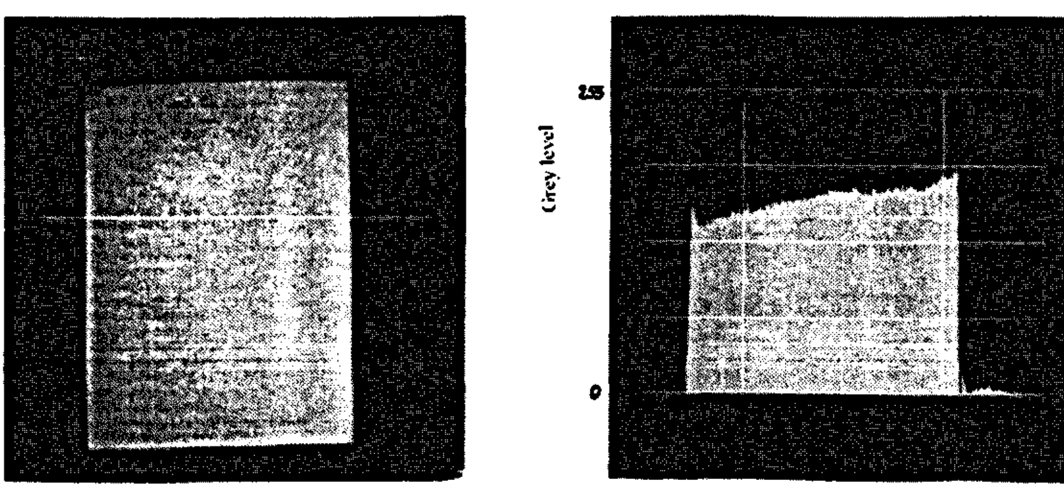


Figure G.1, Recorded white board without using an interferece filter and the corresponding line histogram (exposure time = 250 µs and distance = 59 cm)

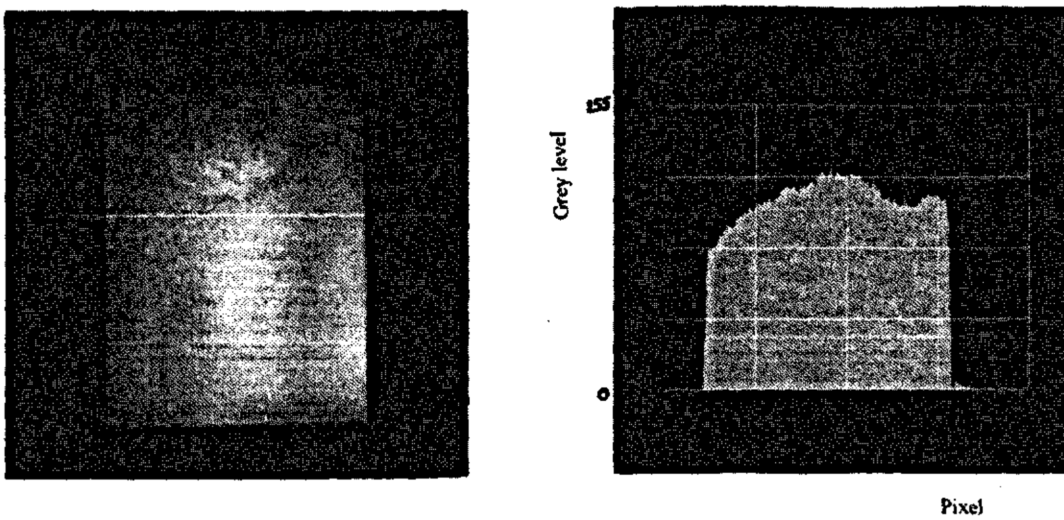


Figure G.2. Recorded white board using the 403 nm interference filter and the corresponding line histogram (exposure time = 200 ms and distance = 59 cm)

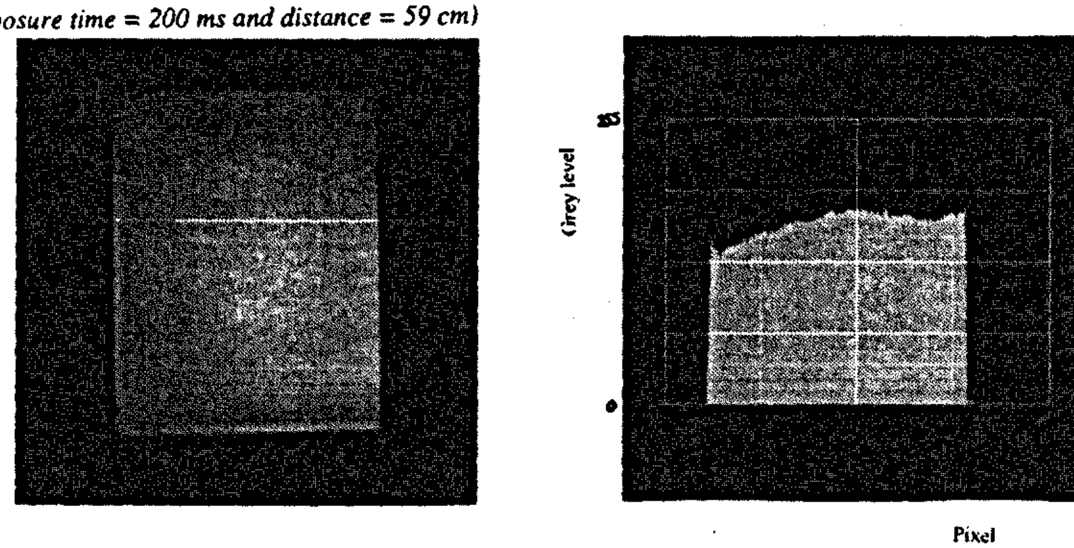


Figure G.3. Recorded white board using the 577 nm interference filter and the corresponding line histogram (exposure time = 20 ms and distance = 59 cm)

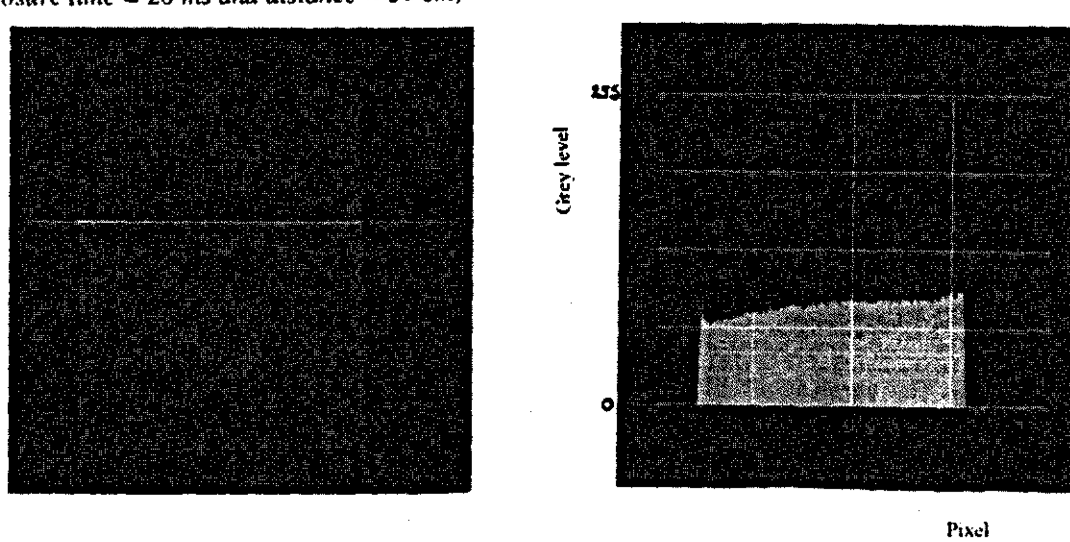


Figure G.4. Recorded white board using the 692 nm interference filter and the corresponding line histogram (exposure time = 10 ms and distance = 59 cm)

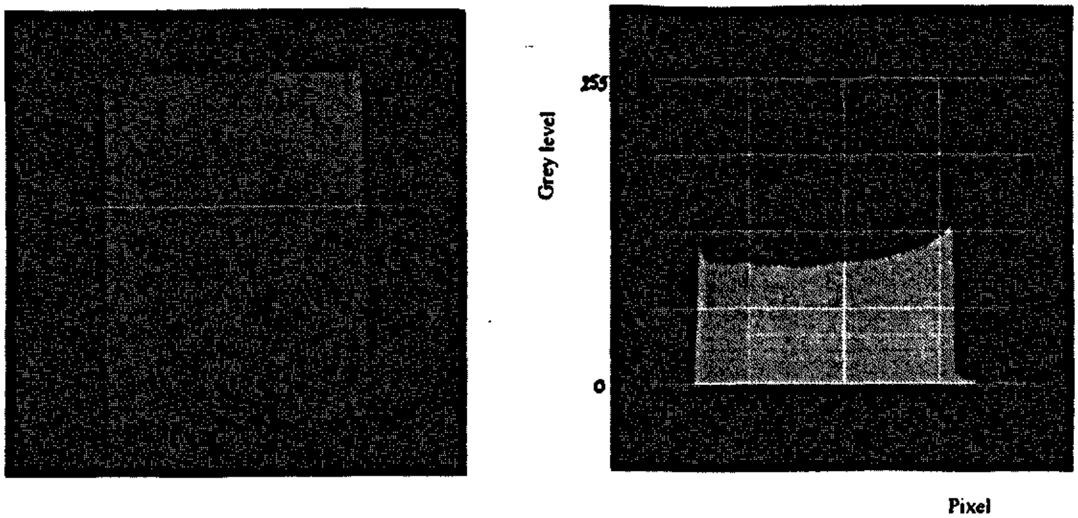


Figure G.5, Recorded white board using the 747 nm interference filter and corresponding line histogram (exposure time = 80 ms and distance = 59 cm)

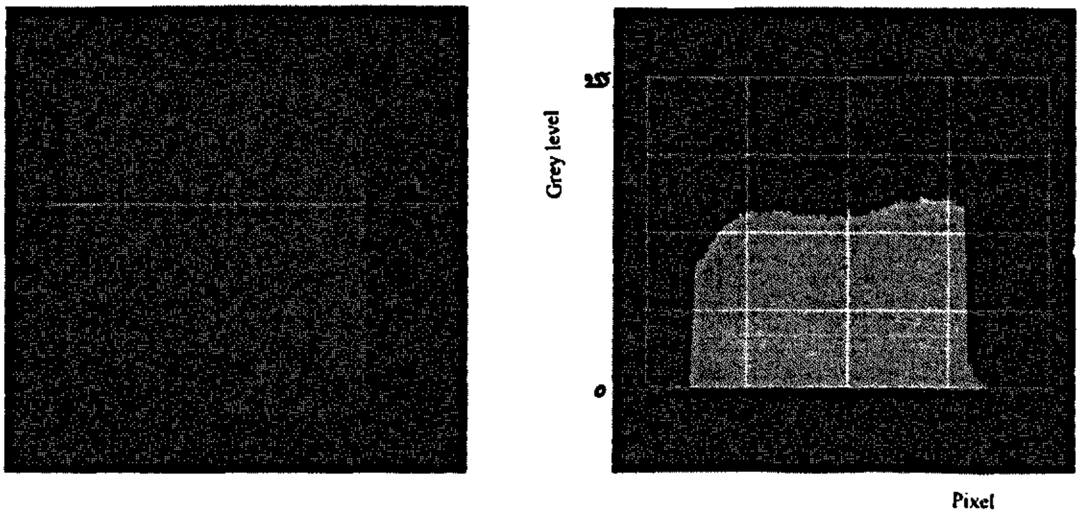


Figure G.6, Recorded white board using the 850 nm interference filter and the corresponding line histogram (exposure time = 20.48 s and distance = 59 cm)

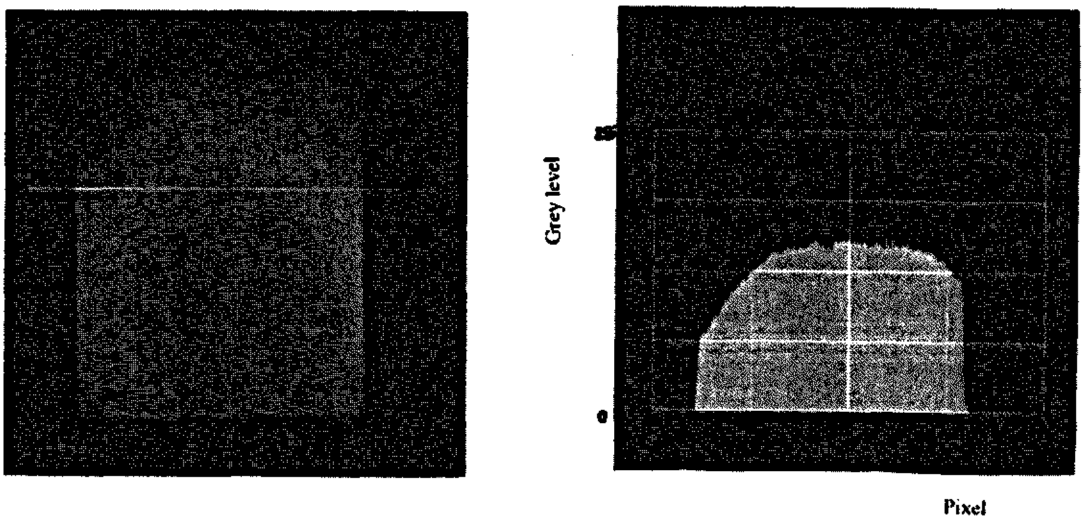


Figure G.7, Recorded white board using the 970 nm interference filter and the corresponding line histogram (exposure time = 41.04 s and distance = 59 cm)

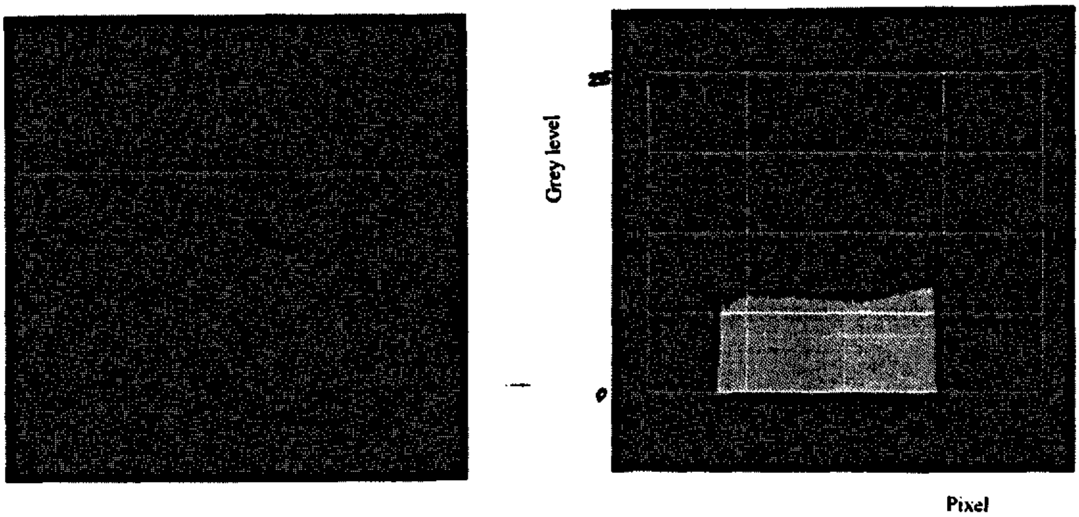


Figure G.8, Recorded white board using the 970 nm interference filter and the corresponding line histogram (exposure time = 41.08 s and distance = 74 cm)

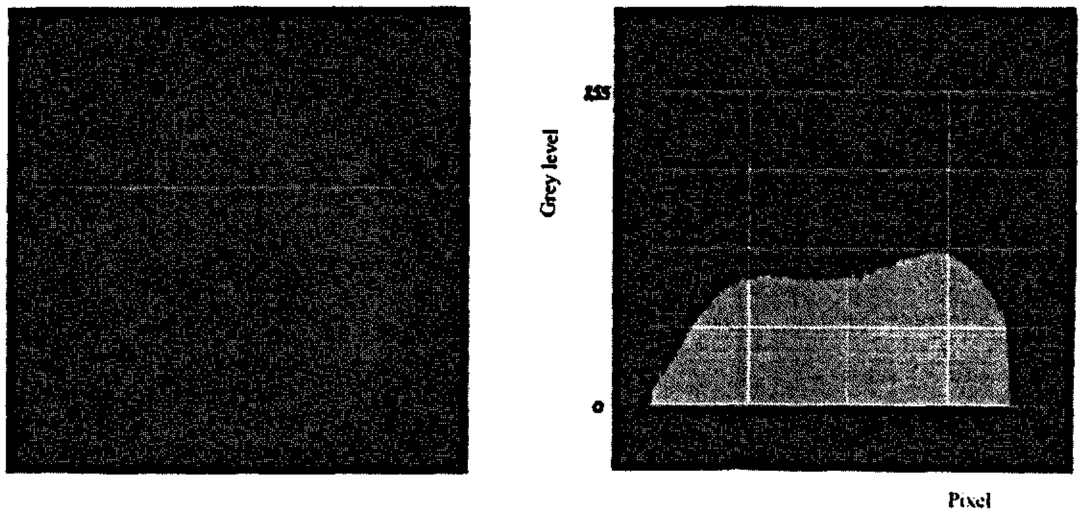


Figure G.9, Recorded white board using the 970 nm interference filter and the corresponding line histogram (exposure time = 20.56 s and distance = 44 cm)

```
/*
      (SCIL) C programma LineHist.c
      Determines the gray values at a given line and depicts this on a
graph
*/


#include "image.h"

linehist(in,out,starty,startx,endx,axis)
IMAGE *in *out;
int starty,startx,endx,axis;
{
      int i, j=0, lijst[2000];

      copy_im(in,out);
      clear_im(out);
      doff();
      for (i=startx;i<=endx;++i)
      {
            lijst[j]=atoi(pix_value_str(in,i,starty,1));
/*          put_pixel(out,i,255-lijst[j],255); */
            draw_line(out,i,255,i,255-lijst[j],180);
            j++;
      }

      if (axis>0)

      {     draw_line(out,startx,0,endx,0,255);
            draw_line(out,startx,64,endx,64,255);
            draw_line(out,startx,128,endx,128,255);
            draw_line(out,startx,192,endx,192,255);
            draw_line(out,startx,255,endx,255,255);

            draw_line(out,startx,255,startx,0,255);
            draw_line(out,startx+(endx-startx)/4,255,startx+(endx-
startx)/4,0,255);
            draw_line(out,startx+(endx-startx)/2,255,startx+(endx-
startx)/2,0,255);
            draw_line(out,endx-(endx-startx)/4,255,endx-(endx-
startx)/4,0,255);
            draw_line(out,endx,255,endx,0,255);
            draw_line(in,startx,starty,endx,starty,255);
      }
        don();
        display_image(out);
        display_image(in);

}
```

APPENDIX I, REFLECTANCE CALIBRATION STANDARDS

REFLECTANCE CALIBRATION STANDARDS

labsphere

CALIBRATION CERTIFICATE

8°/HEMISPHERICAL SPECTRAL REFLECTANCE FACTOR

Customer: OPTILAS BV

Report No.: 14907-A

Standards in Kit: 1 - SRS-99-020
1 - SRS-75-020
1 - SRS-50-020
1 - SRS-02-020

The standards identified above were measured for 8°/Hemispherical Spectral Reflectance Factor using a double beam ratio recording integrating sphere reflectometer. The certified reflectance factor values at an incident angle of 8° from normal were determined in the following way. The radiance of the internal surface of the integrating sphere produced by incident flux reflected from the standards was directly proportioned to that reflected from a laboratory working standard. The laboratory working standards are periodically compared to laboratory master standards. These laboratory master standards, SRM-2019a and SRM-2021 ceramic tiles, SRM-2003-G1 National Institute of Standards and Technology calibrated first surface aluminum mirror, IRS-94-020-M1 diffuse gold standard, and SRS-99-010-M2 diffuse white standard, were calibrated by the National Institute of Standards and Technology using the highly accurate NIST reference reflectometer.

Reflectance factor values are provided at 50nm intervals for a spectral range of 250nm to 2500nm.

NOTE: The random uncertainty of reflectance factor measurements performed by Labsphere, Inc. (expressed as the standard deviation) is estimated to be less than 0.005 over the spectral range: 300-2200nm, and less than or equal to 0.02 over the spectral range: 250-2500nm.

Calibration Date: 11-17-95

Calibrated by: Peggy Walker
Title: Reflectance Lab Technician

Approved by: Lynne Dupuis
Title: Reflectance Lab Manager

[redacted]

Report No.: 14907-A
Standard I.D. No.: SRS-99-020

Wavelength (um)	8°/Hemispherical Reflectance Factor
0.250	0.967
0.300	0.981
0.350	0.987
0.400	0.990
0.450	0.991
0.500	0.992
0.550	0.992
0.600	0.992
0.650	0.992
0.700	0.992
0.750	0.991
0.800	0.990
0.850	0.993
0.900	0.990
0.950	0.991
1.000	0.991
1.050	0.992
1.100	0.990
1.150	0.992
1.200	0.989
1.250	0.991
1.300	0.989
1.350	0.988
1.400	0.988
1.450	0.988
1.500	0.988
1.550	0.987
1.600	0.988
1.650	0.987
1.700	0.985
1.750	0.987
1.800	0.984
1.850	0.981
1.900	0.977
1.950	0.978
2.000	0.974
2.050	0.963
2.100	0.953
2.150	0.952
2.200	0.966
2.250	0.967
2.300	0.962
2.350	0.954
2.400	0.947
2.450	0.945
2.500	0.937

Report No.: 14907-A
Standard I.D. No.: SRS-75-020

Wavelength (um)	8°/Hemispherical Reflectance Factor
0.250	0.766
0.300	0.764
0.350	0.761
0.400	0.760
0.450	0.760
0.500	0.761
0.550	0.761
0.600	0.761
0.650	0.762
0.700	0.762
0.750	0.762
0.800	0.762
0.850	0.765
0.900	0.764
0.950	0.764
1.000	0.765
1.050	0.766
1.100	0.766
1.150	0.767
1.200	0.766
1.250	0.768
1.300	0.768
1.350	0.768
1.400	0.769
1.450	0.770
1.500	0.770
1.550	0.772
1.600	0.773
1.650	0.773
1.700	0.775
1.750	0.776
1.800	0.775
1.850	0.774
1.900	0.774
1.950	0.776
2.000	0.779
2.050	0.779
2.100	0.778
2.150	0.781
2.200	0.780
2.250	0.781
2.300	0.784
2.350	0.782
2.400	0.783
2.450	0.780
2.500	0.779

Report No.: 14907-A
Standard I.D. No.: SRS-50-020

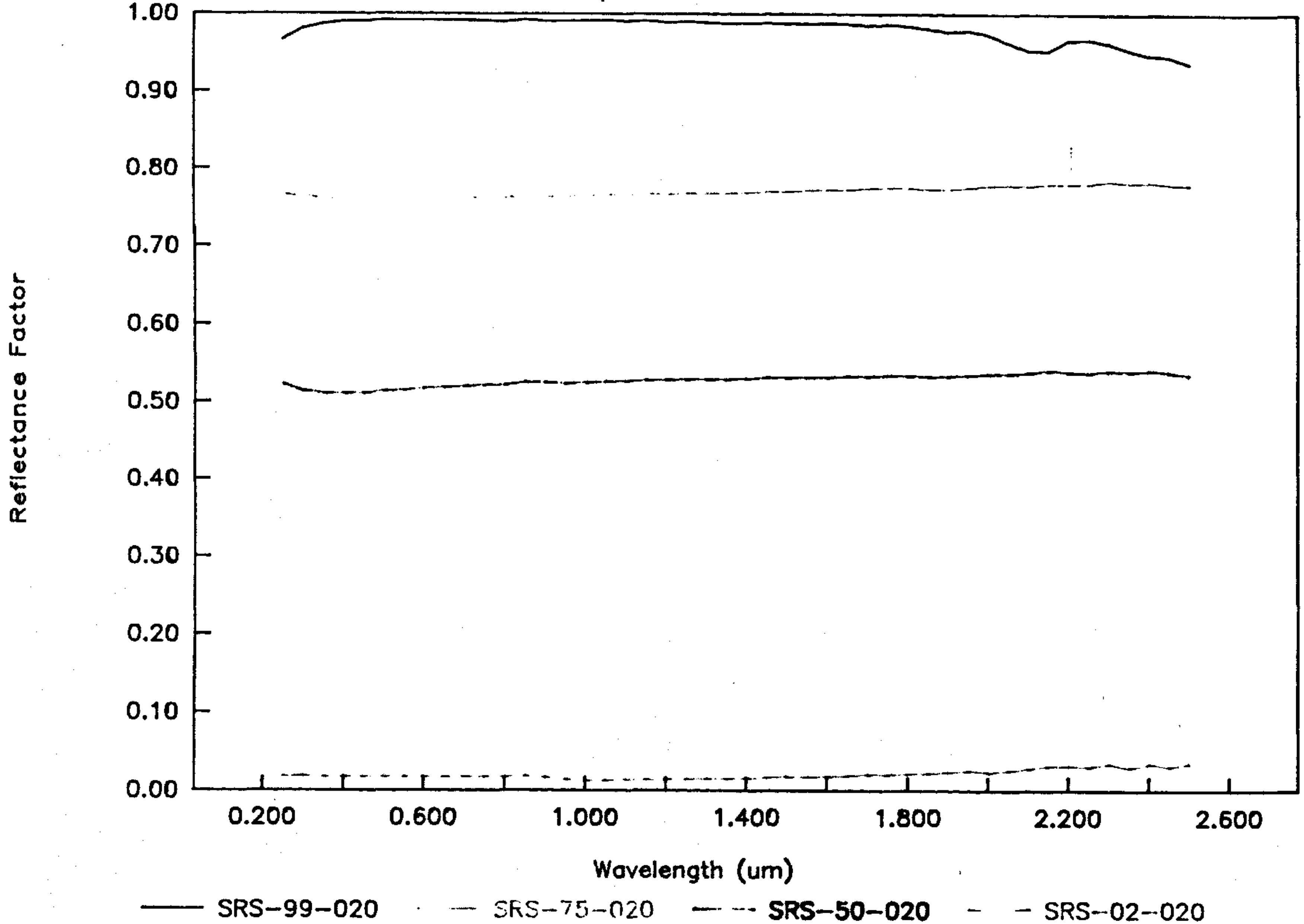
Wavelength (um)	8°/Hemispherical Reflectance Factor
0.250	0.523
0.300	0.514
0.350	0.511
0.400	0.511
0.450	0.511
0.500	0.514
0.550	0.515
0.600	0.517
0.650	0.519
0.700	0.520
0.750	0.522
0.800	0.522
0.850	0.526
0.900	0.525
0.950	0.524
1.000	0.525
1.050	0.527
1.100	0.527
1.150	0.528
1.200	0.528
1.250	0.529
1.300	0.529
1.350	0.529
1.400	0.530
1.450	0.532
1.500	0.531
1.550	0.532
1.600	0.533
1.650	0.533
1.700	0.534
1.750	0.535
1.800	0.534
1.850	0.533
1.900	0.533
1.950	0.535
2.000	0.537
2.050	0.537
2.100	0.538
2.150	0.541
2.200	0.539
2.250	0.538
2.300	0.541
2.350	0.540
2.400	0.541
2.450	0.539
2.500	0.535

Report No.: 14907-A
Standard I.D. No.: SRS-02-020

Wavelength (um)	8°/Hemispherical Reflectance Factor
0.250	0.018
0.300	0.018
0.350	0.018
0.400	0.018
0.450	0.018
0.500	0.018
0.550	0.018
0.600	0.017
0.650	0.017
0.700	0.017
0.750	0.017
0.800	0.017
0.850	0.018
0.900	0.017
0.950	0.014
1.000	0.013
1.050	0.013
1.100	0.014
1.150	0.014
1.200	0.014
1.250	0.014
1.300	0.015
1.350	0.015
1.400	0.016
1.450	0.017
1.500	0.018
1.550	0.017
1.600	0.019
1.650	0.019
1.700	0.021
1.750	0.021
1.800	0.022
1.850	0.022
1.900	0.024
1.950	0.026
2.000	0.024
2.050	0.026
2.100	0.029
2.150	0.032
2.200	0.032
2.250	0.031
2.300	0.035
2.350	0.030
2.400	0.035
2.450	0.031
2.500	0.035

8° /Hemi. Spectral Reflectance Factor

Report No: 14907–A



APPENDIX J, SOME RESULTS OF THE 970 NM INTERFERENCE FILTER

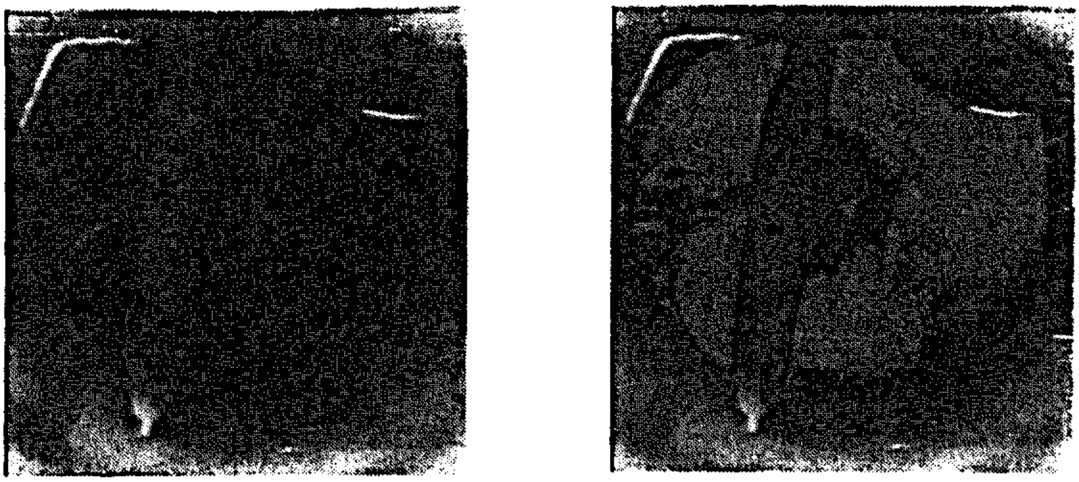


Figure J.3. Resulting SR values, using the 850 nm scene depicted in figure 5.3 and the 970 nm scene depicted in figure J.1, and the use of a threshold which is chosen at 1.0

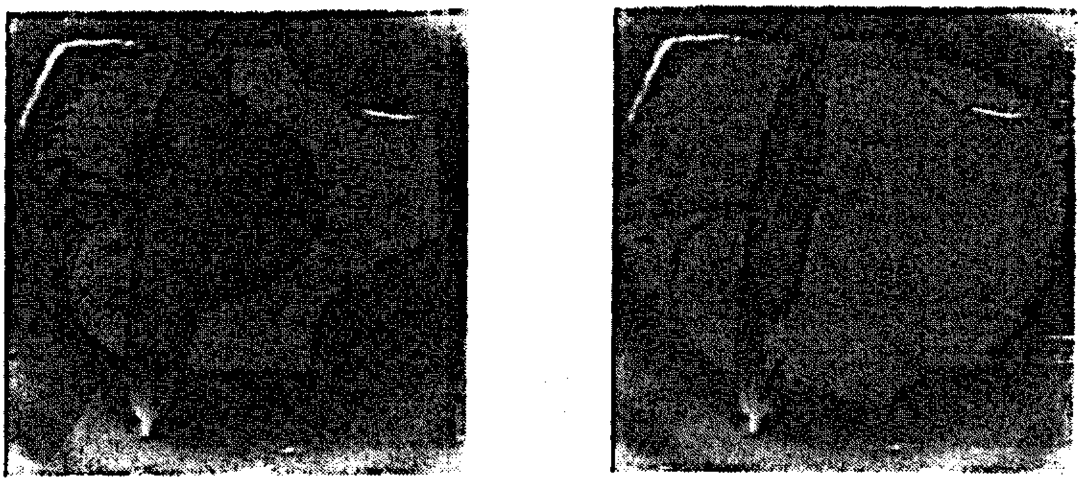


Figure J.4. The chosen thresholds are respectively 0.9 and 1.1

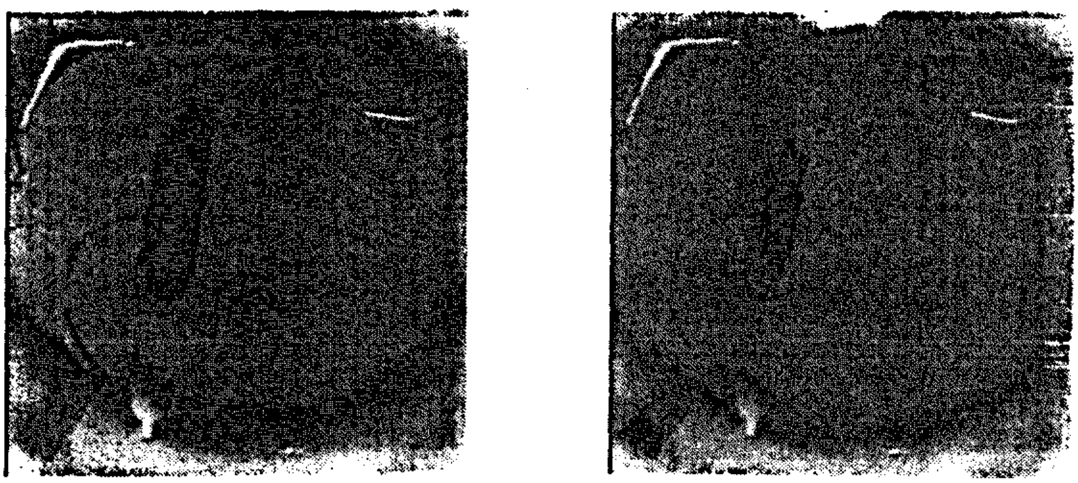


Figure J.5. The chosen thresholds are respectively 1.2 and 1.3

J SOME RESULTS OF THE 970 NM INTERFERENCE FILTER

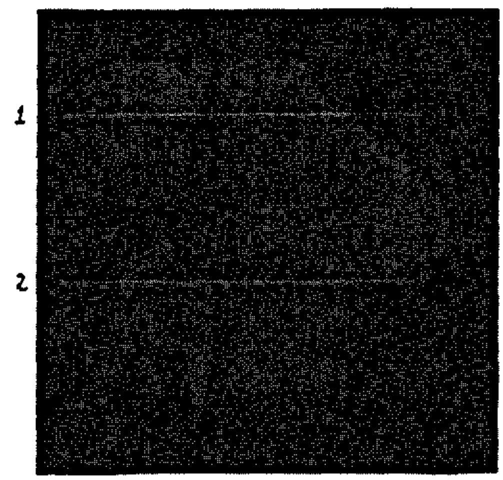


Figure J.1. Recorded scene using the 970 nm interference filter (exposure time = 20.48 s and distance = 0.74 m)

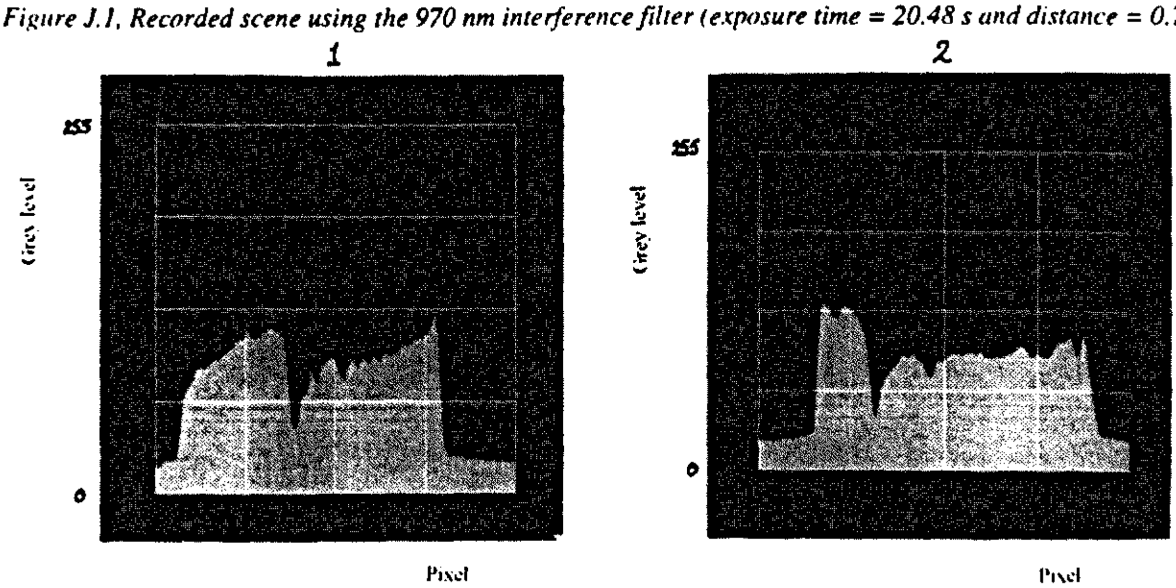


Figure J.2. Corresponding line histograms