

Classification of crops and weeds from digital images: A support vector machine approach

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ABSTRACT

In most agricultural systems, one of the major concerns is to reduce the growth of weeds. In most cases, removal of the weed population in agricultural fields involves the application of chemical herbicides, which has had successes in increasing both crop productivity and quality. However, concerns regarding the environmental and economic impacts of excessive herbicide applications have prompted increasing interests in seeking alternative weed control approaches. An automated machine vision system that can distinguish crops and weeds in digital images can be a potentially cost-effective alternative to reduce the excessive use of herbicides. In other words, instead of applying herbicides uniformly on the field, a real-time system can be used by identifying and spraying only the weeds. This paper investigates the use of a machine-learning algorithm called *support vector machine* (SVM) for the effective classification of crops and weeds in digital images. Our objective is to evaluate if a satisfactory classification rate can be obtained when SVM is used as the classification model in an automated weed control system. In our experiments, a total of fourteen features that characterize crops and weeds in images were tested to find the optimal combination of features that provides the highest classification rate. Analysis of the results reveals that SVM achieves above 97% accuracy over a set of 224 test images. Importantly, there is no misclassification of crops as weeds and vice versa.

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1. Introduction

Increasing productivity and upgrading plantation systems are the major concerns for accelerating agricultural development. Weeds are unwanted pests that can survive and reproduce in agricultural fields. They hinder agricultural development by disturbing production and quality through competing with crops for water, light, soil nutrients, and space. Uncontrolled weeds commonly reduce crop yields from 10 to 95 percent (Young et al., 1978). As a result, weed control strategies are critical to sustain crop productivity. At present, several strategies exist that include removing weeds manually by human labourers, mechanical cultivation, or applying herbicides. Among these, applying herbicides is the most common method which has adverse impacts on both environment and human health. It also raises a number of

economic concerns. In the United States, the total cost of applying herbicides was estimated to be \$16 billion in 2005 (Naeem et al., 2007). In most cases, herbicides are applied uniformly on a crop field, which is a cost ineffective approach. The reason is that, in reality, weeds are aggregated (Rew and Cussans, 1995) and usually grow in clumps or patches (Tian et al., 1999) within the cultivated field. There could be many parts of the field that have none or insignificant volume of weeds, but herbicides are also applied in those parts. On the other hand, applying herbicides by human labourers using back-pack sprayer is very time consuming and costly, which is a common practice in many third world countries. If the same types of herbicides are applied in a field repeatedly for the removal of the weeds population, there is often a chance of emergence of weeds that have become tolerant to those types of herbicides. According to International Survey of Herbicide Resistant Weeds (International Survey of Herbicide Resistant Weeds, 2010), 346 herbicide resistant biotypes that belonged to 194 species (114 dicots and 80 monocots) are spread over 340,000 fields worldwide.

The performance of the agricultural sector has an overwhelming impact on food security, poverty alleviation and

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economic development of a country (Irz et al., 2001). In order to reduce the pressures on the agricultural sector, crops production and quality must be increased with diminishing cost for weeds control. It is here where a machine vision system that has the ability to distinguish crops from weeds so that herbicides can be applied effectively can potentially enhance the profitability and lessen environmental degradation. In this approach, images are taken by an automated system from different parts of a crop field so that weeds can be identified and sprayed accordingly. Two such approaches have been proposed for automated weeds detection in agricultural fields (Thompson et al., 1990). The first approach classifies crops and weeds based on their geometric differences such as leaf shape or plant structure, while the second approach uses spectral reflectance characteristics (Pérez et al., 2000).

In addition, many researchers have investigated other approaches for the automation of the weeds control process. Shearer and Jones (1991) developed a photo sensor based plant detection system which has the ability of detecting and spraying only the green plants. Shape feature analyses were performed by Woebbecke et al. (1995) on binary images to differentiate between monocots and dicots. Colour, shape and texture analyses have been investigated by Zhang and Chaisattapagon (1995) for the classification of weeds and wheat crop. Manh et al. (2001) proposed a new method for weed leaf segmentation based on the use of deformable templates. Later, Søgaard (2005) introduced an image processing method of weeds classification based on active shape models, which was able to identify young weed seedlings with an accuracy that ranged from 65% to above 90%. Naeem et al. (2007) classified narrow and broad leaves by measuring Weed Coverage Rate (WCR) in a system that used a personal digital assistant (PDA) as the processing device. Ahmad et al. (2007) developed an algorithm to categorize images into narrow and broad classes based on the Histogram Maxima using a thresholding technique for selective herbicide application, which achieved an accuracy of up to 95%. Ghazali et al. (2008) obtained above 80% accuracy by using a combination of statistical grey-level co-occurrence matrix (GLCM), structural approach Fast Fourier Transform (FFT), and scale-invariant feature transform (SIFT) features in a real-time weeds control system for an oil palm plantation.

In the last few years, support vector machine has attracted much attention for crop and weed classification. Karimi et al. (2006) used SVM to detect weed and nitrogen stress from hyperspectral images taken over a corn field. Later, Ishak et al. (2008) presented a SVM-based narrow and broadleaf weed detection method that employs Gabor and FFT-based texture features. Wu and Wen (2009) utilized GLCM and histogram statistics-based texture features for weed and corn seedling recognition with SVM classifier. A shape and texture based weed classification method was presented by Zhu and Zhu (2009). More recently, Tellaeche et al. (2011) have introduced a combination of segmentation and SVM-based decision-making approach for weed classification. A sequential SVM-based small-grain weed species discrimination method has been introduced by Rumpf et al. (2012).

The objective of our paper is to present a new model for classifying crops and weeds in digital images using support vector machine and to evaluate its performance in an automated weeds control system. The proposed model employs a combination of size and rotation invariant shape, colour, and moment features to form the feature vector. In addition, different feature selection approaches are exploited, which results in a high accuracy in crop and weeds classification. SVM has been chosen as classifier because of its impressive generalization performance, the absence of local minima, and the sparse representation of its solution (Kurzynski et al., 2007).

2. Materials and methods

2.1. Image acquisition

The images used in this study were taken from a chilli (*Capsicum frutescens* L.) field. In addition, five weed species were included that are commonly found in the chilli fields of Bangladesh. The weed samples were selected from different areas of the field. During image acquisition, all the weed plants were in mature stage. Table 1 lists both the English and the Latin names of chilli and the selected weed species.

The images were taken with an OLYMPUS FE4000 point-and-shoot digital camera. The camera is equipped with a 4.65–18.6 mm lens that was pointed towards the ground vertically while taking the images. To ensure a fixed camera height from the ground, the camera was mounted on top of a tri-pod. The lens of the camera was 40 cm above the ground level. An image would cover a 30 cm by 30 cm ground area using these settings. Each image scene contained a single plant without mutual overlapping with other plant leaves. No flash was used while taking the picture and the image scenes were protected against direct sunlight. The image resolution of the camera was set to 1200 × 768 pixels. The images taken were all colour images. Fig. 1 shows the sample images of a chilli (*C. frutescens* L.) and the other five weed species.

2.2. Pre-processing

Image segmentation was performed on these images to separate the plants from the soil. A binarization technique based on global thresholding was used for this purpose. The fact that plants look greener than soil was used to guide the segmentation. Let 'G' denote the green colour component of an RGB image. A grey-scale image was obtained from the original image by considering only the 'G' value. A threshold value for 'G' was then calculated. Let 'T' denote this threshold value. Those pixels with a 'G' value greater than 'T' were considered as plant pixels while the pixels with a 'G' value smaller than 'T' were considered as soil pixels. From each image, a binary version was obtained, where the pixels with a value '0' represent soil and pixels with a value '1' represent plant.

Next, to remove noises from these images, morphological opening was first applied to the binary images. In morphological opening, an erosion operation is carried out after a dilation operation has been performed on the image. It has the effect of smoothing the contour of objects by breaking narrow isthmuses and eliminating thin protrusions from an image (Gonzalez and Woods, 2004). Then, morphological closing was applied. In morphological closing, a dilation operation is performed after an erosion operation has been applied to the image. It has the effect of eliminating small holes while filling the gaps inside the contour of an image (Gonzalez and Woods, 2004). Thus, a single blob representing the whole plant was obtained for all the images. Fig. 2 shows the result of applying these pre-processing steps on a sample image of *Amaranthus viridis* L.

Table 1
Selected species.

English name	Latin name
Chilli	<i>Capsicum frutescens</i> L.
Pigweed	<i>Amaranthus viridis</i> L.
Marsh herb	<i>Enhydra fluctuans</i> Lour.
Lamb's quarters	<i>Chenopodium album</i> L.
Cogongrass	<i>Imperata cylindrica</i> (L.) P. Beauv.
Bur cucumber	<i>Sicyos angulatus</i> L.

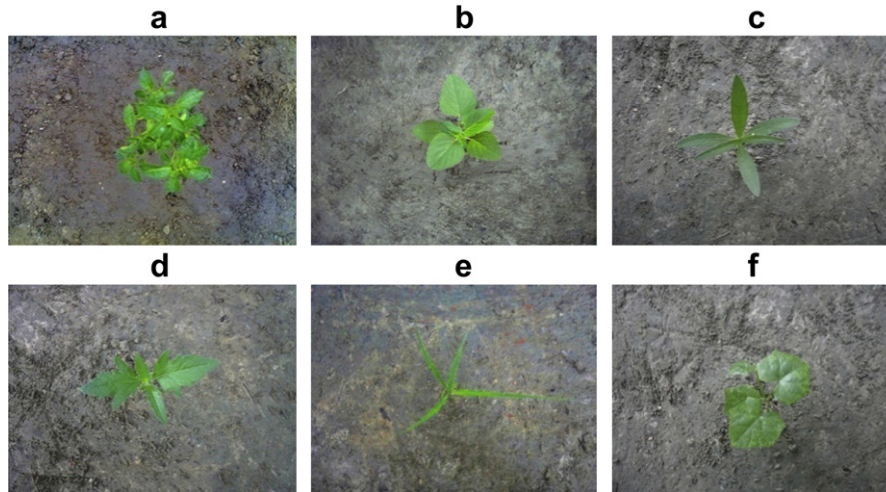


Fig. 1. Sample images of different plants; (a) *Capsicum frutescens* L. (b) *Amaranthus viridis* L. (c) *Enhydra fluctuans* Lour. (d) *Chenopodium album* L. (e) *Imperata cylindrica* (L.) P. Beauv. (f) *Sicyos angulatus* L.

2.3. Feature extraction

A total of fourteen features were extracted from each image. These features were divided into three categories: colour features, size independent shape features, and moment invariants.

2.3.1. Colour features

Let 'R', 'G' and 'B' denote the red, green and blue colour components of an RGB image, respectively. Every colour component was divided by the sum of all the three colour components. It has the effect of making the colour features consistent with different lighting levels.

$$r = \frac{R}{R + G + B} \quad (1)$$

$$g = \frac{G}{R + G + B} \quad (2)$$

$$b = \frac{B}{R + G + B} \quad (3)$$

Here, 'r', 'g' and 'b' are the processed colour components which are independent to different light levels. While calculating the colour features, all the plant image pixels were considered within the pre-processed images. So, the colour features are based on only the plant colour but not the soil (background) colour. The colour features used were: mean value of 'r', mean value of 'g', mean value of 'b', standard deviation of 'r', standard deviation of 'g', and the standard deviation of 'b'.

2.3.2. Size independent shape features

Size independent shape features are useful descriptors as they are dimensionless and independent of plant size, image rotation, and plant location within most images (Woebbecke et al., 1995). Four size independent shape features were selected for this study: *form factor*, *elongatedness*, *convexity* and *solidity*. For a circle, the value of *form factor* is '1' while for all other shapes it is less than '1'. Similarly, long narrow objects have a high *elongation* value than short wide objects. For an object that is fairly convex, the value of *convexity* will be close to '1'. This value decreases as the shape of an object becomes more straggly. On the other hand, *solidity* is a measure which specifies the proportion of the pixels in the convex hull that are also in the object region.

These shape features can be calculated as follows:

$$\text{Form factor} = 4\pi \frac{\text{area}}{\text{perimeter}^2} \quad (4)$$

$$\text{Elongatedness} = \frac{\text{area}}{\text{thickness}^2} \quad (5)$$

$$\text{Convexity} = \frac{\text{convex_perimeter}}{\text{perimeter}} \quad (6)$$

$$\text{Solidity} = \frac{\text{area}}{\text{convex_area}} \quad (7)$$

Here, *area* is defined as the number of pixels with a value '1' in the binary image. *Perimeter* is defined as the number of pixels with a value '1' for which at least one of the eight neighbouring pixels

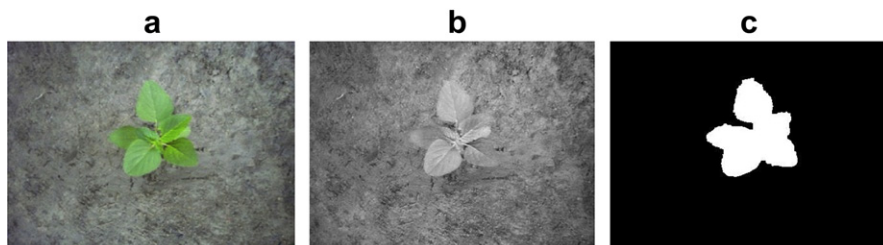


Fig. 2. Images of an *A. viridis* L.; (a) RGB image (b) grey-scale image (c) segmented binary image.

has the value '0', implying that *perimeter* is the number of border pixels. *Thickness* is twice the number of shrinking steps needed to make an object disappear within an image. The process is defined as the elimination of border pixels by one layer per shrinking step (Guyer et al., 1986). *Convex area* is defined as the area of the smallest convex hull that covers all the plant pixels in an image. *Convex perimeter* is the perimeter of the convex hull that contains all the plant pixels in an image.

2.3.3. Moment invariant features

Moment invariants refer to certain functions of moments that are invariant to geometric transformations such as translation, scaling, and rotation (Jain, 1986). Only central moments are considered in our study.

Let, $f(x, y)$ denote a binary image of a plant. Then, $f(x, y)$ is '1' for those (x, y) that correspond to plant pixels and '0' for those that correspond to soil pixels. Under a translation of co-ordinates, $x' = x + \alpha$, $y' = y + \beta$, invariants of the $(p + q)^{th}$ order central moments are defined as:

$$\mu_{p,q} = \sum_x \sum_y (x - \bar{x})^p (y - \bar{y})^q f(x, y), \quad p, q = 0, 1, 2, \dots \quad (8)$$

Here, \bar{x} and \bar{y} are the co-ordinates of the region's center of gravity (i.e., the centroid). Normalized moments (Jain, 1986), which are invariant under a scale change $x' = \alpha x$ and $y' = \alpha y$, can be defined as:

$$\eta_{p,q} = \frac{\mu_{p,q}}{(\mu_{0,0})^\gamma} \quad (9)$$

where

$$\gamma = \frac{p + q + 2}{2} \quad (10)$$

These normalized moments are invariant to size change. The moment invariants selected for this study are listed below:

$$\phi_1 = \eta_{2,0} + \eta_{0,2} \quad (11)$$

$$\phi_2 = (\eta_{2,0} + \eta_{0,2})^2 + 4\eta_{1,1}^2 \quad (12)$$

$$\phi_3 = (\eta_{3,0} - 3\eta_{1,2})^2 + (\eta_{0,3} - 3\eta_{2,1})^2 \quad (13)$$

$$\phi_4 = (\eta_{3,0} + \eta_{1,2})^2 + (\eta_{0,3} + \eta_{2,1})^2 \quad (14)$$

Here, ϕ_1 and ϕ_2 are second-order moment invariants and ϕ_3 and ϕ_4 are third-order moment invariants. These are also known as Hu moments (Hu, 1962). These moment features are invariant to rotation and reflection, which were calculated on the object area. The natural logarithm was subsequently applied to make the value of the moment invariants linear.

2.4. Classification using support vector machine

SVM (Burges, 1998; Cortes and Vapnik, 1995) is a machine learning approach based on modern statistical learning theory (Vapnik, 1998). The principle of structural risk minimization is the origin of SVM learning (El-Naqa et al., 2002). The objective of SVM is to construct a hyper-plane in such a way that the separating margin between positive and negative examples is optimal (Harikumar et al., 2009). This separating hyper-plane works as the decision surface. As SVM provides binary decisions,

multi-class classification can be achieved by adopting the one-against-rest or several two-class problems approach. In our study, we used the one-against-rest approach, where a binary classifier is trained for each class to discriminate one sample from all the others, and the class with the largest output is selected as the result. Even with training examples of a very high dimension, SVM is able to achieve high generalization. When used together, kernel functions enable SVM to handle different combinations of more than one feature in non-linear feature spaces (Kudo and Matsumoto, 2001).

A classification task in SVM or any other classifier requires first separating the dataset into two different parts. One is used for training and the other for testing. Each instance in the training set contains a class label and the corresponding image features. Based on the training data, SVM generates a classification model which is then used to predict the class labels of the test data when only the feature values are provided. Each instance is represented by an n -dimensional feature vector,

$$X = (x_1, x_2, \dots) \text{ where } n = 14 \quad (15)$$

Here, 'X' depicts n measurements made on an instance of n features. In our study, there are six classes, namely *C. frutescens* L., *A. viridis* L., *Enhydra fluctuans* Lour., *Chenopodium album* L., *Imperata cylindrica* (L.) P. Beauv., and *Sicyos angulatus* L.

In the case of SVM, it is necessary to represent all the data instances as a vector of real numbers. As the feature values for the dataset can have ranges that vary in scale, the dataset is normalized before use. This is to avoid features having greater numeric ranges dominate features having smaller numeric ranges. The LIBSVM 2.91 (LIBSVM – A Library for Support Vector Machines) library was used to implement the support vector classification. Each feature value of the dataset was scaled to the range of [0, 1]. The RBF (Radial-Basis Function) kernel was used for both SVM training and testing which mapped samples non-linearly onto a higher dimensional space. As a result, this kernel is able to handle cases where non-linear relationship exists between class labels and features. A commonly used radial-basis function is:

$$K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2), \quad \gamma > 0 \quad (16)$$

where

$$\|x_i - x_j\|^2 = (x_i - x_j)^t (x_i - x_j) \quad (17)$$

Here, x_i and x_j are n -dimensional feature vectors. Implementation of the RBF kernel in LIBSVM 2.91 requires two parameters: ' γ ' and a penalization parameter, 'C' (LIBSVM – A Library for Support Vector Machines). Appropriate values of 'C' and ' γ ' should be specified to achieve a high accuracy rate in classification. A grid search can be carried out for selecting appropriate parameter

Table 2
Classification results using all features.

Latin name of samples	Number of samples	Number of misclassified samples	Success rate
<i>Capsicum frutescens</i> L.	40	0	100%
<i>Amaranthus viridis</i> L.	40	5	87.5%
<i>Enhydra fluctuans</i> Lour.	31	2	93.5%
<i>Chenopodium album</i> L.	33	0	100%
<i>Imperata cylindrica</i> (L.) P. Beauv.	45	0	100%
<i>Sicyos angulatus</i> L.	35	2	94.3%
Average Success Rate			95.9%

Table 3

Confusion matrix of classification using all features. Rows represent true class and columns represent classification.

		1	2	3	4	5	6
1	<i>Capsicum frutescens</i> L.	40	0	0	0	0	0
2	<i>Amaranthus viridis</i> L.	0	35	0	0	0	5
3	<i>Enhydra fluctuans</i> Lour.	0	0	29	2	0	0
4	<i>Chenopodium album</i> L.	0	0	0	33	0	0
5	<i>Imperata cylindrica</i> (L.) P. Beauv.	0	0	0	0	45	0
6	<i>Sicyos angulatus</i> L.	0	2	0	0	0	33

values, as suggested in (Hsu and Lin, 2002). After repeated experiments, $C = 1.00$ and $\gamma = 1/n$ were chosen.

2.5. Optimal feature selection

To select the set of features that gives the optimal classification result, forward-selection and backward-elimination methods were attempted. In forward-selection, the selection process starts with a set having only one feature. The rest of the features are then added to the set one at a time. In each step, every feature that is not a current member of the set is tested if it can improve the classification result of the set or not. If no further improvement is detected, forward-selection is stopped; otherwise, it continues to find a better classification rate. In backward-elimination, the selection process starts with a set that includes all the features. The feature that has the least discriminating ability is then chosen and removed from the set. This process continues until an optimal classification result is obtained. These two methods can also be combined in a stepwise feature selection procedure to discover the optimal features combination. In stepwise feature selection, features are added to the set one at a time just like forward-selection. Next, backward-elimination is applied on the set obtained from the first step.

3. Results and discussion

To evaluate the proposed method, the full dataset can be divided into two subsets: the training dataset and test dataset. The training set is used to train the SVM classifier while the test set is used to predict the accuracy of the classifier. Cross validation is an

improved testing procedure that prevents the over-fitting problem. Ten-fold cross validation was applied in testing. In a ten-fold cross validation, it is required to split the whole training set into ten subsets, each having an equal number of instances. Subsequently, one subset is tested using the classifier trained on the remaining nine subsets. The cross validation accuracy is the average percentage of correctly classified test data when each subset of the full dataset has been used in testing.

The cross validation accuracy of the proposed method that used all 14 features was 95.9% over the set of 224 images. All the crop images were classified correctly by SVM. However, for the weed images, there were some misclassifications. Five images of *A. viridis* L. were misclassified as *S. angulatus* L., two images of *S. angulatus* L. were misclassified as *A. viridis* L., and two images of *E. fluctuans* Lour. were misclassified as *C. album* L. No weed image was misclassified as *C. frutescens* L. (the crop). The overall classification result and the confusion matrix are shown in Table 2 and Table 3, respectively.

To reduce the feature dimension and find the best feature set, both forward-selection and backward-elimination were attempted. Using forward selection, a set of eight features was obtained that achieves a classification rate of 96.4%. These eight features are: Convexity, Solidity, Elongatedness, Mean value of 'r', Mean value of 'b', Standard deviation of 'b', $\ln(\Phi_1)$ of area, and $\ln(\Phi_2)$ of area. On the other hand, using backward-elimination approach resulted in a set of nine features that achieves a classification rate of 96.9%. These nine features are: Solidity, Mean value of 'r', Mean value of 'b', Standard deviation of 'r', Standard deviation of 'b', $\ln(\Phi_1)$ of area, $\ln(\Phi_2)$ of area, $\ln(\Phi_3)$ of area, and $\ln(\Phi_4)$ of area. It can be observed that, features selected using both forward selection and backward-elimination increased the overall classification rate. However, the best feature combination was found using stepwise feature selection. Using this approach, a set of nine features was obtained from the fourteen features, which achieves the highest classification rate. These nine features are:

- Solidity
- Elongatedness
- Mean value of 'r'
- Mean value of 'b'
- Standard deviation of 'r'
- Standard deviation of 'b'

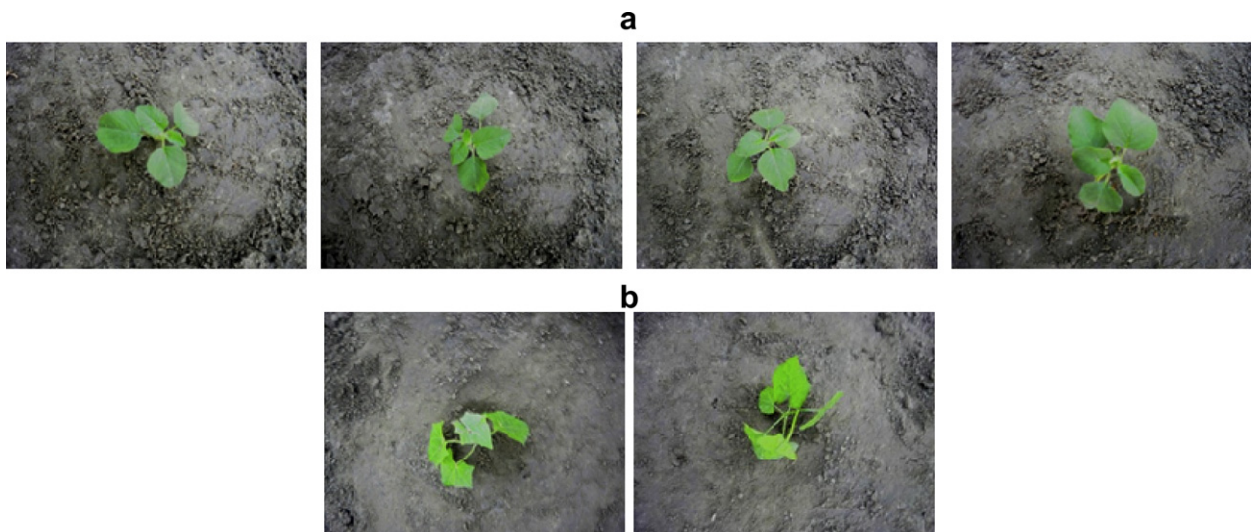


Fig. 3. Images of misclassified plants using the best feature set, (a) images of *A. viridis* L. misclassified as *S. angulatus* L., (b) images of *S. angulatus* L. misclassified as *A. viridis* L.

Table 4
Comparison of the classification rates using different feature selection methods.

Method	Number of samples	Number of misclassified samples	Classification rate
Forward selection	224	8	96.4%
Backward-elimination	224	7	96.9%
Stepwise feature selection	224	6	97.3%

- $\ln(\Phi_1)$ of area
- $\ln(\Phi_2)$ of area
- $\ln(\Phi_4)$ of area

The accuracy of ten-fold cross validation using these nine features was 97.3%. The misclassified plant images are shown in Fig. 3. Here, only four images of *A. viridis* L. were misclassified as *S. angulatus* L. and two images of *S. angulatus* L. were misclassified as *A. viridis* L. All other images were classified correctly. Table 4 shows the comparison of the classification rates obtained using different feature selection approaches. The overall classification result using the best feature set and the corresponding confusion matrix are shown in Tables 5 and 6, respectively.

It is difficult to compare the results of this study with the other existing methods due to the highly different boundary conditions in each of the studies. Here, we selected two existing SVM-based weed classification model for performance comparison. One of the models was presented by Zhu and Zhu (2009), where a set of shape and texture features were employed to form the feature vector. The other one is the classification model presented by Wu and Wen (2009), where GLCM and statistical properties of the histogram of grey-level images were used to calculate different texture features. Table 7 shows the performance comparison of the proposed method against these two existing models. It can be observed that, the proposed method achieves the highest classification rate of 97.3% with only 6 misclassifications using the best feature set. The superiority of the proposed model is due to the integration of size and rotation invariant shape features with colour-based plant features and the use of optimal feature selection techniques in order to find the best feature set.

Computation time is an important issue for assessing the performance of any real-time system. The model presented in this paper was implemented in a computer with a Core 2 Duo 2.20 GHz CPU. Using this setup, the average calculation time of all the features from a 448×336 pixels image was 0.72s, which is plausible for real-time decision-making. This computation time can be further reduced by using lower resolution images in the feature extraction process.

This research was intended to study the feasibility of using SVM with a combination of different types of features for crop and weed

Table 5
Classification result using the best feature set.

Latin name of samples	Number of samples	Number of misclassified samples	Success rate
<i>Capsicum frutescens</i> L.	40	0	100%
<i>Amaranthus viridis</i> L.	40	4	90%
<i>Enhydra fluctuans</i> Lour.	31	0	100%
<i>Chenopodium album</i> L.	33	0	100%
<i>Imperata cylindrica</i> (L.) P. Beauv.	45	0	100%
<i>Sicyos angulatus</i> L.	35	2	94.3%
Average Success Rate			97.3%

Table 6
Confusion matrix of classification using the best feature set. Rows represent true class and columns represent classification.

		1	2	3	4	5	6
1	<i>Capsicum frutescens</i> L.	40	0	0	0	0	0
2	<i>Amaranthus viridis</i> L.	0	36	0	0	0	4
3	<i>Enhydra fluctuans</i> Lour.	0	0	31	0	0	0
4	<i>Chenopodium album</i> L.	0	0	0	33	0	0
5	<i>Imperata cylindrica</i> (L.) P. Beauv.	0	0	0	0	45	0
6	<i>Sicyos angulatus</i> L.	0	2	0	0	0	33

Table 7
Comparison of the success rates of different SVM-based models for crop and weeds classification.

Method	Number of samples	Number of misclassified samples	Success rate
Proposed model with the best feature set	224	6	97.3%
Zhu and Zhu (2009) weed classification model	224	35	84.4%
Wu and Wen (2009) weed classification model	224	10	95.5%

classification. The experimental results indicate that, the proposed feature set has potential for effective feature vector representation of crop and weed images for the classification task. The study was conducted on field images in order to assess the performance of the proposed model in natural condition. In addition, lowering the cost of sensing equipments is an important issue for practical agricultural applications. Therefore, in our study, a low-cost camera was used for image acquisition. However, larger number of images is required to construct a more robust SVM-based classification model as it will be easier for SVM then to find the support vectors in order to construct the separating hyper-planes. Although the proposed method is able to segment plants from soil background, there existed segmentation errors in the form of plant holes and noise backgrounds. Therefore, more effective and efficient image enhancement techniques should be introduced prior to feature extraction in the real-time systems.

4. Conclusion

The ability of locating and classifying crops and weeds in digital images could lead to the development of autonomous vision-guided agricultural equipments for site-specific herbicide application. It could also be integrated with equipments for collecting weed distribution data in order to generate weed maps for precision spraying, where different weed species that are sensitive to the same herbicides are grouped together in the map and the corresponding application rate is defined based on some economic threshold. In this paper, we have proposed a classification model based on support vector machine (SVM) and verified its ability to classify crop and weeds in digital images effectively in order to reduce the excessive use of herbicides in agricultural systems. For our experiments, a total of fourteen features which characterize crops and weeds in images were evaluated to determine the optimal combination that provides the highest classification rate. Analysis of the results reveals that SVM achieves above 97% accuracy over a set of 224 test images using ten-fold cross validation. Importantly, there is no misclassification of crops as weeds and vice versa. To enable further increase in the classification rate, our future task will involve making the image

pre-processing steps more robust to noises that will inevitably be introduced by the operating environment.

References

- Ahmad, I., Naeem, A.M., Islam, M., Nawaz, S., 2007. Weed Classification Using Histogram Maxima with Threshold for Selective Herbicide Applications. In: 19th International Conference on Computer, Information and Systems Science and Engineering (CISSE 2007), Bangkok (Thailand), vol. 19, pp. 331–334.
- Burges, C.J.C., 1998. A Tutorial on Support Vector Machines for Pattern Recognition. In: Data Mining and Knowledge Discovery, vol. 2 (2), pp. 1–47.
- Cortes, C., Vapnik, V., 1995. Support-vector networks. *Machine Learning* 20, 273–297.
- El-Naqa, I., Yang, Y., Wernick, M.N., Galatsanos, N.P., Nishikawa, R.M., 2002. A support vector machine approach for detection of microcalcifications. *IEEE Transactions on Medical Imaging* 21 (12), 1552–1563.
- Ghazali, K.H., Mustafa, M.M., Hussain, A., 2008. Machine vision system for automatic weeding strategy using image processing technique. *American-Eurasian Journal of Agricultural & Environmental Science* 3 (3), 451–458.
- Gonzalez, R.C., Woods, R.E., 2004. *Digital Image Processing*, second ed. Pearson Education, Singapore, 528 p.
- Guyer, D.E., Miles, G.E., Schreiber, M.M., Mitchell, O.R., Vanderbilt, V.C., 1986. Machine vision and image processing for plant identification. *American Transaction of the American Society of Agricultural Engineering* 29, 1500–1507.
- Harikumar, R., Vasani, A.K., Kumar, M.L., 2009. Performance Analysis of Support Vector Machine (SVM) for Optimization of Fuzzy Based Epilepsy Risk Level Classifications from EEG Signal Parameters. In: 13th International Conference on Biomedical Engineering, vol. 23, Track 1, pp. 351–354.
- Hsu, C.W., Lin, C.J., 2002. A comparison on methods for multiclass support vector machines. *IEEE Transaction on Neural Networks* 13 (2), 415–425.
- Hu, M.K., 1962. Visual pattern recognition by moment invariants. *IRE Transactions on Information Theory* 8 (2), 179–187.
- International Survey of Herbicide Resistant Weeds, <http://www.weedscience.org/in.asp> (accessed 08.09.10.).
- Irz, X., Lin, L., Thirtle, C., Wiggins, S., 2001. Agricultural productivity growth and poverty alleviation. *Development Policy Review* 19 (4), 449–466.
- Ishak, A.J., Mustafa, M.M., Tahir, N.M., Hussain, A., 2008. International Symposium on Information Theory and its Applications, Auckland, pp. 1–4.
- Jain, A.K., 1986. *Fundamentals of Digital Image Processing*. Prentice Hall Information and System Sciences Series, New Jersey, U.S.A. 380 p.
- Karimi, Y., Prasher, S.O., Patel, R.M., Kim, S.H., 2006. Application of support vector machine technology for weed and nitrogen stress detection in corn. *Computers and Electronics in Agriculture* 51 (1–2), 99–109.
- Kudo, T., Matsumoto, Y., 2001. Chunking with Support Vector Machines. North American Chapter of The Association For Computational Linguistics, Second Meeting of the North American Chapter of The Association for Computational Linguistics on Language Technologies, pp. 1–8.
- Kurzynski, M., Puchala, E., Wozniak, M., Zolnierek, A. (Eds.), 2007. *Computer Recognition System*, vol. 2. Springer Berlin Heidelberg, New York.
- LIBSVM – A Library for Support Vector Machines. <http://www.csie.ntu.edu.tw/~cjlin/libsvm/> (accessed 10.08.10.).
- Manh, A.-G., Rabatel, G., Assemat, L., Aldon, M.-J., 2001. AE – Automation and emerging technologies: weed leaf image segmentation by deformable templates. *Journal of Agricultural Engineering Research* 80 (2), 139–146.
- Naeem, A.M., Ahmad, I., Islam, M., 2007. Weed Classification Using Two Dimensional Weed Coverage Rate (2D-WCR) for Real-Time Selective Herbicide Applications. In: 19th International Conference on Computer, Information and Systems Science and Engineering (CISSE 2007), Bangkok (Thailand), vol. 19, pp. 335–339.
- Pérez, A.J., López, F., Benlloch, J.V., Christensen, S., 2000. Colour and shape analysis techniques for weed detection in cereal fields. *Computers and Electronics in Agriculture* 25 (3), 197–212.
- Rew, L.J., Cussans, G.W., 1995. Patch Ecology and Dynamics – How Much Do We Know?. In: *Proceeding of Brighton Crop Protection Conference BCPC Publications*, pp. 1059–1068.
- Rumpf, T., Römer, C., Weis, M., Sökefeld, M., Gerhards, R., Plümer, L., 2012. Sequential Support Vector Machine classification for small-grain weed species discrimination with special regard to *Cirsium arvense* and *Galium aparine*. *Computers and Electronics in Agriculture* 80, 89–96.
- Shearer, S.A., Jones, P.T., 1991. Selective application of post-emergence herbicides using photoelectrics. *ASABE Technical Library, Transactions of the ASABE* 34 (4), 1661–1666.
- Søgaard, H.T., 2005. Weed classification by active shape models. *Biosystems Engineering* 91 (3), 271–281.
- Tellaiche, A., Pajares, G., Burgos-Artizzu, X.P., Ribeiro, A., 2011. A computer vision approach for weeds identification through support vector machines. *Applied Soft Computing* 11 (1), 908–915.
- Thompson, J.F., Stafford, J.V., Miller, P.C.H., 1990. Selective Application of Herbicides to UK Cereal Crops. *American Society of Agricultural Engineers Paper*, St. Joseph, MI. 90–1629.
- Tian, L., Reid, J.F., Hummel, J., 1999. Development of a precision sprayer for site-specific weed Management. *Transactions of the ASABE* 42 (4), 893–900.
- Vapnik, V.N., 1998. *Statistical Learning Theory*. John Wiley & Sons, New York.
- Woebbecke, D.M., Meyer, G.E., Bargen, K.V., Mortensen, D.A., 1995. Shape features for identifying young weeds using image analysis. *ASABE Technical Library, Transactions of the ASABE* 38 (1), 271–281.
- Wu, L., Wen, Y., 2009. Weed/corn seedling recognition by support vector machine using texture features. *African Journal of Agricultural Research* 4 (9), 840–846.
- Young, D., Miller, S., Fisher, H., Shenk, M., 1978. Selecting appropriate weed control systems for developing countries. *Weed Science* 26 (3), 209–212.
- Zhang, N., Chaisattapagon, C., 1995. Effective criteria for weed identification in wheat fields using machine vision. *Transactions of the A.S.A.E* 38 (3), 965–974.
- Zhu, W., Zhu, X., 2009. The Application of Support Vector Machine in Weed Classification. In: *IEEE International Conference on Intelligent Computing and Intelligent Systems, China*, pp. 532–536.