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Image analysis system to determine crop row and plant positions for an intra-row weeding machine

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Abstract: This paper describes computer vision methods to trace crop row positions and to locate the single crop plant positions in the rows. For the determination of the crop row a template fitting algorithm was developed. Detection of individual crop plant positions was based on a Fast Fourier Transformation (FFT). The results show that it is possible to detect the crop row and crop plant positions in a robust manner for different crops and different growth stages. On average less than 1% of the crop plants were not detected and less than 1% of the weed plants were classified as crop.

Keywords: FFT, Image processing, Lettuce, Celeriac, Weed control

1. INTRODUCTION

In the current discussion about healthy food and environmental pollution the reduction of herbicides applied to a crop has gained much attention. Mechanical weed control is an alternative, chemical free method to control the weed. Numerous solutions for hoeing between the crops rows are available, whereas most mechanical intra-row weeding concepts are still in the research phase or only available for certain crops. In order to perform automated mechanical weed control in the crop row, an accurate detection system to locate the plant rows and the plants in the row is needed. Furthermore, a fast but robust mechanical actuator is required.

Numerous research projects have been carried out in the last decades on the subject of weed detection and weed control (Lee et al., 1997, Kielhorn et al. 2000; Hemming and Rath 2001, Tillet et al., 2002; Åstrand snd Baerveld, 2002, Nieuwehuizen et al., 2007 and many others). Recently, the first commercial products have appeared on the market, like the Robocrop2 from the company Garford Farm Machinery (http://www.garford.com).

2. OBJECTIVE

The objective of this research was to develop computer vision methods to trace crop row positions and to locate the single crop plant positions in the rows. This information was used to guide an implement onto the exact crop row centers and to control intra-row hoeing actuators in real-time for up to 6 rows simultaneously. The system should be able to work in different crops and different crop stages. The actuator development is not described in this paper.

3. MATERIALS AND METHODS

Experimental field

The algorithms were developed and tested on images of lettuce (*Lactuca sativa*) and celeriac (*Apium graveolens*) acquired from an experimental field. The length of the field was about 70 m and consisted of 6 rows of celeriac (row spacing 0.5m, plant spacing 0.37m) and 8 rows of lettuce (row and plant spacing 0.35m). The plants were manually planted and images of the plants were recorded every few days or weeks. Table 1 gives an overview of the recording dates and the accompanying plant diameters.

Table 1: Recording dates and mean plant size

Date	Lettuce plant diameter	Celeriac plant diameter
04-09-2008	0.09m	-
10-09-2008	0.11m	-
18-09-2008	0,13m	0.05m
24-09-2008	0.15m	0.07m
20-10-2008	0.22m	0.10m
27-10-2008	0.25m	0.12m

Recording device

The developed apparatus which was carried behind a tractor consisted of 4 colour cameras, lamps for illumination, an encoder wheel, a microcontroller, side shift hydraulics, out of work sensor, mechanical hoeing actuators and an industrial computer. Figure 1 shows a photo of the device attached to a tractor. All components were powered by the battery and the engine of the tractor. The cameras were mounted on the implement facing straight downwards (Figure 2). Natural lighting was blocked by a cover. Artificial lighting was used to illuminate the scene using regular Xenon work lamps for tractors mounted next to the cameras. Figure 3 gives an overview of the system components. For the research described here, only the information from one camera recording three or four plant rows simultaneously was used. The camera used was a 1 CCD camera with Bayer colour filter (Marlin 201C, Allied Vision Technologies) with a maximum image resolution of 1628x1200 pixels and an IEEE1394b interface. Core of the data processing system was a 1.5 GHz Intel Core2 Duo CPU fanless industrial PC with solid state drive (SSD) and a sun readable touch screen as graphical user interface (GUI). Software was programmed using National Instruments Labview 8.5 with Windows XP operating system.

Figure 1: System carried behind a tractor

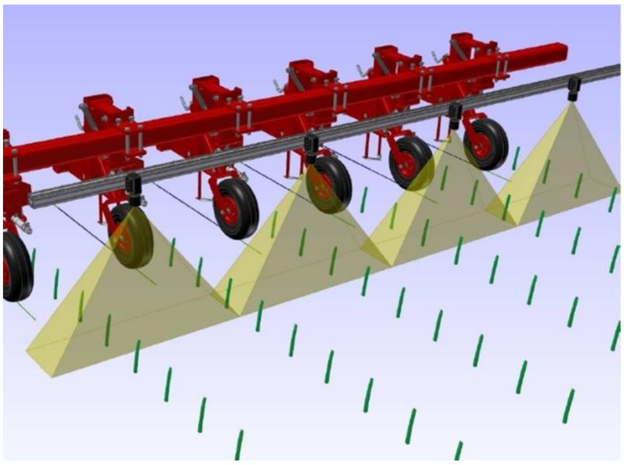


Figure 2: Schematic overview of the camera positions

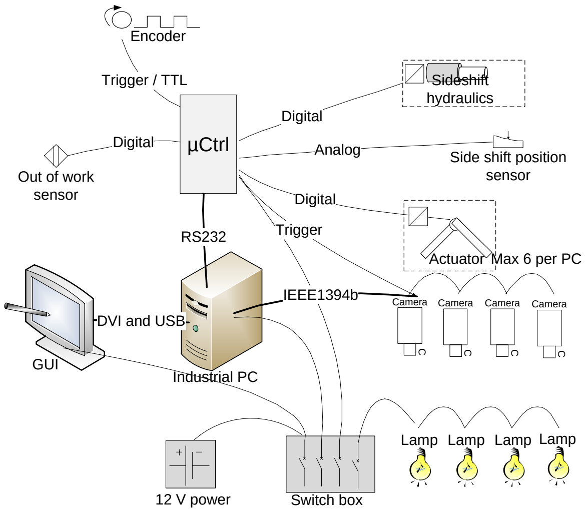


Figure 3: System components

Every 0.2m forward movement the camera was triggered by the information obtained from an encoder wheel. An image stroke of 1628x200 pixels was grabbed, representing an area of approximately 0.2m length by 1.5m width.

To obtain sufficient information for crop row and crop plant localization a history of the last 8 images was maintained in a rolling buffer for further processing. Figure 4 shows a colour image merged from 8 single grabbed image strokes.

Image processing and analysis

The imaged plants were distinguished from the soil using the excessive green vegetation index image (ExG) introduced by Woebbecke et al. (1995):

$$ExG = 2G - R - B \qquad (1)$$

where R, G, and B are the chromatic coordinates of the normalized pixel values from the images based on each the red, green and blue (RGB) channel. A fixed threshold value of 24 was set to binarize the ExG image based on examining histograms of the data. In the binary image, pixel values of 1 represent plants and pixel values of 0 represent background. See Figure 5 for a plant segmentation result image.

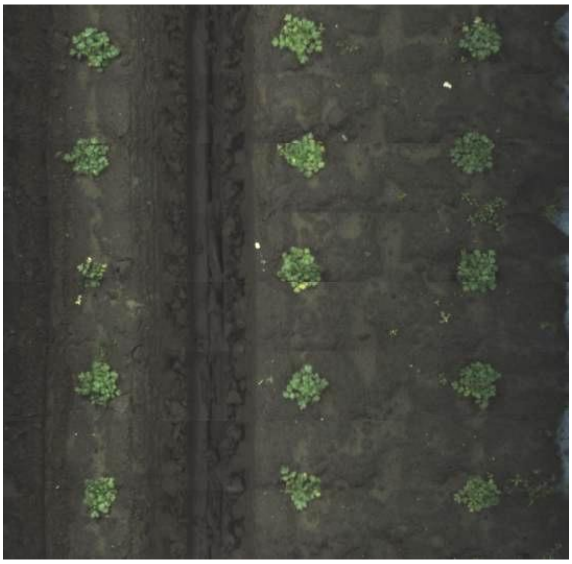


Figure 4: Colour image of 3 rows of a celeriac crop. 8 successive grabbed image strokes of 0.2m length by 1.5m width were merged to build this image.

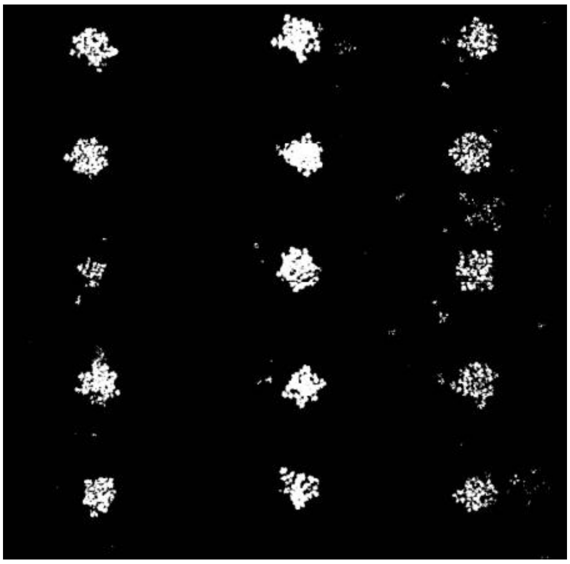


Figure 5: Plant segmentation result of the image shown in Figure 4.

Determination of crop row position

In order to guide the hoeing implements onto the exact row centres via the hydraulic sideshift cylinder the crop row position must be detected in the recorded images. Using prior knowledge of the row configuration and the mounting positions of the weeding actuators a camera to actuator position calibration is performed beforehand. The determination of the crop row position from the images is done for each crop row separately. As illustrated by Figure 6 a search area centred at the position of the expected row position is defined. Within that search area all intensity values of the binary image are added in vertical direction per column of the search area. This signal can be set out in a graph as shown in Figure 7. Templates for all image rows were built using a Gaussian bell-shaped curve per row (see solid line in Figure 7 for an example of such a template). By fitting the template on the intensity signal using cross correlation techniques the most likely position of the plant row was determined. Figure 8 shows the scores of the cross correlation and in Figure 6 the determined row position is overlaid in the plant image. This analysis is repeated every new image frame. The offset of the row position is thus calculated with the frequency of the captured image frames. Using a least square algorithm a straight line is finally fit through the positions of the last 8 frames. As a result the position offset of the camera (and thus the whole implement) with respect to the crop rows was known. The sideshift cylinder was then actuated to minimize the offset and to guide the implement onto the exact row centres.

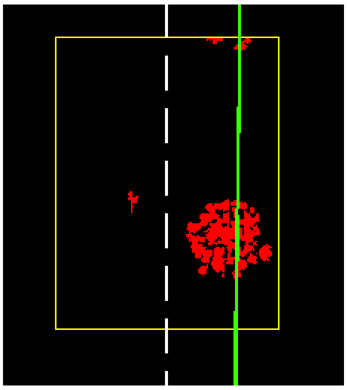


Figure 6: Determination of crop row position. Plant (red), search corridor (yellow box), target row position (white dashed line), determined row position (green solid line).

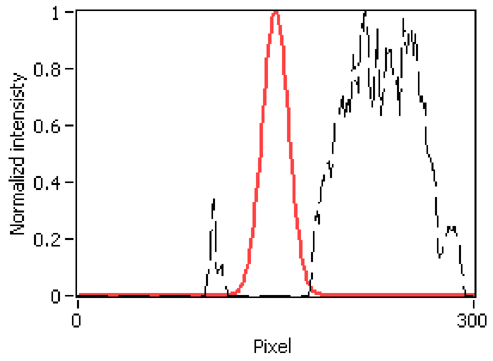


Figure 7: Row template (solid line) and plant signal (dashed line) of the image shown in Figure 6.

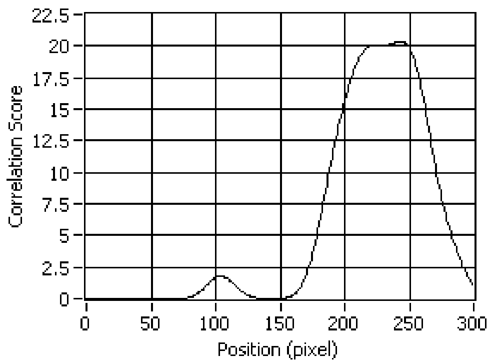
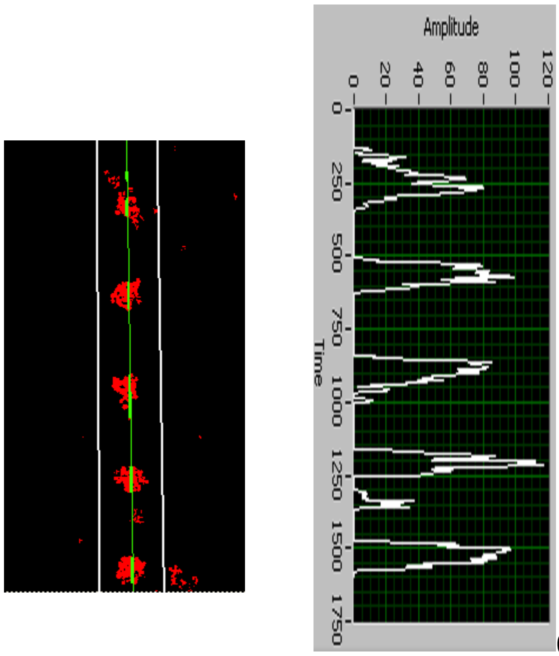


Figure 8: Cross correlation score of template and plant signal shown in Figure 7 for different offset positions, the maximum value indicates the best match

Determination of crop plant positions

Once the crop row position was known, the detection of individual crop plant positions in the row could take place. Also this procedure was carried out for each crop row available in the image separately. It can be assumed that the distances between the crop plants will be approximately constant in transplanted or precision drilled crops. Furthermore it can be assumed that the place where weeds appear is random.

The time domain signal of the crop plant positions can be understood as a signal of a certain frequency. The Fourier transform is a mathematical operation that decomposes a signal into its constituent frequencies. Furthermore the fast Fourier transform (FFT) is an efficient algorithm to compute the discrete Fourier transform (DFT) and its inverse. Bontsema et al. (1991) showed that a data sequence of weed and sugar beet plant positions processed with FFT and inverse FFT can reveal the crop plant positions. Bontsema et al. used a number of infrared light barriers to measure the plant signal at different heights. In our research we have the possibility to use the full information obtained by the image processing system described above. First step is the definition of a search corridor left and right of the crop row position. The width of the corridor was set to 2x the expected plant diameter. To generate the data signal, the number of pixels representing plants (weed and crop) within the search corridor were summed up per image row. The resulting intensity graph (Figure 6) was transformed from the time domain to the frequency domain using a FFT. It can be expected that the weed signal contributes to all frequencies in the spectrum, whereas the contribution of crop plants positions accumulates in a certain frequency band. In further data processing, only this frequency band was used and finally the real crop plant positions were revealed applying an inverse FFT. The authors want to emphasize that it is not mandatory that the crop plants are exactly spaced equally to reveal the individual plant positions. The allowed deviation a crop plant may have from the expected spacing can be parameterized in the software.



(b)

(a)

Figure 9: (a): Search corridor for the detection of plant positions in the row. Plants (red), determined row position (green centre line), border of search area (white lines). (b): associated intensity graph (see text for details)

Assessment of the detection score

For every iteration in the image analysis procedure (after the acquisition of every new image stroke of

1628x200 pixels) the following parameters were determined by scoring the images manually as well:

1. The number of correctly classified crop plant positions.
2. The number of incorrectly classified crop plants positions (positions where no crop plants are located).
3. The number of not detected crop plants.
4. The number of correctly classified weed plants in the row.
5. The number of not detected weed plants in the row.
6. Position of crop row detected/not detected. The crop row is classified as detected if the calculated line intersects the crop plants

From these numbers the following data is derived:

A. % incorrectly classified crop plants in relation to the total number of crop plants
B. % not detected crop plants
C. % detected weed plants
D. % correctly detected crop row position

4 RESULTS

Only qualitative information was available on the image segmentation process but it can be stated that the applied excessive green vegetation index algorithm together with the artificial illumination system and a fixed threshold for binarization worked convincing to segment the plants from the background. Figure 4 and Figure 5 show an example image.

Table 2 summarizes the classification results in the lettuce crop. The characters in the most left column of the table refer to the definition given in the previous section about the assessment of the detection score. On the first recording days the number of weeds in the field was very small which makes it difficult to judge the result of weed detection. In no case more than 1.2% of the crop plants are not detected. In the early crop stage all weed plants are detected. This number gradually decreases to 54.1% on the last day.

The position of the crop row was correctly detected in more than 99% of the images at all days. Problems in detection of the crop row occasionally occurred in situations where a number of crop plants were successive missing in the row. Figure 10 shows one example image of the lettuce crop in the mean crop stage recorded with the described setup. Overlaid on this image are the positions of the detected crop rows and the positions of the crop plants on these crop rows. The control signal to the actuator is derived from this information. At the position of the dotted lines the actuator is shifted in the row to hoe between the single crop plants.

Table 3 shows the classification results for the celeriac crop. The compact, well defined and circular shape of the plants worked beneficial for the classification algorithms. At all days less than 1% of the crop plants are not detected. The detection percentage for weed was 93.5% in the early crop stage and ended with 75.0% on the last measurement date. The position of the crop row was correctly determined for 100% of the cases. Figure 11 shows an example image in the celeriac crop in the same way as described for the lettuce crop.

Table 2: Classification results lettuce

Date	4-sep	10-sep	18-sep
Number of crop plants	687	664	675
Number of weed plants	4	5	11
A [%]	0.0	0.0	0.1
B [%]	0.6	0.0	0.1
C [%]	100.0	80.0	81.8
D [%]	99.9	100.0	100.0
Date	24-sept	20-okt	27-okt
Number of crop plants	630	421	419
Number of weed plants	90	199	220
A [%]	0.0	1.2	0.7
B [%]	0.0	0.2	1.2
C [%]	85.6	74.9	54.1
D [%]	100.0	99.4	99.1

Table 3: Classification results celeriac

Date	18-sep	24-sep	20-oct[1]	27-oct[1]
Number of crop plants	570	599	353	378
Number of weed plants	0	46	53	108
A [%]	0.0	0.2	0.8	0.0
B [%]	0.0	0.0	0.0	0.0
C [%]	-	93.5	73.6	75.0
D [%]	100.0	100.0	100.0	100.0

[1] for these days only a subset of the recorded images are analysed

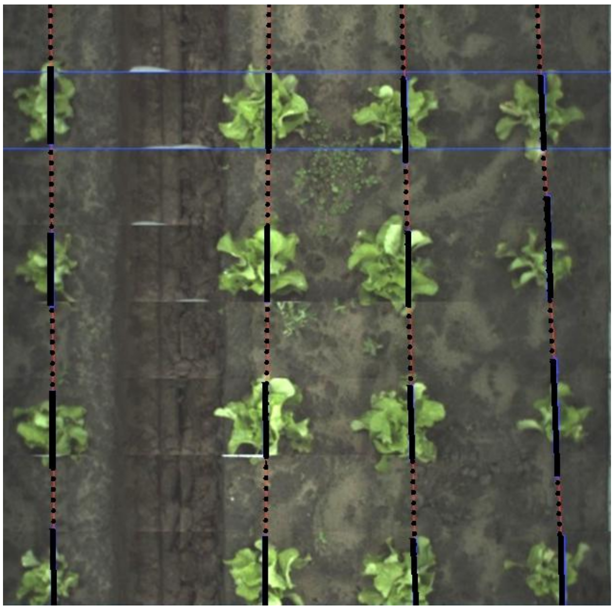


Figure 10: Example image of classification result 24-sep, lettuce. Determined row positions (dotted lines). Detected crop plant regions on the row (solid line)

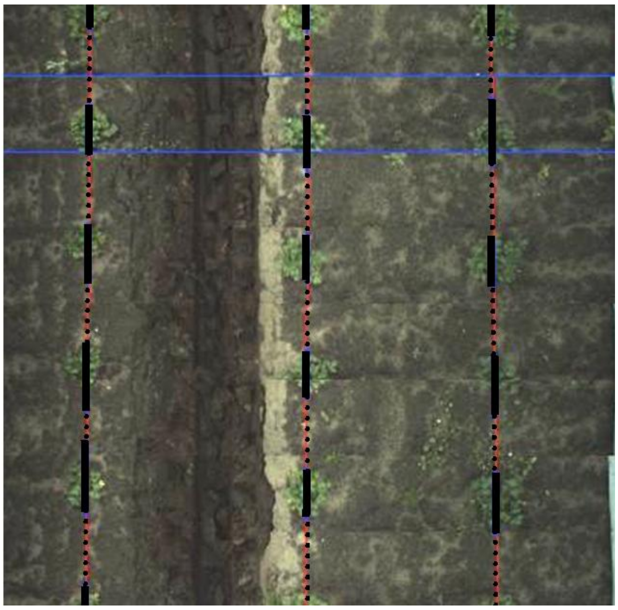


Figure 11: Example image of classification result 10-oct, celeriac. Determined row positions (dotted lines). Detected crop plant regions on the row (solid line)

The current system is capable to process up to 8 frames per second, corresponding to a maximum working speed of 1.6 m/s or 5.8 km/h. However, the critical factor concerning speed is in the current development stage not the processing of the images but the accurate control of the hoeing actuators.

5. DISCUSSION AND CONCLUSION

The described system was capable to determine the crop plant positions with a high success percentage in a lettuce and celeriac crop. Based on this information a control signal for a mechanical hoeing actuator was sent out in a way that the actuator enters the crop row only in-between the single crop plants in order to remove weed. Because the system was guided onto the exact row centres, weed between the crop rows can be controlled with standard fixed hoeing elements mounted on the same machine at the same time. The system can be configured for different row and plant spacings, plant sizes and crops.

The amount of weed plants was small in the beginning of the field experiments. More experiments are needed to answer the question how robust the system will perform in crops with high and very high weed pressure. From the theoretical point of view crop plants should be detectable as long as the signal derived from the crop plants predominates the signal derived from the weeds.

Problems in detecting the correct row position in situations a successive number of plants were missing in the row can possibly be solved by introducing adaptive filter techniques with outlier detection like e.g. a Kalman filter. Studies on this subject are already in progress. To ensure the correct working of the classification algorithms the user must pre-configure a number of parameters of the system such as expected plant size and plant spacing in the row. Simulations which are not part of this paper showed that in the case of a variable environment the use of adaptive and self-learning algorithms can significantly improve the results. Future research will focus on this subject.

The device described was tested in lettuce and celeriac but it can be expected that it can be applied to most transplanted or precision drilled crops as e.g. sugar beets, cabbage or endive. In the meantime on-going promising field test with a complete real-time system consisting out of 4 cameras and 6 weeding actuators are currently carried out.

6. REFERENCES

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