Plant recognition and localization using context information

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Abstract - **Most crops are cultivated in rows in a defined sowing pattern, i.e. with a constant inter-plant distance. This is an important feature that can be used for crop/weed discrimination. We present two novel methods, one pixel-based and one plant-based, for crop identification taking advantage of the knowledge of the sowing pattern. The pixel-based method uses a lateral histogram of plant pixels along the row direction. The lateral histogram forms a signal with a frequency that corresponds to the distance between crops. The plant-based method first segments out all plants and then uses the location of each plant as feature to find the crops among the weeds. The methods were tested on a set of 143 colour images each covering 80 cm of the sugar beet row. For the pixel-based and the plant-based method, 92% and 96% of the crops were found respectively. The plant-based method has been implemented on a weeding-robot and tested under field conditions. The method is sufficiently fast and robust for real-time control of an intra-row weed-tool performing intra-row cultivation, able to identify 99% of the crops and remove about half of the intra-row weeds. It may be concluded that the methods are well suited for discrimination. However, to be able to recognize and remove a larger amount of weed, the methods need to be completed by recognition methods based on particular features of individual plants such as colour and shape. The weed removal device also needs to be further developed. The advantage of using context information is that the method is not restricted to a specific crop. The most crucial parameters for successful discrimination through our methods are crop upgrowth and weed pressure. For moderate weed pressure (ca. 50 weeds/m^2) and moderate upgrowth (ca. 70 %), as in our case, context information can be used as an important feature for crop/weed discrimination.**

I. INTRODUCTION

As most crops are cultivated in rows and sown in a defined pattern, taking advantage of the geometrical properties of the scene could highly improve the result of crop recognition and localisation. Onyango et al. [1] developed a crop/weed segmentation algorithm that combined colour with the knowledge about the planting grid to increase the classification compared to colour alone. The distribution of crop plant pixels about the grid point was modelled as a bivariate Gaussian distribution. They reported a crop plant classification rate between 82-96% and a weed classification rate between 68-92%. In [2] the objective was to establish what performance that can be achieved through geometric segmentation alone. Crop plants were segmented from weed using a grid representing prior knowledge of their planting geometry. They also use an extended Kalman filter (EKF) based tracking algorithm that was used to track the grid from image to image for improvement precision and robustness to weeds and missing crop plants. They showed using field tests, that real time segmentation of crop from weeds was practical and EKF was able to track the individual crops through successive images. Bontsema et al. [3] model the crop row as a periodic one dimensional binary signal there plant material is one and no-plant is zero and weed is regarded as noise. Segmentation between crops and weed was achieved through low-pass filtering the signal, with a cut-off frequency higher than the expected crop period. In the find filtered signal, crop-positions appears as the highest peeks, where as peeks corresponding to weed is suppressed due to the fact that weed appearing between the crops have more uniform distribution in the frequency spectrum. They have also developed a mechanical weed tool and show that the system is able to perform intra-row weed control.

The aim of this paper is to present a vision based crop-grid matching algorithm for determination of crop location based on geometry only. The goal is to perform intra-row weed control. Weed control could be divided into three areas [4]: the area between the rows (inter-row), within the rows (intra-row) and close-to-crop, see Fig. 1. The last decade, a lot of efforts have been put into automatic guidance systems for inter-row guidance [5]. This has resulted in an improvement of the inter-row treatment, i.e. that the untreated band could be reduced to a few centimetres. However, the challenging tasks are still to perform intra-row and close-to-crop cultivation. The problem with weed control within the seed line is to determine the crop positions. When the crop is located, a mechanical tool or a precision sprayer could be used to remove the weed.

II. METHOD AND MATERIALS

A. Data collection

A total number of 143 colour images each covering 80 cm of a sugar beet row was collected using the weeding robot platform described in [6]. Changes in illumination cause

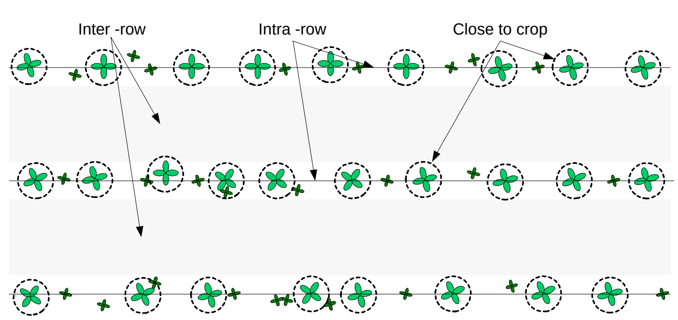

Fig. 1 Targets for weed control: inter-row, intra-row and close-to-crop.

colour shifts, and therefore, the colour camera is mounted inside an enclosure to avoid natural light using halogen lamps only as light. The size of the images was 768x576 pixels. The sugar beets was in their first true leaf stage and the upgrowth is about 71% and the intra-row weed pressure was in average 50 weeds/m^2. The inter-crop distance was 171 mm and the standard deviation was 23.5. There was no overlap between the images and in all images the position (defined as where the stem meets the soil) of the crops was recorded manually. The alignment error of the crops relative the plant row had zero mean and a standard deviation of 3.2 mm. An example of an image is found in Fig. 4 (top).

B. Image segmentation

To segment plant material from soil, a linear discriminant in the normalized RGB colour space [7] was used, see (1). Too dark pixels (intensity below 50) were classified as soil. The discriminant function was generated by manually sub-sampling pixels belonging to foliage and soil from each image in the data set. The discriminant parameters for the data set were: $k_{discrim}$ = 0.86 and $m_{discrim}$ = 0.06.

$$\left.\begin{array}{l} \mathrm{g}_{\mathrm{n}} - \left(r_n * k_{discrim} + m_{discrim}\right) > 0 \\ AND \\ \dfrac{\left(R+G+B\right)}{3} > I_{Threshold} \end{array}\right\} \Rightarrow \text{Plant pixel} \qquad (1)$$

where g_n = G/(R+G+B) and r_n = R/(R+G+B).

C. Model of a crop row

Knowing that the crops are sown in rows and with a certain, constant distance between them, it is possible to recognize and locate the crops based on this information instead of looking only at individual features of a plant, e.g. morphological or spectral properties. The distance between crops follows a Gaussian distribution [3], see Fig. 2. The distribution of the crop distance was tested for normality with D'Agostino's normality test with a 95% confidence level. Under assumption of normality, the crop-row can be modelled as a set of Gaussian bells [8], see Fig. 3, where the distance between the bells is the mean inter-crop distance, μ_d, and with a distribution that corresponds to the standard deviation of the crop distance, s_d, and the standard deviation of the alignment error of the crops relative the crop row, s_e. The N-set of Gaussian bells are defined as:

$$p(x,y) = \frac{1}{N\sqrt{2p s_d^2 s_e^2}} \exp\left\{-\frac{1}{2}\left[\frac{(x-nm_d)^2}{s_d^2} + \frac{(y-m_e)^2}{s_e^2}\right]\right\} \qquad (2)$$

$$n = 1 \ldots N, x = 1 \ldots X, y = 1 \ldots Y.$$

where X, along the row direction, and Y, perpendicular to the row, is the width and height of the image and N is the number of Gaussian bells and μ_e is the row position.

In (2) it is assumed that the bells could be placed exactly over the crop row. However, in a real situation, i.e. when driving along the row, the exact position of the row structure is not known because of the movement of the camera. This has the largest impact on the lateral position of the row, while the error due to heading is negligible. To solve this, (2) could either be extended by including the standard deviation of the movement of the camera or get the row offset and heading from a guidance system. In this data set, the lateral offset caused by the lateral movement of the camera has zero mean and a standard deviation, s_{lm}, of 12.4 mm.

A second extension to (2) is to add the difference between the true crop positions and the estimated crop position. The crop position is defined as where the stem meets the soil. However, this position is often difficult to estimate by computer vision and therefore the centre of the boundary-box around the plant foliage is used to estimate the plant position.

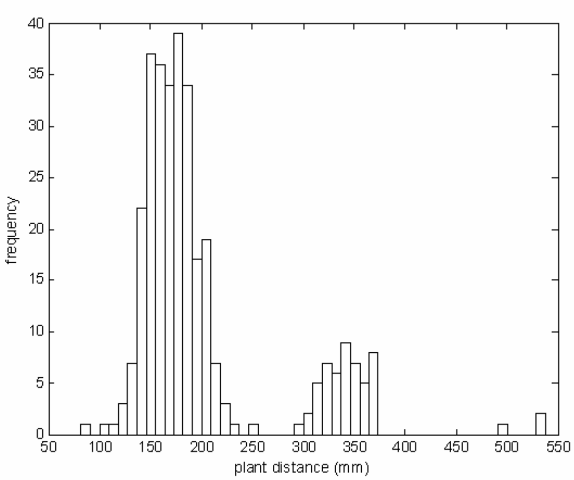

Fig. 2. Crop distance follows a Gaussian distribution. The second peek is due to missing plants.

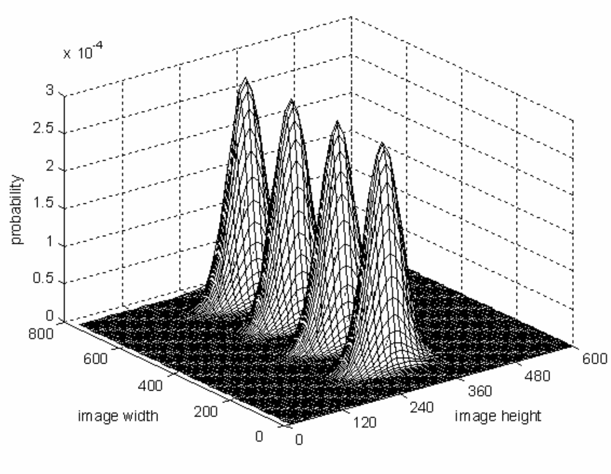

Fig. 3. Gaussian bells that correspond to average crop distance and alignment error of the crop row.

The difference between the estimated position and the true position was included in (2). The extensions for (2) are defined as:

$$s_{d'}^{2} = s_{d}^{2} + s_{pc}^{2}$$
$$s_{e'}^{2} = s_{e}^{2} + s_{pc}^{2} + s_{lm}^{2} \qquad (3)$$

where s_{pc} (4.7mm) is the standard deviation between the estimated crop position and the true crop position and s_{lm} is the standard deviation of the lateral movement of the camera.

In this paper we present two different methods for finding the position of the crops based on this crop-row model. The first method, that is a more heuristic approach, is pixel-based and uses a lateral histogram of plant pixels along the row direction. This method is used for comparison with a second, more formal approach. The second method is a plant-based method where all plants in the image are first segmented out before the row model is fitted.

The plant-based method uses extension (3) for (2). For the pixel-based method (2) is extended as:

$$s_{d'}^{2} = s_{d}^{2}$$
$$s_{e'}^{2} = s_{e}^{2} + s_{py}^{2} + s_{lm}^{2} \qquad (4)$$

where s_{py} (31.8mm) is the standard deviation of crop-pixels in the lateral direction of the crop row. In the following sections the methods are described in detail.

D. Pixel-based method

The pixel-based method uses a lateral histogram of the plant pixels along the row direction, see Fig. 4. All pixels segmented as plant pixels (2) are applied in three steps: First, the probability in the y-direction was calculated with the difference that, instead of the lateral offset of the plant positions, the position of the plant-pixel was used, see (4). The second step was to sum up all pixels per column with a probability greater than zero, thus forming a signal with a frequency that corresponds to the average crop distance. The histogram is then low-pass filtered with a cut-off frequency at least twice the expected number of crops in the image. In our case the expected number is between 4-5 crops and experiments showed that a cut off frequency of 15 Hz gives a smooth signal where the peeks corresponds to crop candidates. Weed-pixels are regarded as noise that is added onto the periodic signal of crop-pixels. Some of the weeds are suppressed by the low-pass filtering. The remaining is candidates for being a crop. The third step is to find the most probable crops in the signal. For this x-part of (2), a set of Gaussian bells, is fitted to the peeks of filtered signal. Only the position of the peek is used to fit to the Gaussian bells. Fig. 5 shows the amplitude of all peeks (logarithm) in the lateral histogram and the corresponding best fit with five Gaussian bells. The reason why the logarithm is used, is to suppress clusters of weed, or weed/crops grown together, and level out differences in crop size. Moreover, as seen in Fig. 5, the Gaussian bells are not complete but truncated meaning that the Gaussian bells are restricted to ± 1.96σ.

An alternative approach to the Gaussian bell fitting, is to fit a sinusoid to the lateral histogram. This idea has been used for identifying crop-rows as described by Olsen in [9]. The intention here is to use the sinusoid to find the periodic properties of crops instead of the row structure. The sinusoid, *s*, is defined as:

$$s = a\sin(2pd) + b\cos(2pd) \qquad (5)$$

where *d* is the distance between crops and the terms *a* and *b* is found by least square fit. This gives the phasing of the signal. The most probable crop is then found by looking for the peeks closest to the sinusoid peeks, see Fig. 6. The advantage of the sinusoid method is that it is faster than the Gaussian bell approach.

The advantage of the pixel-method is that it is simple and do not require a lot of computer power. It is also less sensitive to movements of the camera. However, since the upgrowth is not 100% there will always be weed standing at crop position and consequently some weed will be classified

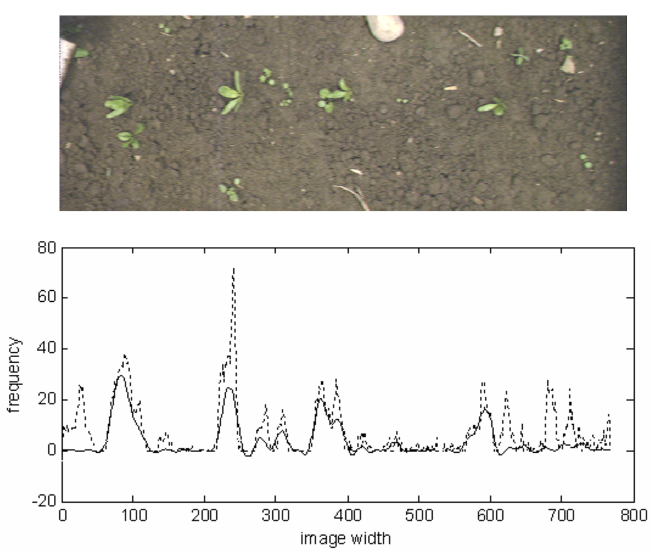

Fig. 4. Original image (above). Histogram of plant-pixels (dotted) and corresponding filtered signal (solid)(below).

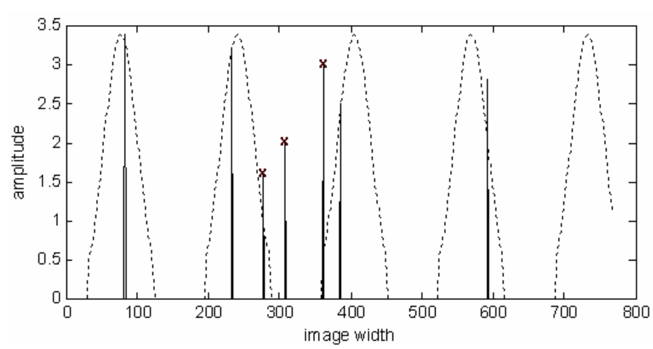

Fig. 5 Fitted Gaussian bells (dotted) where peeks are crops found and marked peeks (x) are weed. The peeks correspond to the logarithm of the peek amplitude in the lateral histogram.

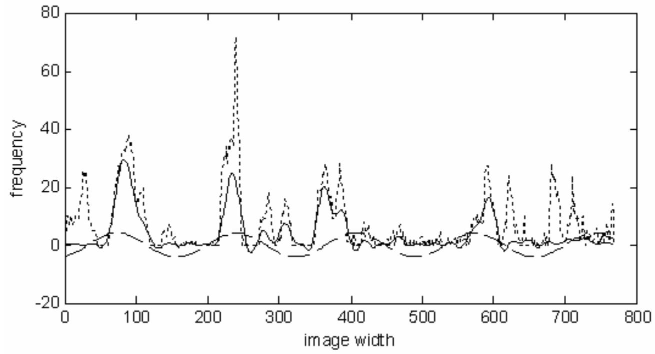

Fig. 6. Lateral histogram with a sinusoid (dashed) fitted to the low-pass filtered signal (solid)

as crops. Using the pixel method there is no direct way of handling this by further classification, i.e. by plant features or colour. Therefore, we have also developed a plant-based method.

It is also worth mentioning that row-cultivation before intra-row weeding improves the performance of the pixel-method. It is also common that row-cultivation is performed before the hand-hoeing of the intra-row weeds in ecological farming of sugar beets. If the row-cultivation is efficient, the vertical filter (y-direction of (2)) can be left out.

E. Plant-based method

The second method is a plant-based method. This means that all plants are segmented before the Gaussian bells are fitted. The first step is to binarize all pixels belonging to plant pixels according to the segmentation algorithm described above. The objects are then merged into complete plants by merging all objects within a given distance, i.e. the distance between the centres of the objects. In this dataset the merging distance was found experimental and set to 27.6 mm. This simple merging algorithm led, in some cases, to over-segmentation but this problem is beyond the scope of this paper and therefore plants merged together was treated as one plant. The centre of each plant is then calculated with the boundary-box, see Fig. 7 (middle). Each plant is then given the weight one and the Gaussian bells is fitted to the position of each plant. Giving the weight one means that all plants are given the same probability. However, if further

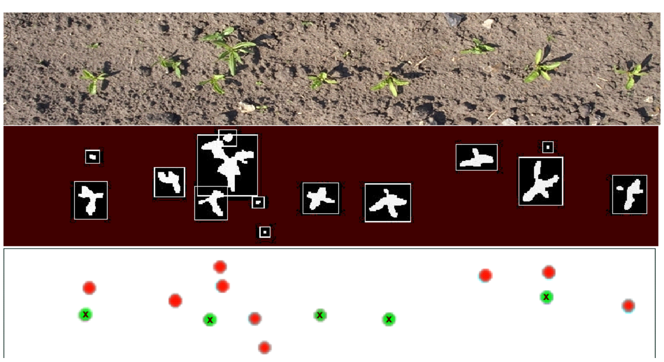

Fig. 7 Original image (top) segmented image with the boundary-box representing one plant (middle) and found crop (x) and weed with Gaussian bell fit (bottom)

classification is applied to the plant, i.e. if colour and shape features are included the probability of being a crop or weed can be added before fitting. But, in this paper we only investigate the properties of recognition and localisation using geometric properties only. Therefore, the weight for each plant is set to one.

To speed up the computing the Gaussian bells (2) is divided into an x-part and a y-part first calculating the lateral probability (y-direction) before fitting the x-direction (set of one-dimension Gaussian bells).

III. RESULTS

A. Pixel-based method

Table I show the result from the sinusoid fit and Table II the results from the Gaussian bell fit. Both methods identified over 90% of the sugar beets and about half of the weeds were identified.

TABLE I
USING SINUSOID FIT. CLASSIFICATION RATE 80%

	Classified as sugar beet	Classified as weed
Sugar beets	91% (418)	9% (39)
Weeds	34% (194)	66% (384)

TABLE II
USING GAUSSIAN BELL FITTING. CLASSIFICATION RATE 80%

	Classified as sugar beet	Classified as weed
Sugar beets	92% (421)	8% (36)
Weeds	34% (197)	66% (381)

It is important to notice that no compensation for the movement of the camera, i.e. the robot, is used.

B. Plant-based method

Table III and IV show the result from the plant-based method with and without compensation for the movements of the camera. When comparing the results from crop classification in table I and II with table III, it can be concluded that the pixel-based method is less sensitive to lateral movement compared to the plant-based. However, when the movement is compensated, i.e. by correcting heading and offset, the plant-based perform better, see table IV.

TABLE III
NO COMPENSATION FOR THE MOVEMENT OF THE CAMERA SYSTEM (THE ROBOT). CLASSIFICATION RATE 77%

	Classified as sugar beet	Classified as weed
Sugar beets	88% (404)	12% (53)
Weeds	44% (117)	56% (151)

TABLE IV
COMPENSATION FOR THE MOVEMENT OF THE CAMERA SYSTEM (THE ROBOT). CLASSIFICATION RATE 82%

	Classified as sugar beet	Classified as weed
Sugar beets	96% (437)	4% (20)
Weeds	39% (108)	61% (166)

IV. FIELD TEST

The plant-based method was implemented on the weeding-robot described in [6]. The robot is able to follow the sugar beets row by itself. It uses a camera facing forwards with a near-infrared filter to find the position of the row structures. A colour camera system is then looking down used for individual plant identification. The colour camera is mounted inside the robot perpendicular to the ground and all natural light is excluded using only halogen lamps for light. The camera looks in a window, covering about 30x47 cm, along one row structure, see Fig. 8. The sugar beets were sown with 5.2 crops per metre. This means that two crops appear in each image, as the average distance was about 19 cm.

To increase robustness, multiple images are combined to a single image. In our case, we used a combination of three images covering 1.4 m of the row. This means that at least seven crops could be expected.

The field test was performed at an organically cultivated sugar-beet field in June 2004. The upgrowth was high, about 80%, and at the time of cultivation the crops where in their first true leaf stage with a diameter of about 5-7 cm. The system was set up for two test runs. All sugar beets and weed, in a band of a few cm around the crop row, were counted manually before and after cultivation. The result is presented in Table V.

TABLE V
THE NUMBER OF SUGAR-BEETS AND WEEDS BEFORE AND AFTER CULTIVATION

Run		Before weeding	After weeding
1. Distance 24m	Sugar beet	100	99
	Weed	117	69
2. Distance 25m	Sugar beet	100	99
	Weed	119	56

The test shows that 99% of the sugar beet where not removed and between 41-53% of the weed was removed. However, since that the upgrowth was about 80% there was some weed that was placed at crop position, see Table VI missing crop weed. This weed was not detected by the algorithm and the weed was classified as crop. A second group of weed that was not removed were those that stood close to crop. By close-to-crop means the weed that are located a few centimetres from the crop. Examples of close-to-crop errors are; weed that grows together with the crop or is merged together in the pre-processing step, when single plants is formed from multiple objects. Some of the weed in this category is also located out of reach of the weeding tool, and therefore not removed. The speed of the weeding-tool is limited e.g. that some weed was missed. The number of weed that was missed is found in Table VI, called close to crop weed.

TABLE VI
THE POSITION OF THE REMAINING WEEDS AFTER INTRA-ROW CULTIVATION

Run	Missing crop weed	Close to crop weed	Other	Total
1	7	19	43	69
2	15	20	21	56

Other reasons to that not all weed was removed were that some weed also stands out of reach of the weed-tool because of the lateral movement of the robot. Another reason for error was that plants were merged together forming lager clusters. When a cluster was merged together with a crop, the cluster was treated as a single plant that resulted in the weed not being removed. Remaining weed due to these kinds of errors is found in the "other" category in Table VI.

The average intra-row weed pressure was 50 weeds/m^2 in these tests. Increasing weed pressure results in that more weed being classified as crops since the upgrowth not is 100%. Increasing weed-pressure also increase the probability for crops and weed to grow together. Upgrowth and weed pressure is the most critical parameters for successful discrimination.

V. CONCLUSION AND FUTURE WORK

In this paper, we present two methods that address the problem with recognition and localisation of intra-row weed in row-cultivated crops. The methods are based on geometric features e.g. that no additional features like colour or shape are used. The advantage of this approach is that the methods are not restricted to a specific crop and only a few parameters have to be known in advance. Moreover, the methods could also be applied in an early crop-stage when the crop is not possible to identify with colour or shape feature.

Both methods presented in this paper are sufficient to recognize and locate the sowing pattern and able to classify over 90% of the crops even with the presence of weeds. However, since crops do not have 100% upgrowth, some weed will be classified as crops, i.e. weed positioned at "crop positions". This problem grows with increasing weed pressure. Increasing weed pressure also brings on more overlapping plants that lower the performance of the system, especially when weed is merged with crops. The pixel-based method is therefore more suited when the weed-pressure is low and the upgrowth is high. With higher weed-pressure and/or lower upgrowth the plant-method is preferable.

The plant-based method has been implemented on a weeding-robot and tested under real field conditions. The method is sufficiently fast and robust for real-time control of an intra-row weed-tool performing intra-row cultivation, able to identify 99% of the crops and remove about half of the intra-row weeds.

Future work will address the problem of weed standing close to crop, and causes crops and weed to merge together, and the problem of weed classified as crops. This will be achieved by improving the segmentation algorithm and the

Fig. 8. Example image from field tests with sugar beet encircled.

plant-based method will also be extended with methods for plant identification based on colour and shape features. The possibility to automatic identification of the crop distance will also be investigated. There will also be a further improvement of the weeding-tool addressing the problem of weed standing out of reach of the weeding-tool and dynamic issues of the weeding-tool.

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VII. REFERENCES

[1] C.M Onyango, J.A. Marchant, "Segmentation of row crop plants from weeds using colour and morphology", *Computers and Electronics in Agriculture*, vol. 39, 2003, pp. 141-155.

[2] N.D. Tillett, T. Hague and S.J. Miles, "A field assessment of a potential method for weed and crop mapping on the basis of crop planting geometry", *Computers and Electronics in Agriculture*, vol. 32, Issue 3, October 2001, pp. 229-246.

[3] J. Bontsema, C.J van Asselt, P.W.J. Lempens and G. van Straten, "Intra-row weed control: A mechatronic approach", *1st IFAC Workshop on Control Applications and Ergonomics in Agriculture*, Athens, Greece, June 15-17, 1998.

[4] H.-W. Griepentrog, M. Nørremark, H. Nielsen, S. Blackmore, "Individual plant care in cropping systems" *4th European Conference on Precision Agriculture*, Berlin, Germany, July 2003.

[5] Åstrand, B., *Mechatronics in Agriculture - Row Guidance System for Agricultural Field Machinery*, Licentiate thesis, School of Electrical and Computer Engineering, Chalmers University of Technology, Göteborg, Sweden, October 2000.

[6] B. Åstrand and A.-J. Baerveldt, "An agricultural mobile robot with vision-based perception for mechanical weed control", *Autonomous Robots*, vol. 13, 2002, pp 21-35.

[7] H.D. Cheng, X.H. Jiang, Y.Sun, Jingli Wang, "Color image segmentation: advances and prospects", *Pattern Recognition*, vol. 34, 2001, pp.2259-2281.

[8] J. Fredriksson, T. Turujlija, *Classification of Sugarbeet Plants based on Contextual Information*, Technical Report, Centre of Computer System Architecture, Halmstad University, January, 1999.

[9] H.J. Olsen, "Determination of row position in small grain crops by analysis of video images", *Computers and Electronics in Agriculture*, vol. 12, 1995, pp. 147-162.