Unsupervised weed detection in spinach seedling organic farms

Eftim Zdravevski

Unsupervised weed detection in spinach seedling organic farms

Petre Lameski, Eftim Zdravevski, Andrea Kulakov and Dejan Gjorgjevikj
University of Sts. Cyril and Methodius in Skopje, Macedonia
Faculty of Computer Science and Engineering
{petre.lameski, eftim.zdravevski, andrea.kulakov, dejan.gjorgjevikj}@finki.ukim.mk

***Abstract*— Weed removal during the early phase of seedling development is a very important process in agriculture. It helps the useful plants to sprout quickly and use most of the soil's organic materials for their own development. The increasing number of human population in the world increases the amount of food that needs to be produced thus the automation of the process of plant based food production is required. In this paper we present an unsupervised approach towards automated weed detection in spinach seedling farms. The images are taken under natural conditions and their green regions are segmented to detect the plants in the images. After that, image descriptors are generated for each plant segment and unsupervised clustering is performed to separate the weeds from the spinach seedlings. The results of the unsupervised learning are compared with the results obtained with supervised learning on the same data. The conclusions are presented in the paper.**

***Keywords*—** *Precision agriculture, Image Processing, Unsupervised Learning*

I. INTRODUCTION

The increasing number of the human population requires increased efficiency in the process of food production. According to the research presented in [1], the availability of the arable land decreases with the process of urbanization and within the next 50 years, according to the current urbanization trends, the available land for food production would fall below the minimum needed per human. This trend requires either increasing the available land area in the world, or increasing the food production per available land area. One of the ways to increase the food production is with automation of the production process. This process is also required in the organic plant food production. Although many of the aspects of food production have already been automated, there are still areas in the organic farming where parts of the plant growing processes are manually performed by farmers. Such process is the weeding of plants.

The weeding is an important process especially in the early plant development because it allows the useful plants to use most of the organic material in the ground for their own development. This on the other hand increases the yield of food per land unit. There is existing research and commercially available solutions for automated weed control of the plants in different levels of their development. There have been some early attempts to automate this process by using mechanical tools for weeding without the usage of any sensors. According to [2] precise agriculture machines have already been deployed, but their availability and robustness is very limited. Nevertheless, in the areas and plant species for which this technology is applied, increased productivity has been reported.

The importance of machine learning and image processing techniques for future precision agriculture development has been emphasized in [3] and [6]. Some efforts towards using robotic systems for automated weed control and segmentation have been reported in the literature. In [4] a direct application actuator for herbicides that increases the efficiency of the applied chemicals is described. In [5] the authors use specific color manipulation to segment the green plants from the land and after that employ artificial neural network based classification to distinguish the weed from the useful plants. In [8] and [9] the authors propose an automated approach towards the plant segmentation from the soil and automated weed segmentation.

There are also quite a few commercial companies that invest their resources towards precision agriculture solutions [3]. Many other approaches have been suggested in the literature, however most of them base their methods on supervised learning of plant models and plant recognition based on those models. In this paper, we present an unsupervised learning attempt to generate a model for the regular plant and distinguish it from the weed. Our approach is motivated by the need of a robust robotic platform that would automatically remove the unwanted plants from the soil and that would learn the plant model without the need of human intervention. This would allow the robot to be used on any plant field without the need of retraining or switching the plant model.

II. SEGMENTATION AND PREPROCESSING

The first part of the learning process is the data retrieval. For this part we have obtained a dataset of spinach seedling images. The dataset we use in this paper is consisted of 13 images taken by camera from spinach seedlings under varying light conditions. The seedlings in the images are not seeded in a row as is usual in agricultural fields but randomly. This makes the segmentation and classification of the plants much more difficult. The images contain plant, soil and other parts that are not in our interest. This is why the first part of the data processing is the segmentation of the image. Any robot that is to use a camera as a sensor for plant detection would need to segment the image to soil and plants. For the segmentation of the plants we use the VEG index reported in [7]. The VEG index is calculated by first normalizing the values of the RGB image as in (1):

$$r = \frac{R}{R+G+B}, g = \frac{G}{R+G+B}, b = \frac{B}{R+G+B} \tag{1}$$

After the normalized values are calculated, the lighting variations are partially compensated. This allows the detected green to be more resilient to lighting variation. The VEG index is calculated as in (2):

$$VEG = \frac{g}{r^{\alpha} * b^{1-\alpha}} \tag{2}$$

According to [7] the best results are obtained for α=0.6667. The vegetation index gives green areas for values of VEG>1.0. In our experiment we were using VEG>1.1 to eliminate false positives as much as possible. The VEG index is reported to be invariant to illumination, which was the goal of the work done in this paper, to have an unsupervised way of detecting weed in areas of randomly positioned seedlings.

Using a thresholding technique, we generate an image mask, which has value 1 for each pixel of the image that has value VEG>1.1 and 0 otherwise. Then we detect the connected components in the image and generate separate patches that contain a green area.

After the segmentation of the image, a manual labeling of the data was performed. The data consisted of 116 patches containing weed, 91 patches containing seedling and 76 patches that contained greenish land. The 76 patches were manually removed from the data. In a practical implementation of a system for automated weed control, we assume that an additional sensor for removing the false positives will be present.

To make the selected patches universal, we resize each patch to 128 X 128 pixels while preserving the aspect ratio and centralize the connected component. The exterior points of the connected components are the shape of the green areas, or the shape of the plants. After that we separate each image to 8 regions pointing towards 0 degrees, 45 degrees, 90 degrees etc. Then we count the points in each region and rotate the image so that the largest region is always pointing towards the 0 deg. Since we already have the green area shapes, we only extract the exterior contours of the masked regions [10]. With this we have the edges or the contours of each plant.

III. Descriptor Generation

We use Histogram of Oriented Gradients (HOG)[13] descriptor to generate descriptor for the image patches. This approach of using HOG descriptor, after the edges of the image are detected, is mentioned in [11] and [12]. The HOG descriptor used for describing each patch has 72 dimensions. The HOG descriptor is not rotation invariant, so we address this in the preprocessing phase by trying to direct the patches in the same direction in order for them to have similar rotation. Note however that due to the segmentation and the different size of the plant, we have cases where the positive examples are consisted of different number of parts as shown on Fig 1.

(a)

(b)

Fig. 1. Spinach seedlings examples from dataset-segmented patches (a) Positive examples, (b) weeds

For this reason, prior to extracting the descriptor for the patches, we merge near patches so that a single patch can cover the full plant. This procedure does not always work because the seedling might be covered with dirt in the middle. Owing to the VEG index we are able to get good contours of the plants. For each of the patches we generate the HOG descriptor. The mask obtained using the VEG index and the thresholding and the image that the regions are selected from are depicted in Fig. 2. The merge of patches can

Fig. 2. Real image and masked image obtained using the VEG index and thresholding

To improve the classification of the plants we also include the color information. Since we are interested only in the plant region, we use the segmented parts of the patches only to generate a histogram of colors. The histogram we generate is based on the VEG index only. We use the VEG index of the green areas of the patches only. The value is first normalized between 0 and 1 and we generate a histogram with 128 bins and the values are again normalized to compensate for the different number of green pixels in the images. This histogram is added to the HOG descriptor and we obtain a descriptor with a total dimension of 200. We use this descriptor for the unsupervised learning of the images and compare the results with the results obtained by supervised learning of the examples with Support Vector Machines (SVM) [17].

IV. Experimental results

Using unsupervised learning would allow online learning based on the acquired image data. The goal is to divide the images on two classes, weed and spinach. This can be done with clustering of the data. We use K-means clustering [14] with K=2 for the unsupervised learning. We use the WEKA [16] implementation of both of these algorithms to generate the classification models. The results for the K-means are presented in Table 1. The obtained precision is 64.3%. The clusters are done on the full set and the evaluation is done based on the labels, which were manually assigned to each patch.

To compare and validate the results obtained from the unsupervised learning approaches we used a supervised learning approach by manually labeling each of the segmented patch to 'weed' and 'spinach'. We used a Radial Basis Function (Gaussian) kernel based Support Vector Machines (RBF-SVM) to generate the classification model for the patches for the same HOG descriptors. To obtain the best results for the supervised approach we used grid search as suggested in [17]. The best results on 10-fold cross validation of the patches was obtained for C=1024 and gamma=0.016, with average precision of 68.1%. The average confusion matrix is given in Table 1.

TABLE I. Confusion matrix for RBF-SVM classification and for K-means clustering

Classified (clustered) as ->	Weed	Spinach	Cluster 0	Cluster 1
Weed	*93*	*23*	*77*	*39*
Spinach	*43*	*48*	*37*	*54*

V. Conclusion

In this paper the results of unsupervised learning for weed detection are presented. The results are compared with the results obtained with supervised learning performed on the same data. The unsupervised learning results are very close to the results obtained with supervised learning. This shows that based on the data, both the EM, K-Means clustering and the SVM supervised learning approach perform similarly. Although the results are promising, further research is needed to generate a more robust descriptor that would allow better classification or clustering of the image patches. Further, a modification in the segmentation is needed either with combination of different indexes as suggested in [9] or by using additional sensors for detecting the existence of a plant in a given area. Another problem that arises from the unsupervised learning is that the initial data of the clusters does not exist. There is no prior information about which cluster contains the wanted and which cluster contains the unwanted plants. The usage of unsupervised learning is possible in well-localized seedling plantations where the seedlings are located in rows. This information can be used to obtain the information about which cluster belongs to which class and use this information to select only the unwanted plants and perform adequate action on them. The use of unsupervised learning for automated crop detection is possible and should be employed in practice after major improvement of the classification. The usage of unsupervised learning would allow an automated robotic system to learn the environment, perform initial learning of the seedling model, and after that use this information to remove any unwanted weed from the plantation. Based on the initial results, we see this possible in near future where automated robotic systems would perform the weed control in plantations seeded with any kind of plant, without the need of learning of specific models.

Acknowledgment

This work was partially financed by the Faculty of Computer Science and Engineering at the Ss. Cyril and Methodius University in Skopje, Macedonia.

References

[1] Pimentel, D., and M. Giampietro. 1994. Food, land, population, and the U.S. economy. Carrying Capacity Network, Washington, DC.

[2] Young, Stephen L. and Meyer, George, "Precision and automation weed control technology" (2012). West Central Research and Extension Center, North Platte. Paper 74.

[3] Young, Stephen L., George E. Meyer, and Wayne E. Woldt. "Future directions for automated weed management in precision agriculture." Automation: The Future of Weed Control in Cropping Systems. Springer Netherlands, 2014. 249-259.

[4] H Jeon, Hong Y., and Lei F. Tian. "Direct application end effector for a precise weed control robot." Biosystems engineering 104.4 (2009): 458-464.

[5] Jeon, Hong Y., Lei F. Tian, and Heping Zhu. "Robust crop and weed segmentation under uncontrolled outdoor illumination." Sensors 11.6 (2011): 6270-6283.

[6] Comba, L., et al. "Robotics and automation for crop management: trends and perspective." International Conference on Work Safety and Risk Prevention in Agro-food and Forest Systems, Ragusa, Italy. 2010.

[7] Hague, T., N. D. Tillett, and H. Wheeler. "Automated crop and weed monitoring in widely spaced cereals." Precision Agriculture 7.1 (2006): 21-32.

[8] Guijarro, Maria, et al. "Automatic segmentation of relevant textures in agricultural images." Computers and Electronics in Agriculture 75.1 (2011): 75-83.

[9] Riomoros, I.; Guijarro, M.; Pajares, G.; Herrera, P.J.; Burgos-Artizzu, X.P.; Ribeiro, A., "Automatic image segmentation of greenness in crop fields," *Soft Computing and Pattern Recognition (SoCPaR), 2010 International Conference of* , vol., no., pp.462,467, 7-10 Dec. 2010

[10] Suzuki, S. and Abe, K., Topological Structural Analysis of Digitized Binary Images by Border Following. CVGIP 30 1, pp 32-46 (1985)

[11] Hu, R., Barnard, M., Collomosse, J. P., 2010. Gradient field descriptor for sketch based retrieval and localization. In: ICIP. pp.1025-1028

[12] Chalechale, A., Naghdy, G., Mertins, A., 2005. Sketch-based image matching using angular partitioning. in: IEEE Trans. Systems, Man, and Cybernetics, pp. 28-41.

[13] Dalal, N.; Triggs, B., "Histograms of oriented gradients for human detection," Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on , vol.1, no., pp.886,893 vol. 1, 25-25 June 2005 doi: 10.1109/CVPR.2005.177

[14] MacQueen, James. "Some methods for classification and analysis of multivariate observations." Proceedings of the fifth Berkeley symposium on mathematical statistics and probability. Vol. 1. No. 14. 1967.

[15] Chih-Wei Hsu, Chih-Chung Chang, and Chih-Jen Lin. A practical guide to support vector classification. Technical report, Department of Computer Science and Information Engneering, National Taiwan University, Taipei, 2003. http://www.csie.ntu.edu.tw/~cjlin/libsvm/

[16] Mark Hall, Eibe Frank, Geoffrey Holmes, Bernhard Pfahringer, Peter Reutemann, Ian H. Witten (2009); The WEKA Data Mining Software: An Update; SIGKDD Explorations, Volume 11, Issue 1.

[17] Burges, Christopher JC. "A tutorial on support vector machines for pattern recognition." Data mining and knowledge discovery 2.2 (1998): 121-167.