

# **BRAINWEED - TEACH-IN SYSTEM FOR ADAPTIVE HIGH SPEED CROP / WEED CLASSIFICATION AND TARGETING**

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## **ABSTRACT**

Conducting inter row mechanical weeding requires the precise location of each individual crop plant is known. One technique is to record the global position of each seed when sown using RTK-GPS systems. Another approach is to capture images of the crop row and then use image processing and machine learning to identify crop and weed plants based on leaf shapes. A third approach is to distinguish crops from weeds by detecting the relative location of all plants and use the fact that many crop plants are sown in a distinct patterns to maximize the yield.

Although using precision RTK-GPS systems the position estimate still have a significant error. Crop detection in images using object recognition techniques suffer from the fact that local factors both regarding time and geographically location influence the plant structure and color.

This paper addresses the problem of inter row weeding by suggesting a system that uses spatial information in an offline algorithm to detect the most likely crop plants in recorded data. The detected crop and weed plants are then used to construct a shape based classifier to be used for online classification of unknown plant objects. The practical approach is to first record a small amount of data from the field in question. This data is then analysed and plant objects obeying a specific grid pattern is marked as crop plants and used in the second step to train a shape based classifier. Now the rest of the field can be treated using the specialized shape classifier. This system is more robust since it learns the current appearance of the crop in a field instead of relying on a general model. Tests have been conducted where the practical approach have been followed. Sample data has been recorded with the Robovator precision weeder in several beet-fields.

**Keywords:** precision weeding, machine learning

## INTRODUCTION

Precision agriculture requires detailed information about fields. If the weed density or composition of weed species in a small patch is known an intelligent application of herbicides can be conducted considering economic and environmental trade offs. If weeding is to be done on a single plant scale it is not enough to consider patches - one have to address single plants. Research have been conducted involving the development of systems capable of classifying single plants (Tian et al., 1997, Weisa et al., 2007, Giselsson, 2010) and have done so with relative success but still no general, robust system exists.

Systems that utilize the fact that many crops are sown or transplanted in rows or grids are widely used. Row detection systems for steering mobile farming equipment are already commercially available e.g Claas Cam Pilot([claas.com](http://claas.com)). Some researchers tries to exploit the fact that to optimize yield, crops are often placed with a certain spacing inside the rows. Onyango and Marchant, 2003, fit a grid onto images of patches and use this information to build a statistical model of the likelihood of crop plant pixels with respect to pixel coordinate in the system. Åstrand and Baerveldt, 2005, had a similar approach as Onyango and Marchant, 2003, except that they fitted a gaussian mixture model onto segmented images and found the most likely crop plants.

Midtiby, 2012, uses spatial context information to do real time predictions of the position of the next unseen crop on the basis of the latest few detected crops. In this paper we take one step further towards a general system capable of distinguishing crops from weeds using both spacial context information and object shape appearance. The hypothesis is that building a training set of samples present in the field in question makes is possible to better take into account variations in the plants due to e.g. growth stage, nutrition and weather conditions. To accomplish this the procedure is to first record data from the field and carry out offline analysis of the data using knowledge about sowing geometry or detect the most dominant systematic geometry in all plant material. The result of this offline process is candidates of crops and weeds. Highly likely crops and weeds are extracted and used as training samples for a shape based classifier. This classifier can be used online to recognize plants in the rest of the field in question. To improve accuracy of the classifier context information of detected crops are also used online to predict positions. Results from simulated field data indicated that the concept works and have potential to overcome the difficulties in constructing a general plant classifier. Further test have been planned to verify the usability of the procedure.

## MATERIALS AND METHODS

As mentioned the weeding procedure that is documented in this paper have 2 phases. First phase is the learning phase where the condition of the crops in a specific field is learned. In the second phase weeding is executed using acquired information. In the following section used equipment and methods are described.

## Mechanical tools

The physical aspects of this process can be carried out by the Robovator field robot developed by Frank Poulsen Engineering (see [visionweeding.com](http://visionweeding.com)). The Robovator has the ability to both carry out data acquisition and mechanical weeding.

Data is stored in the form of bispectral images recorded by two line cameras recording the red and near-infrared wavelength respectively. It records in a continuous manner and track displacements mechanically so the end result are image lines of red and near-infrared stamped with a relative displacement. This makes it possible to stitch image lines together where speed changes have been taken into account. The physical resolution of each pixel is approximately 1.1 mm x 1.1 mm. The fact that image line data can be collected into long strips obeying a fixed physical resolution enables the analysis of plant positions over long distances. The use of bispectral cameras ease the segmentation of plant material from soil by using the widely applied NDVI color mapping (Rouse et al., 1973) followed by thresholding.

Weeding is conducted by knives placed horizontally and slicing through the soil 1 to 2 cm below the surface. These knives are mounted on pneumatic arms that are able to either place the knives inside the crop row or in the inter row strip. The Robovator can be seen on figure 1.



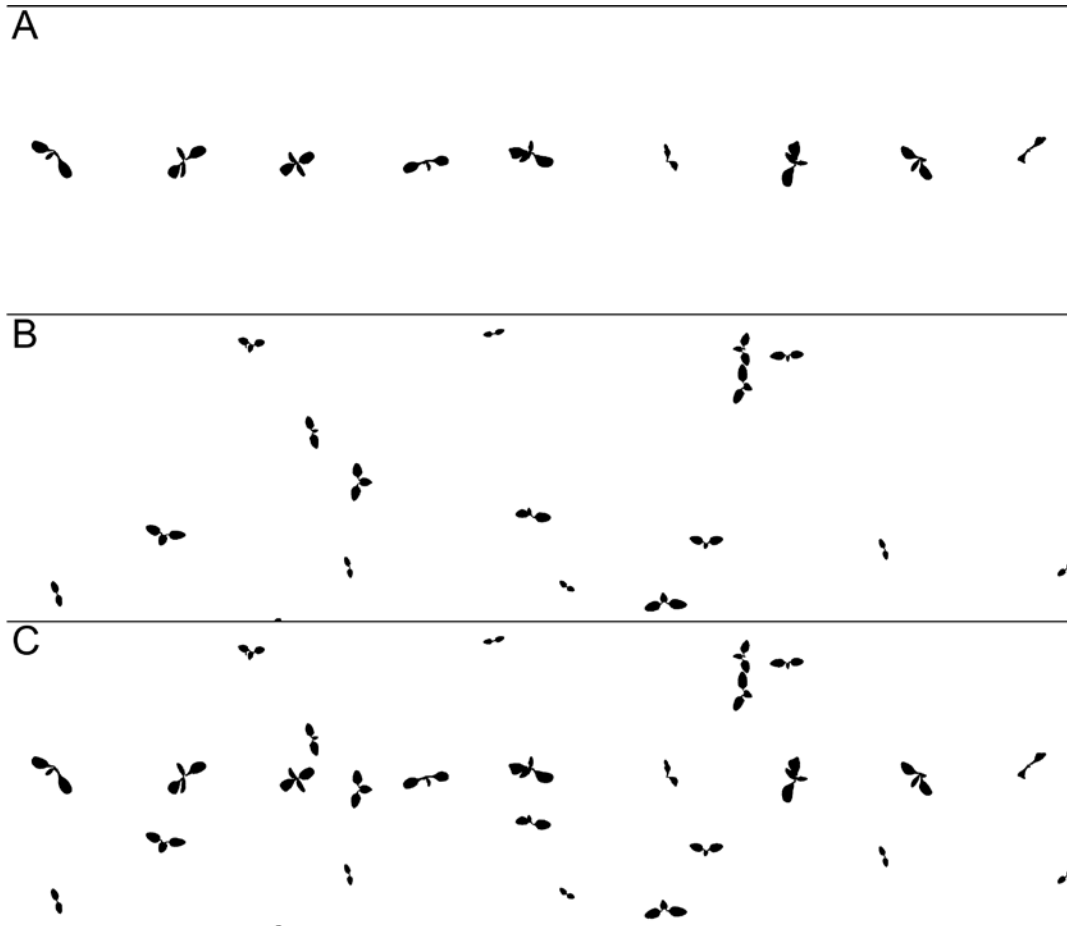
**Fig. 1. Picture of the Robovator performing mechanical weeding in transplanted lettuce. Source: [visionweeding.com](http://visionweeding.com)**

## **Detecting whether plants is inside the row structure, phase 1**

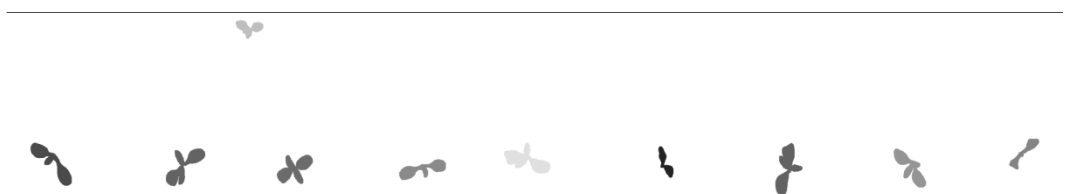
From the acquired image we want to extract vegetation blobs that are highly likely to belong to either the crop or weed class. These samples are determined by calculating a position score for each of the observed plants. High values of the position score indicates that the plant is a part of the row structure and similarly low values indicate plants placed outside of the row structure. For calculating the position score, the expected distance between neighbouring crop plants must be known, this distance is used to find the location of expected neighbour crop plants. The two nearest expected crop plant locations were determined and the position score was calculated based on the distance from the expected crop plant location to the nearest plant to that location. The position score is described in detail in (Midtiby, 2012).

The plants were ordered by their position scores. Training samples for the crop class consisted of the  $N$  plants with highest position scores.  $N$  was defined as 90% of the expected number of crop plants,  $C$ , in the acquired image. Weed training samples consisted of the  $0.5 M$  plants with lowest position scores, where  $M$  was the number of plants observed subtracted the expected number of crop plants.

The method was tested on simulated data where crops were placed with a fixed spacing although subject to variation according to a noise model. Weed plants were placed random in the field. A subpart of the simulated field strip is depicted in figure 2. Figure 2.A shows the true crops and figure 2.B the true weeds and figure 2.C is the combined field strip. Figure 3 shows the result of applying the position score algorithm. Plants with dark shading have high position score.



**Fig. 2 A: Subpart of true crop plants - corn flower (*Centaurea cyanus*) is used as crop. B: Subpart of true weed plants - night shade (*Solanum nigrum*) is used as weed. C: Subpart of the generated field strip with both crops and weeds.**



**Fig. 3. Outcome from position score algorithm where intensity of each plant is related to its calculated position score value.**

## Training classifier, phase 2

Using the output from the offline algorithm which consist of highly likely crop samples and highly likely weed samples a shape classifier is trained. For each sample a number of shape features are calculated. In Giselsson et al. (2012) 21 numeric shape features widely used in the literature of object recognition (e.g. in Du et al., (2007), Åstrand & Baerveldt (2002), Woebbecke et al., (1995), Mei (2010), Weis & Gerhards (2007)) were compared with shape features based on a parametrization of a distance transform, referred to as LPFS. In this work we have chosen to only use the Legendre Polynomial Feature Set (LPFS) since the former mentioned paper concluded that this feature set perform equally well or better than often used standard shape features. This feature set consist of 10 numerical features.

The performance of the LPFS features can vary with different data preprocessing. In this work we have chosen to conduct a data normalization step on the calculated distance maps as described in Giselsson et al. (2012). This normalization means that the generated features will be robust against scale changes.

As a classifier scheme for this research we chose a nonlinear Radial Basis Function Support Vector Machine, RBF-SVM, since it has been reported to achieve good results (Giselsson et al, 2012, Giselsson, 2010, Singh, 2010). The SVM is based in statistical learning theory and finds the best separating plane between two classes by maximizing the margin between the separating plane and those samples from each class that are closest to the separating plane. The training process therefore consist of solving a optimization problem. The method can handle non separable classes by introducing slack variables into the optimization problem and thereby also introducing a parameter,  $C$ , that controls the trade off between allowed misclassifications and speicalization of the classifier. Using the kernel trick the method can be expanded to be nonlinear. The kernel used in this research is the widely used Radial Basis Function kernel that introduces another parameter,  $\gamma$ . The training phase contains the need to estimate optimal or suboptimal values for  $C$  and  $\gamma$  and to solve the optimization problem. In this research the Prtools matlab toolbox (Pekalska et al., 2007) have been used for parameter estimation, training and testing.

## RESULTS

In the simulation 141 plant objects were found. According to the known inter crop plant distance a total of 48 crop plants were expected so  $C=48$  and hence  $N$ = approximately 43. The quantity  $M$  was  $141-43 = 98$  so the number of extracted highly likely weed plants was  $98*0.5 = \text{approx } 49$ . This means that the classifier will be fet with 43 likely crop plants and 49 likely weed plants. In the simulation the extracted crop plants consisted of 37 true crop plants, 3 mislabelled weed plants and 2 unknown objects. Likewise the extracted weeds consisted of 40 true weeds, 0 mislabelled crop plants and 4 unknown samples. In total 86 samples were extracted of which 77 were true positives resulting in a accuracy of 90 %.

Using likely crop and weed samples from the context based learning phase a SVM-RBF classifier is trained. Used samples amounted to 43 likely crop samples and 49 likely weed samples. Using stratified cross validation with 10 folds on this data set result in a classification accuracy of 82.8 %. Parameters used for the RBF-SVM classifier were  $C=0.4138$  and  $\text{gamma} = 0.088$ . It is important to remember that this classifier is trained with data containing mislabeled samples and therefore the classification accuracy will be lower for that reason. When using the trained classifier on unseen but correctly labeled data consisting of 69 samples of crops and 30 samples of weed a classification accuracy of 85 % was achieved.

## CONCLUSION

Extraction of highly likely crops and weeds from a simulated field strip using only context information achieved an accuracy of 90 %.

A classification accuracy of 85 % was achieved on correctly labeled samples after training an RFB-SVM classifier on data with 10 % label errors. The classifier was based on shape features called LPFS.

## REFERENCES

- Midtiby, H. S. 2012. Real time computer vision technique for robust plant seedling tracking in field environment. University of Southern Denmark.
- Giselsson, T. M. 2010. Real Time Crops and Weeds Classification from Top Down Images of Plant Canopies. Master thesis. University of Southern Denmark.
- Giselsson, T. M., H.S. Midtiby, and R.N. Jørgensen. 2012. Seedling Discrimination using Shape Features derived from a Distance Transform. (*submitted to Sensors*).

- Onyango, C. M., and J.A. Marchant. 2003. Segmentation of row crop plants from weeds using colour and morphology. *Computers and Electronics in Agriculture*, 39(3):141-155.
- Pekalska, E., D.D. Ridder, D.M.J. Tax, and S. Verzakov. 2007. A Matlab Toolbox for Pattern Recognition. *Pattern Recognition*, 1(August):1-61.
- Rouse, J.W., R.H. Haas, J.A. Schell, and D.W. Deering. 1973. Monitoring vegetation systems in the Great Plains with ERTS. *In* S. C. Freden & M. A. Becker (Eds.), *Proceedings of the Third ERTS Symposium* (Vol. 1, pp. 309-317).
- Singh, K., I. Gupta, and S. Gupta. 2010. SVM-BDT PNN and Fourier Moment Technique for Classification of Leaf Shape. *International Journal of Signal Processing, Image Processing and Pattern Recognition*. 3(4):67-78.
- Tian, L., D. Slaughter, and R. Norris. 1997. Machine Vision identification of tomato seedlings for automatic weed control. *Transactions of the ASAE*. 40(6):1761-1768.
- Weis, M., & Gerhards, R. (2007). Feature extraction for the identification of weed species in digital images for the purpose of site-specific weed control. *Precision agriculture'07*. Papers presented at the 6th European Conference on Precision Agriculture, Skiathos, Greece, 3-6 June, 2007. (pp. 537-544).
- Woebbecke, D.M., G.E. Meyer, K. Von Bargen, and D.A. Mortensen. 1995. Shape features for identifying young weeds using image analysis. *Transactions American Society of Agricultural Engineers ASAE*, 38(1):271-281.
- Åstrand, B., and A. Baerveldt. 2005. Plant recognition and localization using context information and individual plant features. *Mechatronics and Robotics 2004 special session Autonomous Machines in Agriculture*.