Development of Enhanced Weed Detection System with Adaptive Thresholding and Support Vector Machine

Dheeman Saha
Department of Electrical Engineering and Computer Science, South Dakota State University
Brookings, SD, 57006, USA
Dheeman.Saha@sdstate.edu

Austin Hanson
Department of Electrical Engineering and Computer Science, South Dakota State University
Brookings, SD, 57006, USA
berdon@gmail.com

Sung Y. Shin
Department of Electrical Engineering and Computer Science, South Dakota State University
Brookings, SD, 57006, USA
Sung.Shin@sdstate.edu

ABSTRACT
This paper proposes a sophisticated classification process to segment the leaves of carrots from weeds. In the early stages of the plants' development, the color of both the plants and the weeds are similar, making it difficult to differentiate between the two. The process becomes even harder if the weeds and plants overlap. The proposed system addresses this problem by creating a sophisticated mean for weed identification. The major components of this system are composed of three processes: image segmentation, feature extraction and decision-making. In the image segmentation process, the input images are processed into lower units where the relevant features are extracted. In the decision-making process, the system makes use of the Support Vector Machine to analyze and segregate the weeds from the plants. Afterward, the findings are used to dictate which plants receive herbicides and which do not. The main priority for the image segmentation process is on the overlapping images where weeds need to be isolated from plants so that they can be used for cultivation purpose.

The evaluation of the approach is done using an open dataset of images consisting of carrot plants. The system is able to achieve 88.99% accuracy for weed classification using this dataset. This methodology will help to reduce the use of herbicides while improving the performance and costs of precision agriculture.

CCS Concepts
•Computing methodologies → Feature selection; Computing Methodologies → Support vector machines;

Keywords
Weed Identification; Support Vector Machine; Image Segmentation; Automatic Greenness Identification; Automatic Thresholding; Precision Agriculture

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1. INTRODUCTION
In recent studies, research has focused on specific site based weed and herbicide control. The spot control of weeds has the potential to reduce the amount of chemicals applied by as much as 80% for improved farm profitability and water quality [1]. This leads to a reduction of the usage of the herbicides in the agricultural fields and will have a great, positive impact on environmental pollution.

Many different approaches are employed for weed control in precision agriculture. In most cases, the use of extracted features like shape, color, aspect ratio, and length ratio are used to determine the presence of weed in fields [2-5]. Researchers have even made use of different classification algorithms for discerning weeds from plants [6, 7]. The most common machine learning algorithm that is used in recent research is the Support Vector Machine (SVM) for identifying regions of weeds or infected regions in an agricultural field. In Tellaeche and Shi's studies [8, 9], input images of the crop fields are subdivided into different cells then SVM is used to identify those regions that consist only of crop plants.

Although improvements have been made in identifying weed regions, the above techniques are not suitable for detecting weed overlapping crop plants. Weed growth is stochastic in nature and thus overlap is a very realistic occurrence. It is thus valuable to focus on those regions and remove the unwanted foliage around the intended plants. In this way, more plants can be considered for cultivation. The problem becomes more challenging when both plants and weeds have the same green color. In that instance, only an experienced farmer can manually identify the plants from the agricultural fields. However, this manual process for weed identification is time consuming and the accuracy of detection is subject to human error.

The proposed system has taken these issues into account and performs selective spraying on plants. Selective spraying minimizes the wastage of products required for the effective control of weeds, diseases, and pests to ensuring that plants receive adequate nutrients [10]. The method uses SVM for decision making which has two main advantages. First, the model is robust - numerous features can be included into the system which helps to maximize the width of the SVM margin and improve classification. Secondly, the employed SVM makes use of the support kernels which are helpful when multiple features are present within the system. The proposed approach considers three major features to maximize weed region identification: *region area*, *perimeter*, and *convex area*. These features are extracted from the input image and then used for analysis and classification by the SVM. Classification is intended for both overlapping and non-overlapping regions within a field.

2. LITERATURE REVIEW

Haug and Ostermann [18] discussed an approach to discriminate crops from weeds. There are some issues in their approach which are examined in detail. A Vegetation Mask is manually made from the image and a human expert manually annotates each images to determine the locations of weeds and plants. This manual process is subjected to human error. Otsu's Thresholding [12] is also applied manually to extract the greenness part of the images. Manual thresholding quickly becomes prohibitively expensive on larger datasets.

The paper overlooked the overlapping regions of weeds and plants. This is a major issue as skipping such scenarios may infect other portions of the plant and reduce overall cultivated yield. For the classification of weed from plants the authors made use of the Random Forest Classifier [20]. The outcome of the classifier's values are again manually compared to the expert's predictions. These addition of multiple manual steps incurs a tremendous amount of computational cost. In contrast, the method proposed has taken account of these problems and eliminates the need for any manual steps.

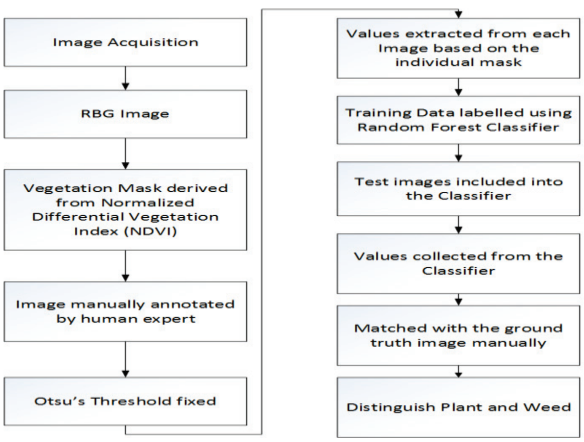

Figure 1. The flowchart of the weed and plants detection system using Random Forest Classifier.

3. PROPOSED METHOD

This section describes the proposed method's structure and implementation. The following figure depicts the general functional flow of the system.

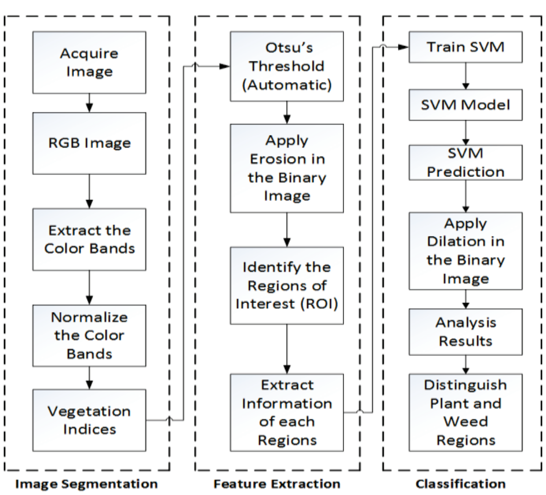

Figure 2. The flowchart of the proposed method for classifying and decision making process.

The system can be subdivided into three principal components: Image Segmentation, Feature Extraction, and Classification. These components are critical for region classification and discerning plants from weeds. The tasks carried out in each component is described in the following subsections.

3.1 Image Segmentation

Initially, an image database of color in-field images are used to produce viable training data. The set is created by highlighting greenness regions of plants and weeds. This is done by extracting each band of color from an RGB image and then normalizing each color components. This is done using the modified equations from Shi, Ma and Weng [9].

$$Normalized\ Red = \frac{red}{red^2 + blue^2 + green^2} \quad (1)$$

$$Normalized\ Green = \frac{green}{red^2 + blue^2 + green^2} \quad (2)$$

$$Normalized\ Blue = \frac{blue}{red^2 + blue^2 + green^2} \quad (3)$$

Equations 1 through 3 are used to find the value of each color band from an RGB image. Then, by using the set of equations below [9], the normalized component values of the image are calculated. These normalized values are then used as a means of highlighting "greenness" regions.

$$r = \frac{Normalized\ Red}{Normalized\ Red + Normalized\ Blue + Normalized\ Green} \quad (4)$$

$$g = \frac{Normalized\ Green}{Normalized\ Red + Normalized\ Blue + Normalized\ Green} \quad (5)$$

$$b = \frac{Normalized\ Blue}{Normalized\ Red + Normalized\ Blue + Normalized\ Green} \quad (6)$$

The "greenness" part of the image relies on the common Vegetation Color Index [11] in Equation 7 to further emphasize the greenness part of the plant. This equation applies more weight to greener regions of the plant and removes other color bands from the image.

$$ExcessGreen = 2 * (g) - (r) - (b) \quad (7)$$

Figure 3(a). Original Image

Figure 3(b). Excessive Greenness

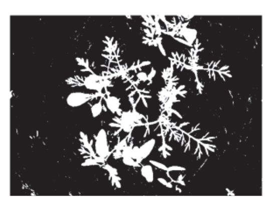

Figure 3(c). Otsu's Thresholding

Figure 3(d). Apply Erosion

Figures 3(a) to 3(d) display images as they go through the segmentation process. The image in Figure 3(a) displays the original RGB image prior to any enhancement. The image's color bands are normalized by (7) and the value of the "greenness" part of the image is displayed in Figure 3(b). Auto thresholding is then applied to get the "greenness" of the plant region. This is done by using Otsu's Thresholding [12] which is helpful in separating the plant's pixels from the background's pixels.

Next, overlapping regions within the image are identified. Figure 3(c) shows that all white pixels are merged together consisting of both plants and weeds. The Morphological Operations are used to separate the weeds from the plants [13] where the primary tasks are to analyze the shape and form of an image. The two main processes of the technique are erosion and dilation. Erosion for an input image is shown in Figure 3(d) where the leaves of the plants are separated from the weeds. After multiple erosion operations, the components are sufficiently separated and it is now possible to collect data from the plants and weeds based on the input features. Dilation is applied to the final image when weed regions are detected by the SVM. In the dilation process, all of the white pixels are remerged to a new black and white image as shown in Figure 3(c).

3.2 Feature Extraction

Feature extraction is performed after the erosion stage, as shown in Figure 3(d). A set of shape and contour features, commonly employed in similar approaches [14, 15], are applied. The list of features that are used for examination are *Area*, *Perimeter* and *Convex Area*. *Area* calculates the regions where the value of a pixel is 1. *Perimeter* defines the number of border pixels with a value of 1. *Convex Area* represents the area of the convex hall of a region. Table 1 delineates the aforementioned feature types and their descriptions. The values of these features are taken from the eroded binary image where all the plants are separated from the weed. As shown in Figure 3(a), plant leaves are rounder than weed's leaves which are much thinner and straighter. Features within interrogated images corresponding to these selected shapes are extracted and the values are stored to be evaluated further.

Table 1. List of Features considered for the experiment

Feature Number	Feature	Description
$feature_1$	Area	Area of the pixels covered by leaves and weeds
$feature_2$	Perimeter	Length of the pixels covered by leaves and weeds
$feature_3$	Convex Area	Area of the Convex Hall for leaves and weeds

3.3 Classification

The Support Vector Machine is a quintessential mechanism for classification. In general, a classifier is constructed in the N-dimensional hyper-plane that optimally separates the two classes [17]. The SVM consists of two phases: training and testing. In the training phase, the dataset is $\{x_i, y_i\},\ where\ i = 1, 2, \ldots l\ and\ x_i \in R^d$ where R is the Vector Space and d is the dimension of input training data [16]. In our case, the extracted dataset of the three features compose the training data while $y_i \in \{-1, +1\}$ comprise output labels -1 and +1, indicating the identified class. The label -1 indicates weed class whereas the label +1 specifies the plant class. The SVM becomes significantly more accurate in classification as the margin along the separating hyper-plane increases [17]. Therefore, it is important that the training dataset produce a maximal hyper-plane margin. The equation of the plane that maximizes the margin is given in Equation 8 where w is the weight vector and b is the intercept term. The value of x is defined as the input dataset from the extracted features.

$$f(x) = sign(w.x + b) \quad (8)$$

The use of SVM for weed detection purpose are carried out in numerous research [21-23]. However, the performance of the SVM can be distinguished by the use of the SVM Kernel functions. The proposed method uses Linear Kernel function, as stated by the authors in [24] that linear classifier performs effectively in high-dimensional feature space and the performance is much faster than other SVM Kernels. The decision function *f(x)* in Equation 8 made use of the Linear Kernel function which is actually a dot product of the input dataset and the weight vector.

4. RESULTS AND ANALYSIS

The test dataset consisted of 60 images from organic carrot fields provided by Haug and Ostermann [18]. The carrot plants dataset is broken into 40 training images and 20 test images. The training images are selected to maximize the interclass variability in order to improve the hyper-plane margin. The selected images include a wide variety of weed to plant ratios, some with a large amount of weeds, others with a large amount of plants.

The 20 images are subdivided into four test cases and each are evaluated separately and the outcome is displayed in Figure 4. The results are compared to those of the human experts and with the values generated from the proposed model. The analysis of the results leveraged using the equation *Percentage Correct Classification (PCC)* [19]. The four different parameters that are considered for Equation 9 are:

True Positive (TP): The number of locations that are correctly identified as leaves.

True Negative (TN): The number of locations that are correctly identified as weed

False Positive (FP): The number of locations that are not correctly identified as leaf, and instead, incorrectly as weed.

False Negative (FN): The number of locations that are not correctly identified as weed, and instead, incorrectly as plant.

$$Percentage\ Correct\ Classification(PCC) = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (9)$$

The Figure 4 displays the outcome of the four test cases. Based on the results, it can be seen that, in Test Case-4, weed classification is much higher than the plants. Conversely, in the other test cases, the detected plant regions are not substantially higher. The test cases are separated to have a better idea about the type of input images that are considered for the evaluation purpose.

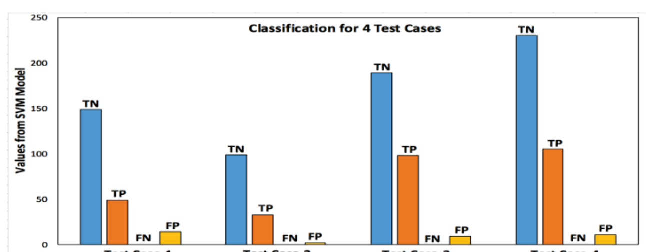

Figure 4. Analysis of the test cases

In total, 1780 regions are located from the 20 test images. Among them, 666 regions are classified as True Negative and 291 regions are identified as True Positive. These results indicate that the input images for the test cases mostly consists of the weeds. Moreover, as overlapping areas are considered, more weed regions are detected. The number of misclassifications of plant leaves and weeds are 36. Therefore, the PCC value of 96.37%

means that the classifier is a viable weed and plant region classifier.

5. CONCLUSIONS

An improved weed and plant detection algorithm is proposed and discussed in this paper. The approach initially gathered the required information from the images and then used them to train the SVM Model to classify the weed from the plants. In order to evaluate the system, four different test cases are carried out where the weed to plant ratio are much higher in all of the test cases. The system is able to identify plant and weed regions with a success rate of 96.37% and the accuracy for the weed detection is 88.99%. The proposed system showed a vast improvement when compared with the weed detection in the paper [18] where the average accuracy mentioned is about 85.9%. This difference in result is due to the fact that the proposed system considered the evaluation of the overlapping images which are omitted from consideration in the paper [18].

The proposed method showed an improvement over the weed extraction mechanism mentioned in paper [18]. Although, the number of steps for weed detection are bit higher but eliminating the use of manual thresholding and the knowledge of the human experts for weed identification overcame those overheads and improved the level of computation.

In successive research, and in order to bolster the credibility of the proposed method, a larger dataset will be evaluated and results compared to the smaller 60 image set are used. Additionally, exhaustive research will be done to locate any existing, similar research performed in weed and plant segregation to compare accuracies.

6. REFERENCES

[1] Timmermann, C., Gerhards, R., and Kühbauch, W. 2003. The economic impact of site-specific weed control. *Precision Agriculture*. 4, 3, 249-260.

[2] Perez, A. J., Lopez, F., Benlloch, J. V., and Christensen, S. 2000. Colour and shape analysis techniques for weed detection in cereal fields. *Computers and electronics in agriculture.* 25, 3, 197-212.

[3] Granitto, P. M., Verdes, P. F., and Ceccatto, H. A. 2005. Large-scale investigation of weed seed identification by machine vision. *Computers and Electronics in Agriculture*. 47, 1, 15-24.

[4] Onyango, C. M., and Marchant, J. A. 2003. Segmentation of row crop plants from weeds using colour and morphology. *Computers and electronics in agriculture*. 39, 3, 141-155.

[5] Neto, J. C., Meyer, G. E., Jones, D. D., and Samal, A. K. 2006. Plant species identification using Elliptic Fourier leaf shape analysis. *Computers and electronics in agriculture*. 50, 2, 121-134.

[6] Søgaard, H. T., and Olsen, H. J. 2003. Determination of crop rows by image analysis without segmentation. *Computers and electronics in agriculture*. 38, 2, 141-158.

[7] Lamm, R. D., Slaughter, D. C., and Giles, D. K. 2002. Precision weed control system for cotton. *Transactions of the ASAE*. 45, 1, 231.

[8] Tellaeche, A., Pajares, G., Burgos-Artizzu, X. P., and Ribeiro, A. 2011. A computer vision approach for weeds identification through Support Vector Machines. *Applied Soft Computing*. 11, 1, 908-915.

[9] Shi, L., Duan, Q., Ma, X., and Weng, M. 2011. The research of support vector machine in agricultural data classification. *In Computer and Computing Technologies in Agriculture V.* Springer Berlin Heidelberg, 265-269.

[10] Kropff, M. J., Wallinga, J., and Lotz, L. A. P. 2007. Modelling for precision weed management. *Ciba Foundation Symposium 210-Precision Agriculture: Spatial and Temporal Variability of Environmental Quality*. (September 2007), John Wiley & Sons, Ltd., 182-207.

[11] Woebbecke, D. M., Meyer, G. E., Von Bargen, K., and Mortensen, D. A. 1995. Shape features for identifying young weeds using image analysis. *Transactions of the ASAE*. 38, 1, 271-281.

[12] Otsu, N. 1975. A threshold selection method from gray-level histograms. *Automatica*. 1, 23-27, 285-296.

[13] Soille, P. 2013. Morphological image analysis: principles and applications. *Springer Science & Business Media*.

[14] Du, J. X., Wang, X. F., and Zhang, G. J. 2007. Leaf shape based plant species recognition. *Applied mathematics and computation*. 185, 2, 883-893.

[15] Hemming, J., and Rath, T. 2001. PA—precision agriculture: computer-vision-based weed identification under field conditions using controlled lighting. *Journal of agricultural engineering research*. 78, 3, 233-243.

[16] Burges, C. J. 1998. A tutorial on support vector machines for pattern recognition. *Data mining and knowledge discovery*. 2, 2, 121-167.

[17] T. Joachims. 1999. Svm: Support vector machine. SVM-Light Support Vector Machine. 19, 4, University of Dortmund. Available at http://svmlight.joachims.org/.

[18] Haug, S., and Ostermann, J. 2014. A crop/weed field image dataset for the evaluation of computer vision based precision agriculture tasks. *Computer Vision-ECCV 2014 Workshops.* (September 2014), 105-116.

[19] Sneath, P. H., and Sokal, R. R. 1973. Numerical taxonomy: The principles and practice of numerical classification.

[20] Breiman, L. 2001. Random forests. *Machine learning*. 45, 1, 5-32.

[21] Zhu, W., and Zhu, X. 2009. The application of support vector machine in weed classification. *Intelligent Computing and Intelligent Systems.* (November 2009). *ICIS 2009.* 4, 532-536.

[22] Tellaeche, A., Burgos-Artizzu, X. P., Pajares, G., and Ribeiro, A. 2007. A vision-based classifier in precision agriculture combining Bayes and Support Vector Machines. *Intelligent Signal Processing,* (October 2007). *WISP 2007.* 1-6.

[23] Guerrero, J. M., Pajares, G., Montalvo, M., Romeo, J., and Guijarro, M. 2012. Support vector machines for crop/weeds identification in maize fields. *Expert Systems with Applications*. 39, 12, 11149-11155.

[24] Deng, W., Huang, Y., Zhao, C., and Wang, X. 2014. Discrimination of Crop and Weeds on Visible and Visible/Near-Infrared Spectrums Using Support Vector Machine, Artificial Neural Network and Decision Tree. *Sensors & Transducers*. 26, 26