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An Agricultural Mobile Robot with Vision-Based Perception for Mechanical Weed Control

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Abstract. This paper presents an autonomous agricultural mobile robot for mechanical weed control in outdoor environments. The robot employs two vision systems: one gray-level vision system that is able to recognize the row structure formed by the crops and to guide the robot along the rows and a second, color-based vision system that is able to identify a single crop among weed plants. This vision system controls a weeding-tool that removes the weed within the row of crops. The row-recognition system is based on a novel algorithm and has been tested extensively in outdoor field tests and proven to be able to guide the robot with an accuracy of ±2 cm. It has been shown that color vision is feasible for single plant identification, i.e., discriminating between crops and weeds. The system as a whole has been verified, showing that the subsystems are able to work together effectively. A first trial in a greenhouse showed that the robot is able to manage weed control within a row of crops.

Keywords: mobile robot, plant recognition, weed control, machine vision

1. Introduction

The world-wide problem of environmental pollution caused by excessive use of herbicides and the increasing cost of chemicals call for alternative methods for crop protection. A potential way to reduce chemicals is to employ precision techniques for various types of agricultural operations so that chemicals can be used where they have an optimal effect at a minimum quantity. It will even be possible in some operations to abandon the use of chemicals and apply other methods, e.g., mechanical weed control. There is political interest in the European Union in increasing the amount of ecologically grown products. The goal is that about 5–10% of the total field area should be processed by organic farming methods by the year 2005. Organic farming is not only a political goal; there is also a push from the market. More and more customers are asking for products that are organically grown. This has led to a problem for companies that need to increase their supplies of organically grown products to meet customer demands. For example, it is difficult to extend the amount of organically grown sugar beets at the present because weed control in the seedline of sugar beets is done by human labor, which implies high costs and difficulties in recruiting workers. The motivation for the work reported here is to reduce the amount of herbicides used for crop protection in agriculture by replacing chemical weed control by mechanical weed control. The elimination of chemical weed control is one of the requirements for a crop's being "ecologically grown". The goal of this paper is to present a vision-guided mobile robot, Fig. 1, that can carry out mechanical weed control between plants in the seedline of sugar beet plants, thus totally eliminating the need for chemical weed control. The fulfilment of the goals will result in considerable savings in both ecological and economic terms.

Section 2 describes the design of the mobile robot, which employs two vision systems. One vision system recognizes the row structure in the field and is able to guide the robot along the rows of sugar beet plants. The row-following system is presented in Section 3. The other vision system, which is based on color images, is able to recognize the sugar beet plants among weeds

Figure 1. Mobile robot.

and controls the weed removing system. This vision system is discussed in Section 4. Finally, preliminary results of a field test are presented.

2. Design of the Mobile Robot

2.1. Approach

Sugar beet plants are cultivated in rows, which divides the problem of weed control into two parts: weed control between and weed control within rows, i.e., in the seedline between crop plants. Weed control between rows requires only the recognition of a row structure whereas weed control within a row requires the recognition of individual sugar beet plants among weeds, which is a more complex perception task. As most crops are cultivated in rows, the focus of the vision-oriented research in general for guiding agricultural implements has been to obtain an estimate of the row position. There have been a number of publications of successful implementations of row following (Marchant, 1996; Marchant and Brivot, 1995; Billingsley and Schoenfisch, 1995; Slaughter et al., 1997; Ollis and Stentz, 1996). However, only a few reports have been published on systems for individual plant recognition tested in the field. Tillet et al. (1998) developed an autonomous robot for precision spraying in a transplanted cauliflower field. Their robot has two driving wheels, with one motor for each wheel, at the front and two passive wheels at the rear. A camera is placed between the front axle, viewing an area of 2 m^2. The vision system estimates plant position and uses this estimate for row-guidance and precision spraying. Segmentation is achieved by several steps of image processing, based on near-infrared images, to be able to discriminate weeds from crops (Brivot and Marchant, 1996). Lee et al. (1997) developed a system based on machine vision for precision spraying in-row weeds in tomato fields. The system is mounted on a vision-guided row cultivator (Slaughter et al., 1997) that is able to track the center of the seedline of the crop. Separate cameras are used for row recognition and for single crop recognition. The reason for this is the often-reported problem of non-uniform illumination. By employing two cameras, the vision system for plant recognition can be encapsulated and thus control can be taken over illumination.

The systems described above focused on precision spraying and not mechanical weed control for in-row weeds, which is the aim of this work. Another important aspect of our work is that the organically grown cultivation we aim at implies a relatively high number of up to twelve weed plants per crop plant (in our case sugar beet plants). Moreover, as sugar beet plants are sown and not planted, the crop and weed have about the same size, see Fig. 3. These two factors make the recognition task of both the row structure and individual plants much more difficult. Existing algorithms for row recognition were not sufficient for our application (Marchant, 1996; Marchant and Brivot, 1995; Billingsley and Schoenfisch, 1995; Slaughter et al., 1997; Ollis and Stentz, 1996; Lee et al., 1997). We thus decided to develop a new row recognition algorithm and a new plant recognition algorithm that fit the requirements imposed by organic farming of sown crops.

Our approach is to separate the task of finding rows and the task of plant identification. A forward-looking camera with a near-infrared filter is used to find the position of the row, see Fig. 2. A color camera system is then used for single plant identification. This is mounted inside the robot to be able to control the illumination, as shown in Fig. 2. A color camera system is especially sensitive to changes in illumination as it causes color shifts, thus making classification more difficult. Therefore, taking control of illumination will most likely increase the classification rate. The robot is designed to intra-row cultivate one row at a time. The forward-looking camera looks at two rows at the same time and along a segment about 5 meters long. Looking at such a relatively large area makes the row-recognition system robust to missing plants and to a relatively high weed pressure, typical for ecological farming. The downward-looking camera looks perpendicular to the ground in a window of 45×80 cm along one row structure. This means that at least four sugar beet plants appear in each image, as the average distance between the plants is about 17 cm. This is of advantage if one tries to classify a plant using contextual information. Instead of looking at one plant at the time, the system will then look at a certain environment containing several plants, as illustrated in Fig. 3. Knowing that the plants are sown in rows and with a certain constant distance among them, it is possible to classify the plants also based on this information instead of looking only at individual features of one plant as described Section 4.

2.2. *Mechanical Design*

The distance between rows in sugar beet fields and other row-cultivated crops is about 50 cm, which restricts the physical width of the robot to about 70 cm. The length of the robot is about 120 cm and the steering mechanism is an Ackerman steering controlled with a

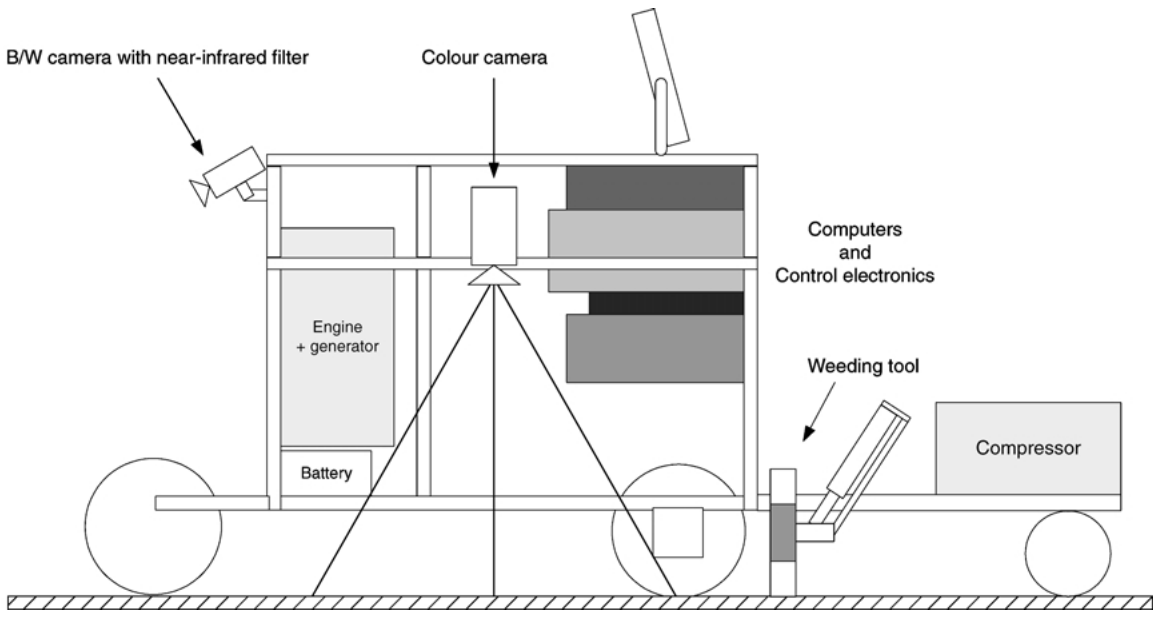

Figure 2. Mobile robot with weeding tool mounted at the rear.

Figure 3. Upper: When crops are sown, the weed and crop, encircled, have about the same size (ecologically grown). Lower: transplanted crops shown for comparison.

DC–servo motor. A potentiometer is used for calibration and an encoder, which has an approximate resolution of 700 pulses/degree, determines the current position of the steering motor. To prevent the steering mechanism from being damaged by the motor there are two end switches for blocking the steering motor if the steering angle is out of range. The robot has two driving wheels at the rear, equipped with encoders with an approximate resolution of 24000 pulses/m. For safety reasons the driving motors are equipped with electrically controlled brakes (brakes if the power goes off). The robot is powered by batteries for indoor testing and by a combustion engine driven generator for field tests. The mechanical weeding tool is a rotating wheel that is rotated perpendicular to the row line. The tool processes only the area between crops in the seedline. If a crop appears, the tool is quickly lifted by a pneumatic cylinder and lowered directly after the crop has been passed. The downward-looking camera identifies and localizes the position of every sugar beet plant. The position is then sent to the controller of the weeding tool. To minimize the time delay between the time of the position estimation and the time at which the weeding tool reaches the plant, the tool should be located as close as possible to the border of the field of view of the camera. The weeding tool is therefore located at the rear of the robot directly after the rear driving axle.

2.3. *Hardware and Sensors*

The robot has two main sensors, the vision system for row following and the vision system for plant identification. Each of these systems has industrial PC-based hardware for grabbing and processing the images. A third computer, the main computer, runs under QNX, a real-time operation system, and controls all the robot's systems and actions. It is equipped with two IO cards for digital and analog input and output as well as an IO card for interfacing the encoders of the motors. The robot is also equipped with two emergency buttons for quick shut down of the system and a joystick for manual operation. All communication between the main computer and the vision sub-systems is done over a serial line.

2.4. *Software Architecture*

The software architecture is based on the blackboard architecture (Harmon et al., 1986). This means that all sensor data are available through a blackboard and in

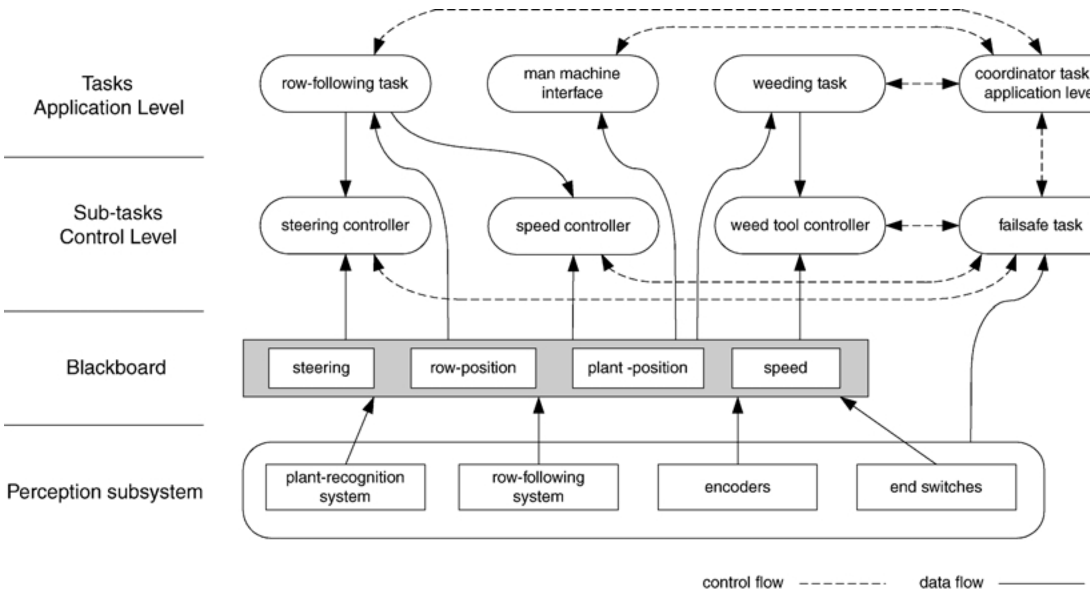

Figure 4. Control layer and application layer receiving sensor data from blackboard.

principle accessible by all tasks, as shown in Fig. 4. This is the main advantage of the approach, as it is very difficult to predict what data may be needed in the future by which task. A special kind of blackboard architecture was designed in our case to make sensor data public. It is common to use a blackboard architecture, which places data in a shared memory, but a multi-client server platform was created in our system. In this architecture, the data of each sensor or group of sensors have their own server process. Every process that needs these data can request them from the appropriate server. The advantage of this is that a blackboard server for a new sensor, for example, as in our case, GPS, which we aim to integrate in the future, can easily be created (without changing the source code of the existing part of the blackboard, which would be the case if a centralized blackboard that serves all data was employed). Another advantage is that a blackboard system uncouples the data representation from the sensor. This means that it is possible to filter the data from the sensor before they are made public, giving the advantage that this filtering needs to be done only once. However, a drawback of this type of architecture is the overhead resulting from additional context switching. Another drawback is, as the sensor data is not read directly from the sensor, that the age of the data must be checked. This is solved by adding a time stamp to all data.

Exchanging data between different tasks in the system is a very important issue when designing the software architecture. Since controllers should not be suspended, waiting for a new desired value, asynchronous communication is necessary. This is the second reason for using server processes in this design. Every task that wants to send data asynchronously to another process writes these data into a so-called *buffer task* that stores the data until they are overwritten or consumed by the other task. A consumer always reads the oldest data. The software architecture is divided into two layers, see Fig. 4: a control layer and an application layer. The motivation for the two-layer approach is to make the control level, which contains a speed, weeding and steering controller, independent of the application layer. This means that the interface to the control layer is fixed and that changes in the application layer should not affect the control layer (Becker, 1999).

3. Row Following

As said in the previous section, existing algorithms for row recognition were not sufficient for our application. No system has been reported to work on high weed pressure, up to twelve weeds/crop plant, with sown crops. A new algorithm for row recognition was thus developed to satisfy these requirements. A forward-looking gray-scale camera with a near-infrared filter is used to find the position of the row. A near-infrared filter gives a high-contrast image, where living plant

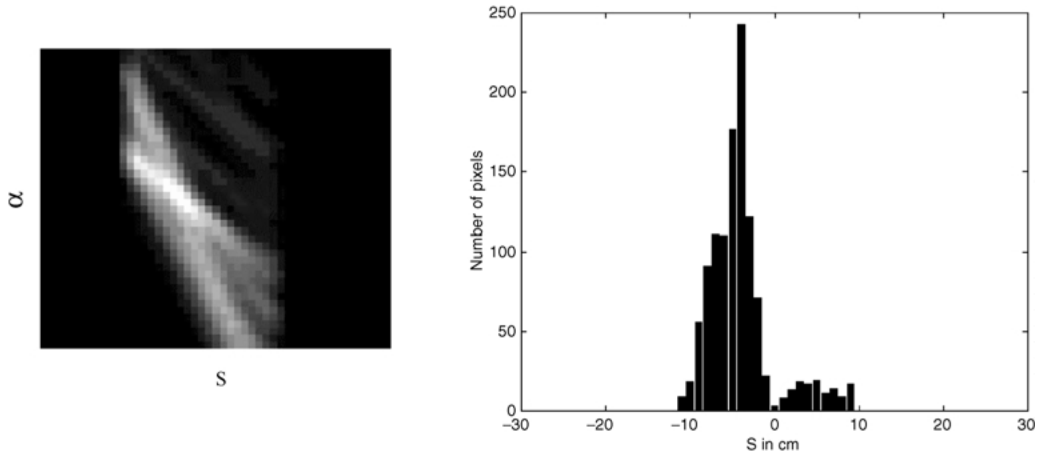

Figure 5. Hough space accumulator and distribution of s for a specific α.

material is bright and the soil is dark (Baerveldt, 1997). To decrease the effect of different light conditions, an opening operation is performed on the image and the result is subtracted from the original image. This results in an intensity-independent gray-level image from which a binary image can be derived with a fixed threshold. In the resulting binary image, plant material from both weeds and crops is white and the rest, coming from soil, stones and residues, is black. On the basis of the binary image the next step is to detect the row of crops in the image. To control a mobile robot or other tool, for example, the offset, s, and the heading angle, α, of the camera relative to the row structure must be known. The Hough transform is a well-known and robust method for finding lines, especially if the lines cover the whole image, as in our case (Shapiro and Haralick, 1992, 1993). Normally the lines are found with their equation in the image space, e.g., $y_i = ax_i + b$, where coefficients a and b are found with the Hough transform. This could also be done on the basis of the binary image of plant material. All pixels coming from the crops contribute to the line and all pixels from the weeds are just noise. However, as shown in Åstrand and Baerveldt (1999a), by using perspective transformation, there is a linear relation between offset to row s and the angle to row α for a given pixel (x_i, y_i). (See Eq. (1), where constants A, B and C are functions of (x_i, y_i)).

$$A\alpha + Bs + C = 0 \tag{1}$$

This means that the Hough transform can be directly performed for s and α. The Hough space, $H(s,\alpha)$, is then an accumulator to which each pixel coordinate (x_i, y_i) in the binary image that is on makes a contribution (even if it belongs to a weed plant). Every such pixel (x_i, y_i) forms a straight line in the Hough space (Shapiro and Haralick, 1992, 1993). The recognition of the row of crops among the weeds is achieved as a result of the fact that weeds are uniformly distributed in the field, whereas all the crops grow exactly in a row, thus leading to a peak in the Hough space, as shown in Fig. 5.

The novelty of this algorithm is that we model a plant row with a rectangular box instead of a line. The width of the box is equal to the average width of the plants and the length of the box is "unlimited" as it fills the whole image. The rectangular box can be described by a set of parallel adjacent lines. These appear in the image as a set of lines that intersect in one virtual point outside the image, as shown Fig. 6, due to perspective geometry.

The number of lines is the width of the box divided by the thickness of the line, which is determined by the pixel size of the image. In our Hough space this means that, for one value of α, the rectangular box corresponds to a number of adjacent s-cells. By summing up the contributions of the adjacent s-cells we obtain the support for a rectangular box, i.e., for the row of plants. The best estimate of s and α is found by searching for the maximum of the sum of adjacent s-cells in our Hough space. Adaptation to different size plants can easily be made by reducing or increasing the number of adjacent s-cells.

Figure 5 shows an example of the Hough space and the corresponding distribution of s for the correct value of α. In this example the sum of three adjacent s-cells is calculated to find the most likely values of s and α.

Figure 6. Rectangular box corresponds to a certain number of adjacent s-cells.

If more than one row is used, each row then has its own corresponding Hough space. Information from the different rows can be fused together by calculating the average of s and α derived from the individual Hough spaces. Another possibility is to sum up the contributions from all Hough spaces for each cell (s, α), thus forming a common Hough space, and extract the most likely value of s and α from this one. The resolution of the Hough space, i.e., the size of the cell (s, α), must be chosen carefully, where the resolution of the camera plays a major role. The size of s and α is chosen such that this corresponds to at least one pixel difference. In this implementation the resolution of s was set to 1 cm and of the heading angle, α, to 0.2 degrees.

3.1. *Performance of the System*

A number of real images were used to evaluate the row-recognition system (Åstrand and Baerveldt, 1999a). Three sets of images of sugar beet plants at three different stages of growth were included. One set of images from a rape field was also used. A sub-set of 70 spatially distributed images was chosen from each set of images. For all images, the real position of the camera relative to the rows was estimated by a human observer. The result of this test set indicated that the row-recognition system shows good performance ranging from a 0.6 cm standard deviation of error to 1.2 cm, depending on plant size. Moreover, it is shown that the accuracy is significantly improved by using two rows instead of one. The row-recognition system was implemented on an inter-row cultivator, see Fig. 7 (Åstrand and Baerveldt, 1999b). The system consists of a tractor that the farmer drives along the rows where the cultivator is mounted at the rear of the tractor. A steering unit based on a very thin steering wheel that cuts through the soil is used to control the position of the cultivator on the basis of the input of the row-recognition system. Extensive field tests have shown that the system is sufficiently accurate and fast to control the cultivator in a closed-loop fashion with a standard deviation of the position between 2.0 and 2.4 cm. The vision system is also able to detect exceptional situations by itself, for example the occurrence of the end of a row (Åstrand and Baerveldt, 2000).

3.2. *Implementation on the Robot*

The robot should be able to follow a row of plants guided by the row-following vision system. A number of tests were done outdoors and indoors to evaluate the row-recognition system. For the indoor tests a number of artificial plants were placed in a corridor. The camera for the row-recognition system was mounted at the front of the robot, looking at two rows simultaneously. At the weeding position, at the rear of the

Figure 7. Field test of the row-recognition system with a tractor and a row-cultivator removing weed between the rows.

robot, see Fig. 2, a second camera was mounted to measure the actual position offset to the row of the robot. The robot drove at a speed of 0.2 m/s during the test. The error of the lateral offset measured by the vision system was ± 1 cm and the error measured with the downward-looking camera at the weeding tool position was ± 0.5 cm, as illustrated in Fig. 8. The length of the corridor was limited, which is why robot could not maintain ± 0.5 cm at the end of the test.

The system was also tested outdoors on about 80 meters of a rape field. The typical offset error was about ± 2 cm during this test as measured by the row-recognition vision system. Thus, at the tool position half of this value can be expected according to the results obtained indoors, which is sufficient for our application.

4. Recognition of Individual Plants

The position of each sugar beet plant must be determined for intra-row weeding. This means that plants have to be classified into two classes, i.e., sugar beet or weed. The approach is to recognize sugar beet plants among weeds, where the vision system analyzes one plant at a time and decides whether this plant is a sugar beet plant or weed. A number of color images were collected from different fields: a total of 214 sugar beet plants and 373 weeds. The pictures were taken with a normal color photo camera and later digitised. For analysis of the object in the image it is essential to distinguish between the object of interest, here plants, and the background, here soil. We use histogram thresholding to segment the image. In our case this means that we use the gray-level distribution on the normalized green component. The proper threshold was found by using Otsu's method (Otsu, 1979). To get rid of noise in the image we performed an opening/closing operation followed by a flood-fill operation (Shapiro and Haralick, 1992, 1993). An example of a sugar beet and weed with corresponding threshold images is given in Fig. 9. A number of features of the objects were derived from the segmented image. A total of 19 features were selected: six color features (standard deviation and mean value for the three normalized color components), seven shape features (area, perimeter, compactness, elongation, solidity, form factor and convexity) and six moment-based features. Please refer to Table A1 in the appendix for a complete description of all features. These features were then used to classify sugar beets and weeds. We use a k-nearest neighbor classifier and the Euclidean distance to calculate the nearest neighbor. As the different features have typical values which differ significantly, a pre-processing step is necessary to rescale the feature values. We used a

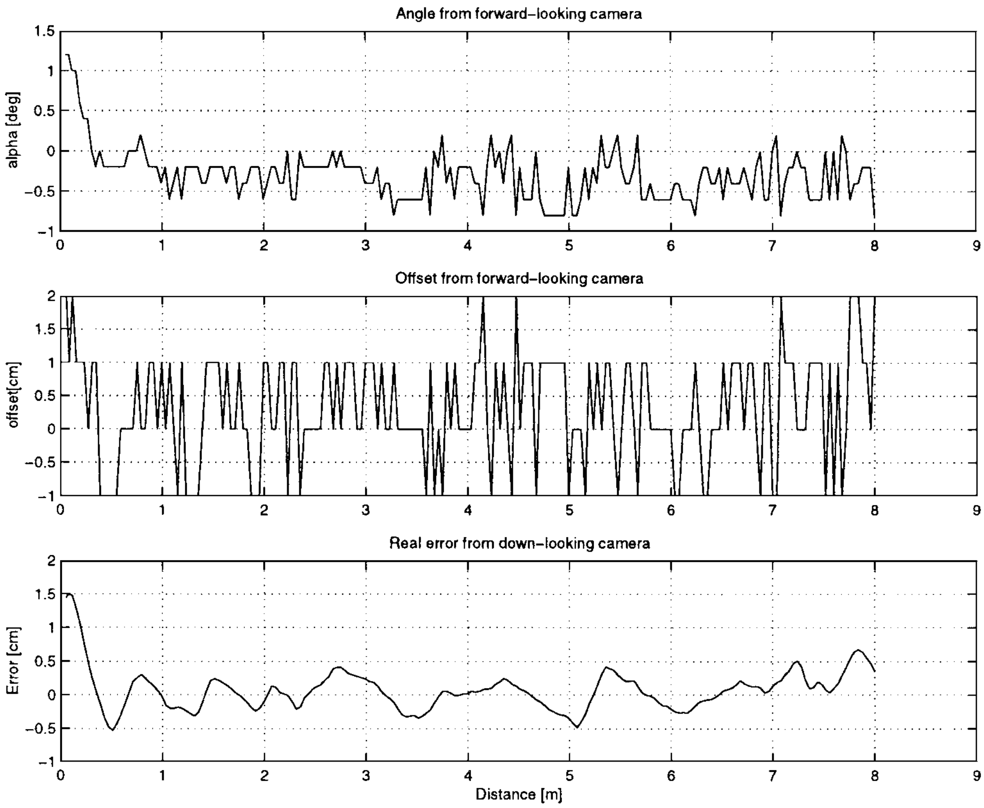

Figure 8. Results of indoor test.

simple linear rescaling so that the transformed variables have zero mean and unit standard deviation. The validation method used was leave one out (Bishop, 1997). The results reported below are based on a 5-nearest neighbor classifier. We also performed the same tests for 1- and 3-nearest neighbor classifier and obtained similar results, however with slightly less classification success-rates (up to minus 3% relative to the results obtained with $k = 5$).

The use of all 19 features gives a very nice classification rate of 97%, see Table 1. The results also show that color features are very important for a good classification rate. Using all six color features only gives a classification rate of 92%. From two aspects the use of color features is positive; they are not sensitive to poor segmentation and are independent of plant size. The weakness of the color features might be that plant color may change due to different soil, fertilizer and the amount of sun. Excluding all color features gives a classification rate of at most 86% (see Table 1). The number of features must preferably be low for real-time implementation reasons. We used forward selection to find the three best features (Bishop, 1997). The procedure begins by considering each of the features individually and selecting the one which gives the highest classification rate. At each successive stage of the algorithm, one additional feature is added to the set, again chosen on the basis of which of the possible candidates at that stage give rise to the largest increase in the classification rate. The three best features found in this way was one color feature, green mean, and two shape features, compactness (area/perimeter^2) and elongation (area/thickness^2). The distribution for each feature is found in Figs. 10–12. Compactness and elongation are both size-independent shape features, which means that they have the advantage to be robust against variations in plant size. The individual classification rate for green mean is 91%, compactness 68% and elongation 67% (see Table 1). With three features, a classification rate of 96% was obtained with a 5-nearest neighbor classifier. So only 1% in performance is lost when the numbers of features is reduced from 19 to 3, while gaining a significant reduction in computational costs (Bondesson et al., 1998). Table 2 shows

Figure 9. Above: Example of sugar beet, left, and weed. Below: Corresponding threshold images.

the distribution of nearest neighbors using three features. The numbers in Table 2 are all rounded to integers. 77% of the sugar beets can be classified with the highest degree of confidence (all neighbors are sugar beets) while 6% can be classified with the lowest degree of confidence.

Table 1. Classification success rate with 5-NN classifier using different sets of features.

Features used	Sugar beets classified as weed	Weed classified as sugar beets	Classification on rate (%)
All features	5	13	97
Color excluded	43	39	86
6 color features	23	25	92
Green mean, compactness, elongation	6	25	96
Green mean	13	28	91
Compactness	47	94	68
Elongation	46	94	67

Employing only three features has the advantage that the classifier can be implemented in a look-up table, resulting in almost no computational costs for the classification process. This is especially valuable for a k-nearest neighbor classifier as the time consuming search for the k-nearest neighbors can be avoided. The success rate of 96% looks satisfying at first sight. However, the process of extraction of individual plants out of a scene has been done manually. In a final system, this should also be done by the vision system. This will reduce the success rate by about 10 to 15% according to preliminary results. We are currently focusing our efforts on improving the recognition algorithms and consider other type of classifiers as well, such as neural networks and Bayesian classifiers based on Gaussian distributions of the features of each class (Bishop, 1997). Moreover, we will not only concentrate on classifying single plants, but also on methods based on contextual information, i.e., examining a certain environment containing several plants. Knowing that the plants are sown in rows and with a certain constant distance among them, it

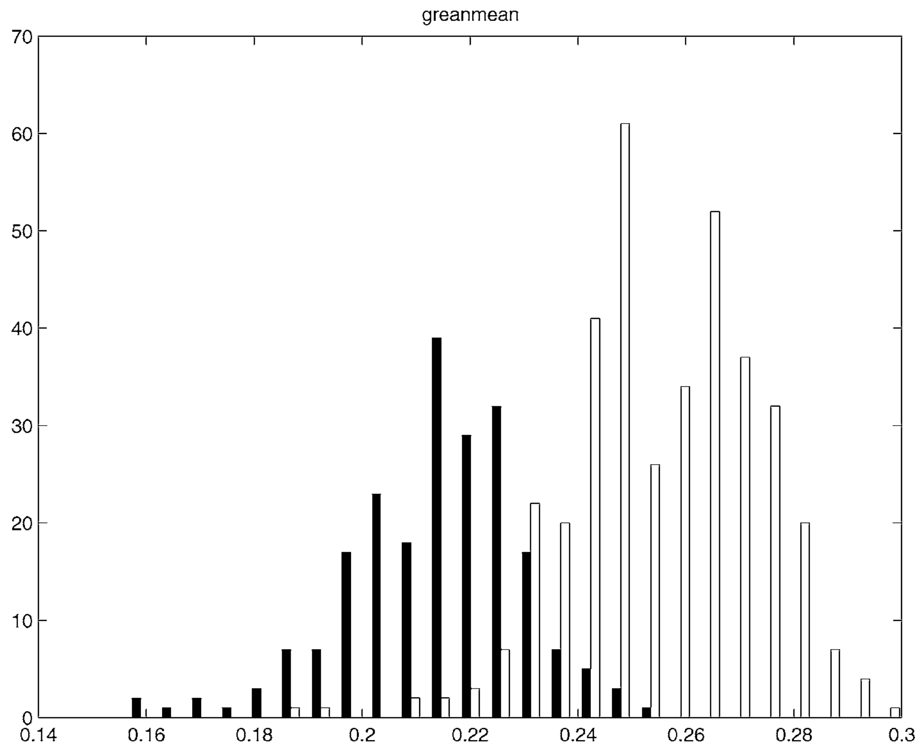

Figure 10. Distribution of *green mean* feature (black bars is sugar beet and white bars weed).

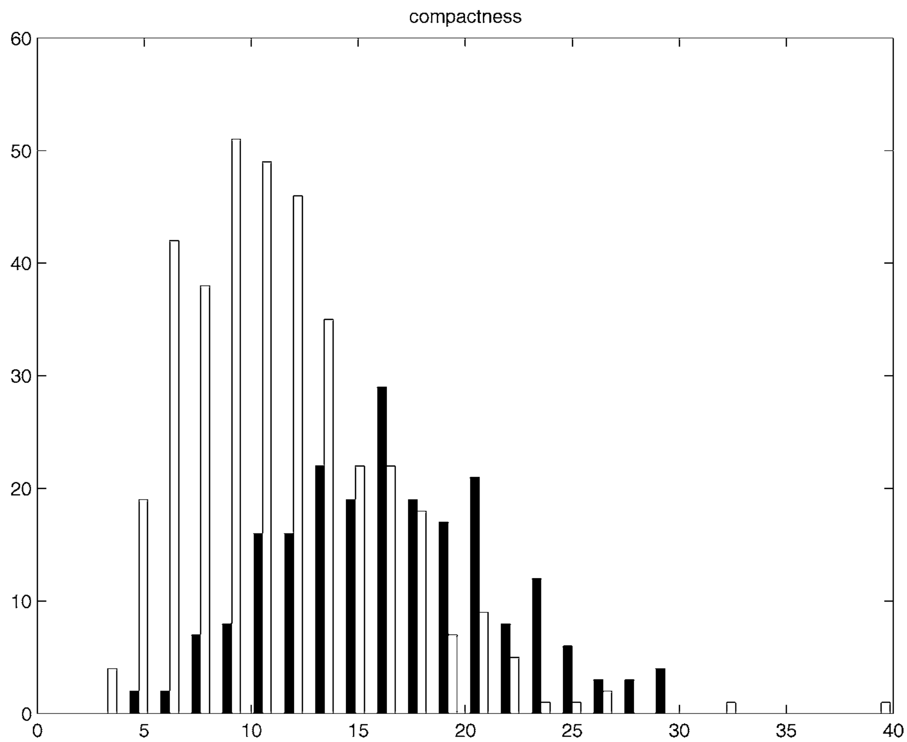

Figure 11. Distribution of *compactness* feature (black bars is sugar beet and white bars weed).

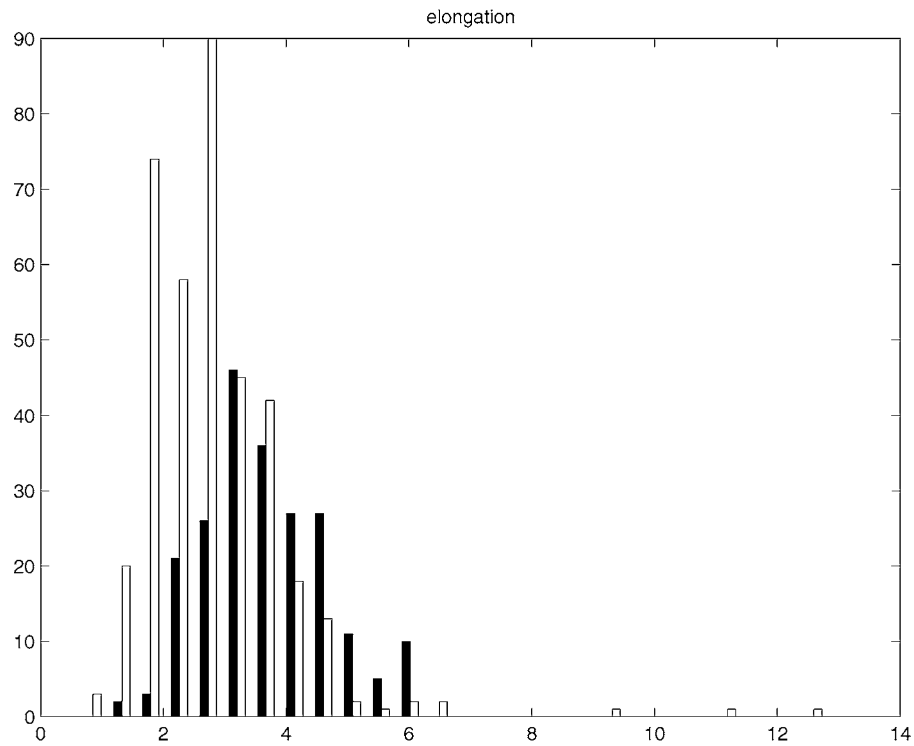

Figure 12. Distribution of *elongation* feature (black bars is sugar beet and white bars weed).

is possible to classify the plants also based on this information.

5. Preliminary Results

An important milestone during the development of a robotic system is the first time that all sub-systems work together. It is not as critical that all sub-systems are fully implemented and optimized but, when closing the loop, it is necessary that the functionality at the system level can be verified. The robot consists of four major systems: the robot control system, the row-recognition system, the plant identification system and the weeding system. All these systems are implemented in the robot, while the plant identification system is implemented with some simplifications, as described below.

Table 2. Distribution of nearest neighbours for all weeds and sugar beets (3 features) with 5NN.

Number of neighbours	5	4	3	2	1	0
Sugar beet (%)	77	15	6	1	0	1
Weed (%)	87	6	3	1	2	1

5.1. Plant Identification System

The plant identification system was implemented with only a few features and a simplified classifier. The features that were implemented were mean green level, area (plant size), and position offset to the row of the plant in the image. An object that was too far from the center of the image was rejected, i.e., too far from the expected plant row. Finally, to be classified as a sugar beet plant, the mean green level and the area of the plant should be within a pre-defined range.

The plant recognition system works as follows: All objects in the image are classified on the basis of the features mentioned above. If an object is classified as a sugar beet, the position of the object is calculated. Every time a new object classified as a sugar beet enters the shadowed area, see Fig. 13, a new index and position are sent to the weed controller. This means that the weed controller has a table of the last known position of the sugar beet plant. Upon receiving the index and the position of a sugar beet plant, the controller estimates, on the basis of the actual speed and the processing latency, the robot position at which the tool should be activated, which includes one position for

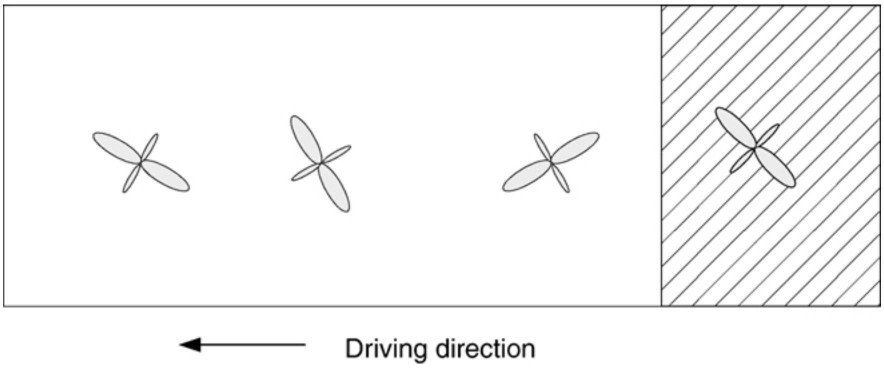

Figure 13. The position of the last object classified as sugar beet is sent to the weed controller.

lifting and one position for lowering the weeding tool. The values are stored in a table and are continuously compared with the actual robot position as measured by the encoders.

5.2. *Test in a Greenhouse*

Due to the short season during which it is possible to do outdoor field tests, sugar beet crops were sown in a greenhouse. As a first test there were no weeds and the sugar beet plants were in their first true-leaf stage at the time of testing (about 5 cm in diameter). The distance between the plants was about 17 cm. The tests showed that all sub-systems worked well and that the design concept proved to have good potential. The robot was able to recognize all the sugar beet plants and the weeding tool worked well.

6. Conclusion and Outlook

This paper has presented a design for an agricultural mobile robot for mechanical weed control in ecologically grown fields. The system consists of the following parts:

- A forward-looking camera system for crop row position estimation, based on a new row-recognition algorithm that is able to recognize crop rows at high weed pressure (12 weeds/crop plant) even when the crops and weeds are of about the same size.
- A downward-looking camera system for single plant identification and position estimation.
- A four-wheeled mobile robot based on the Ackerman steering principle.
- A sensor blackboard software architecture.
- A mechanical weeding tool for in-row weeding.

The row-recognition system has been tested extensively in outdoor field tests and proven to be able to guide the robot with an accuracy of ± 2 cm.

It has been shown that single plant recognition based on color vision is feasible with three features (green mean, compactness, elongation) and a 5-nearest neighbor classifier.

The system as a whole has been verified on a design level, which showed that the sub-systems are able to work together effectively. A first trial in a greenhouse showed that the robot is able to do weed control in the seedline between the crops in a sugar beet row.

Future work will concentrate on the development of robust and high-performance algorithms to distinguish between plants and weeds. Future work will also include extensive field tests at different farms and will also focus on other row-cultivated crops, such as rape and different kind of vegetables.

Appendix

Definition of *formfactor* that is a measure of how much "plant mass" there is in the centre in relation to how much "plant mass" there is in periphery.

$$MEAN_{dist} = \frac{1}{N} \sum \sqrt{(x_i - x_c)^2 + (y_i - y_c)^2}$$

there N is the total number of object pixel and x_c and y_c is the geometrical center of the objects, defined below.

$$x_c = \frac{1}{N} \sum_{i=0}^{N-1} x_i \quad y_c = \frac{1}{N} \sum_{i=0}^{N-1} y_i$$

$$VAR_{dist} = \frac{1}{N} \sum [\sqrt{(x_i - x_c)^2 + (y_i - y_c)^2} - MEAN_{dist}]^2$$

$$formfactor = \frac{MEAN_{dist}}{\sqrt{VAR_{dist}}}$$

Table A1. List of features.

Number	Name	Description
1	Green mean	The mean value, over the hole plant, of the normalized green color, $g = G/(R + G + B)$.
2	Green std	The standard deviation, over the hole plant, of the normalized green color.
3	Red mean	The mean value, over the hole plant, of the normalized red color, $r = R/(R + G + B)$.
4	Red std	The standard deviation, over the hole plant, of the normalized red color.
5	Blue mean	The mean value, over the hole plant, of the normalized blue color, $b = B/(R + G + B)$.
6	Blue std	The standard deviation, over the hole plant, of the normalized blue color.
7	Area	Area is defined as the number of pixels belonging to the plant.
8	Perimeter	Perimeter is defined as the number of pixels of the plant boundary.
9	Compactness	area/perimeter^2
10	Elongation	area/thickness^2, there thickness is defined as the number of shrinking steps of an object until only one pixel is left in the image.
11	Solidity	area/(area of convex hull), there convex hull is described as the area formed if a rubber band would be tighten around the object.
12	Formfactor	See definition above in this appendix.
13	Convexity	perimeter/(perimeter of convex hull).
14	Moment1	These are functions of moments, which are invariant to geometric transformations such as translation, scaling and rotation. Defined in Jain (1989).
15	Moment2	
16	Moment3	
17	Moment4	
18	Moment5	
19	Moment6	

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