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Use of site- specific strategies for weed management to reduce herbicide application

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ABSTRACT

Reducing weeds is a way of enhancing crops per unit area which has led to irregular application of herbicides. Many studies have shown that just 20% to 76% of fields have been devoted to weed. Use of site- specific strategies for weed management can reduce application of herbicides. In this research in order to reduce application of herbicide in corn fields, support vector machine (SVM) was designed based on machine vision system that used geometrical features of shrubs. In order to identify shrubs from background variations in algorithm of image segmentation called Prixelwise were performed. Then for shrub classification, algorithm of SVM classification was created using derivation of seven geometrical features from 100 laboratory images. Identification capacity of algorithm was determined to be 81% based on cross validation assay. In field assay 100 images were taken manually or automatically from corn raws in two different days. SVM could classify weeds at an accuracy of 93% in time of 1.16 s and 65% in time of 2.16 based on images taken. The reason for decreased classification accuracy of automatic way can be traced back to image quality and light undesirable conditions.

Keywords: Support Vector Machine (SVM), Machine vision, weeds management

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INTRODUCTION

Enhancement of agricultural crop production has led to increase in weed application. Although herbicides improve quality and quantity of agricultural crops, aberrant and irrational application of these products has been increased. Marshall et al., (1988) showed that weeds don’t tend to distribute in the field uniformly. Therefore herbicide distribution in a uniform manner is an inappropriate procedure [8]. For this reason site- specific weed management has been increasingly studied and used as a strategy in herbicide application. This means reduction in herbicide application (by more than 48%- 54%) confirmed by several studies [15, 16]. The ability to discriminate filed weeds is a necessary part of weed management diversity of weed species, advent of species resistant to herbicides and the need for adoption a decision on weed control (chemical or mechanical method) make discrimination of weed species necessary. This research is based on the hypothesis that CVM can support machine vision technology for discrimination of weed species in site-specific weed management aiming at reducing herbicide application. Many studies have been done on weed identification using machine vision [5, 9, 11]. Also several studies have been done on weed species discrimination by artificial neural network and discriminate analysis [1, 2]. SVM is a new tool of learning under machine control in the area of artificial mind that has been used in this research for weed species discrimination. The said machine has been used in other areas such as text classification speaker verification etc [17, 18].

MATERIALS AND METHODS

To develop a machine vision system equipped with SVM for weed species discrimination, sure project was divided into two stages. The first stage included laboratory activities during which discrimination algorithm was obtained based on plants grown at greenhouse. In the second stage field assay was carried out by which efficiency and adequacy of algorithm proposed were evaluated based on the field images. Each stage included steps such as image acquisition, image segmentation, and feature extraction of target plants and weeds classification. In the following each step is discussed.

LABORATORY ACTIVITIES

At first common weed species were identified in corn fields, 50 plants of each species was transferred to laboratory and planted into pots for image acquisition.

Fig 1. Broadleaf weeds

Left to right: flower of an hour, velvet leaf and common lamb's quarter, respectively

Fig 2. grass weeds

Left to right: brome chess, barnyard grass and weed planting in pot, respectively

IMAGE ACQUISITION

Images were manually acquired by Canon- A3300 digital camera with a resolution of 16 megapixels. The distance between camera and each pot was 1m and to fix the distance camera was placed on a specific base. Image acquisition was performed under controlled lighting conditions at 12:00 for one week. In general 100 images were acquired from different species of weed in different vegetative times that have been used for obtaining discrimination algorithm of SVM.

IMAGE SEGMENTATION

Here image segmentation means changing a RGB image to a binary image with the aim of bolding green hue. There are different algorithms for image segmentation. Normalized excess green (NExG), modified hue and pixel wise techniques have been frequently reported as excellent methods due to low sensivity to background errors and lighting conditions. Tang et al., (2003) could classify broadleaf and grass weeds using modified hue and artificial neural network[13]. Woebbecke *et al.*, (1995) identified shape features of weeds using NExG method [19]. In a study Chufan *et al.*, (2009) could discriminate between corn crops and weeds using pixel wise method [3]. In the present research advantages and drawbacks of this method are stated followed by comparing this method and presenting a method of least error for image segmentation.

NORMALIZED EXCESS GREEN TECHNIQUE (NExG)

This method uses hue space of RGB and its formula is as follows:

$$NExG= 2g-r-b1 \qquad (1)$$

To carry out this method, RGB value of each image pixel was derived and put into formula 1. By this conversion original image was turned into a gray- scale image of darkened plants background (Fig 3). To make binary gray images, the edge of plants image was developed using Otsu's automatic thresholding method. In this way the difference between pixels of plants and pixels of background was increased. NExG algorithm has been written in MATLAB.

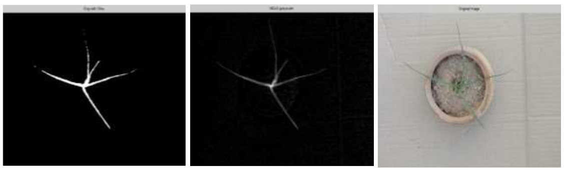

Fig 3. Image segmentation by use of NExG
Left to right: plant derivation from the image, making gray through bolding green color and original image of plant, respectively.

MODIFIED HUE METHOD
This method uses HSI (hue, saturation, intensity). In order to change RGB image to HSI, RGB value of each image pixel was first derived and put into formula 2 to obtain pixel hue value:

$H = \theta \quad if \quad B \leq G$ (2)

or $H = 360 - \theta \quad if \quad B > G$

$$\theta = \cos^{-1}\left(\frac{2R-G-B}{2[(R-G)^2+(R-B)(G-B)^{1}/_{2}}\right)$$

In this system hue value varies from 0 to 360°. Empirically, it can be shown that green hue value of plants inside the photographs acquired is 51°C to 100°C (Fig 4).

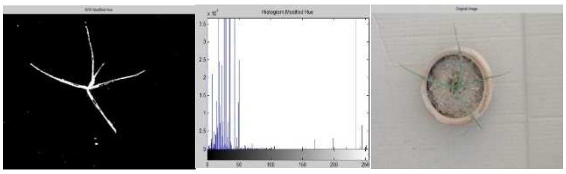

Fig 4. Image segmentation by modified hue method
Left to right: derivation of plant from image, hue histogram, original image of plant

Modified hue algorithm has been written in MATLAB.

PIXEL WISE METHOD
In this method the relationship between RGB channels and pixels belonged to the area containing plant and background was investigated to find out a criterion for image segmentation into two points of plant and background. To this aim the image was segmented by NExG and Ostu's automatic thresholding method. There sholding operation was then manually completed by a serious of adjustments with respect to image histogram. The relationship between B, G, R and pixels belonged to plants and background is as follows:

If G(i,j)>1.03B(I,j) & G(I,j)>1.02R(I,j) & R(I,j)<1.9B(I,j) & G(i,j)>70 (3)

Its plants else
Its back ground
By determination of pixel wise algorithm, image segmentation was performed.

Fig 5. image segmentation by pixel wise method
Left to right: derivation of plant from image and original image of plant, respectively

WEED IDENTIFICATION
Image segmentation leads to creation of a binary image in which green plant and background turn into white and black hue respectively. Identification of weed and classification of its species by SVM require that image characteristics of plant are first derived and used as inputs for SVM. However in laboratory stage the aim of derivation of geometrical characteristics from laboratory images is to create identification algorithm for SVM.

SUPPORT VECTOR MACHINE (SVM)

SVM is a kind of learning method monitoring machine introduced first by Vapnick in 1990 based on statistical learning theory. In fact it is a binary classifier that uses multi-dimensional verification to optimize discrimination, to maximize the discrepancy between two classes and to minimize errors produced. SVM is famous because it does its job in spite of inappropriate and sparse information.

FEATURE EXTRACTION

Image features are descriptor of plant characteristics by which a plant species can be identified. By use of MATLAB different features such as area, perimeter, major and minor axis length encompassing target etc can be extracted easily (Fig 6).

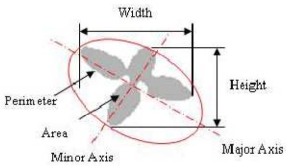

Fig 6. Image geometric characteristic

These features vary with time and different growth stages. Therefore instead of apparent features that contain dimension, descriptor models of plant should be used. Tian *et al.*, (1997), Lee *et al.*, (1999) and Cho *et al.*, (2002) used different patterns to describe plants. Some of them are presented in the following [2, 6, 14]:

1) Area – length ratio (ATL)

$$ATL = \frac{Area}{Major\ Axis\ Length} \quad (4)$$

2) Compactness (CMP)

$$CMP = 16 \times \frac{Area}{Perimeter^2} \quad (5)$$

3) Elongation

$$ELG = \frac{Major\ Axis\ Length - Minor\ Axis\ Length}{Major\ Axis\ Length - Minor\ Axis\ Length} \quad (6)$$

4) Aspectratio

$$ASP = \frac{Major\ Axis\ Length}{Minor\ Axis\ Length} \quad (7)$$

5) Logarithm of the ratio of height to weight

$$LHW = \log_{10} \frac{Height}{Width} \quad (8)$$

6) Ratio of perimeter to broadness

$$PTB = \frac{Perimeter}{2 \times (Height + Width)} \quad (9)$$

7) Ratio of length to perimeter

$$LTP = \frac{Major\ Axis\ Length}{Perimeter} \quad (10)$$

FEATURE SELECTION

A. Determining features having the most effects on classification: Peng *et al.*, (2005) developed a method for feature selection for classifying functions known as minimum redundancy, maximum relevance (MRMR)[10]. MRMR selects features which are different from other features and have the highest effect on classification. To carryout MRMR, the aforesaid plant descriptor patterns were first measured for individual images and analyzed by MRMR functions running in MATLAB plan. B. Determining the relationship between the number of features and accuracy of identification algorithm of SVM: Two identification algorithms with three and seven features were developed regarding MRMR. Accuracy of algorithms made was then assessed by 10 fold cross validation assay. Since time required for weed identification is of high importance, time required for processing each algorithm was also measured.

DETAILS OF SVM METHOD

Making identification algorithm of SVM: Identification algorithm was developed through extraction of seven geometrical features such as area- length ratio, compactness, elongation, and aspect ratio, logarithm of the ratio of height to with (LHW), ratio of perimeter to broadness and ratio of length to perimeter from 100 images of weed acquired under laboratory conditions.

Kernel function selection: To run identification algorithm, kernel function should be selected. For classifingas a multi- fold classification the best function is radial basis function (RBF) since it is a linear simple function (Table 1).

Table 1.Some of non- linear kernel functions for SVM

Kernal	Function
Linear	$K(x.y) = x.y$
Sigmoid	$K(x.y) = \tanh(\gamma x.y + c)$
Polynomial	$K(x.y) = (\gamma x.y + c)^d, \gamma > 0$
Radial Basis Function(RBF)	$K(x.y) = \exp(-\gamma(x-y)^2, \gamma > 0$

POISON SPRAYER DESIGN

Poison sprayer was designed by CATIA software based on our needs in the farm. The poison spray machine was made in workshop from the model (Fig7).

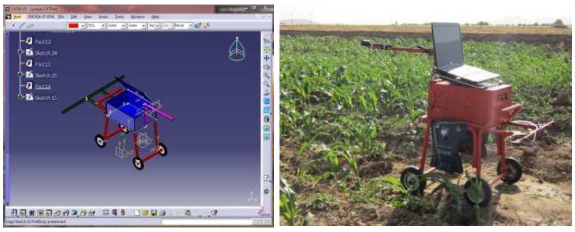

Fig 7. Sprayer

Poison sprayer was designed in a way that it could spray. Poison desired onto the weed regarding weed species. An electrical board links MATLAB software with poison sprayer pumps (Fig 8). When SVM identified weed species it commanded to spray the poison related to the weed species. This command is identified by IC inserted into the board and changed to an electrical current that can turn poison- sprayer pump.

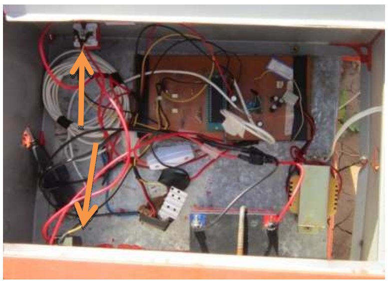

Fig 8. Electrical board, the linkage between SVM and poison- sprayer pumps

Fig 9 Images taken from field sprayer

FARM TEST

IMAGE ACQUISITION

Images were acquired either automatically by sprayer or manually under controlled conditions. A) Automatic image acquisition by sprayer machine: Images were acquired from a 1- hectare corn farm located at Abadeh Tashk village, Neyris town at 12:00 in 15th day of July. The images were acquired by a 5megapixels web camera installed on a specific base in front of the sprayer. The base was designed in such a way that the distance of camera from ground level would be about 80cm. Limits covered by camera are a rectangular with a length of 25cm and width of 75cm.

Camera was positioned in an angle that could be parallel to ground level. The acquired images had the resolution of 480×340. A Dell N5110 laptop was used as an image process (Fig 9).

B) Manual image acquisition under controlled conditions: On 16 July weeds were transferred to a land devoid of any weed species. Weeds were planted without any overlapping. Also width of the raw prepared with respect to corn farm was regarded as to be 75cm (Fig10). Image acquisition was performed by an A3300 model, Canon cameral with resolution of 1200×1400. The distance of camera from ground level was 50cm. To reduce the effect of sunlight, a canopy was used limits covered by camera was a rectangular with a length of 25cm and width of 75cm. The camera was positioned in an angle that could be parallel with ground level.

Fig10. Images taken in the land devoid of any weed

WEED IDENTIFICATION

Weed identification in the field is similar to that craned out under laboratory conditions. It included image segmentation into two parts of plant and background feature extraction and weed classification into broad- leaf and grass weeds.

IMAGE SEGMENTATION

Image segmentation in the field was done according to pixel wise method with respect to light variations with laboratory.

FEATURE EXTRACTION

Factors such as presence of incomplete plants in the edges of images, plant dividing into different segments due to error in segmentation method and presence of several plants in one image reduce accuracy of determined features of plant. Therefore the aforesaid errors should be corrected before determination of plant features.

1. Creation of a single plant

Error in segmentation methods is unavoidable one of the errors occurring in image segmentation is dividing a single plant into different parts (Fig 11).

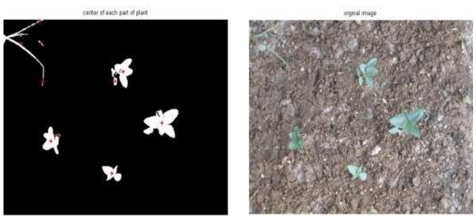

Fig 11: Method (Red points show mass center of each part)

To solve this problem coordinates of mass center of each part were first obtained by centric function. The distance between mass centers was then measured by the following equation:

$$Distanc = \sqrt{(x_1^2 - x_2^2) + (y_1^2 - y_2^2)} \quad (11)$$

With respect to this distance, segmentation error was removed.

2. Omission of incomplete plants in the edge of image

It is obvious that weed species can't be identified from enfetters of an incomplete plant. Therefore incomplete plants appeared in image edge were omitted (Fig 12).

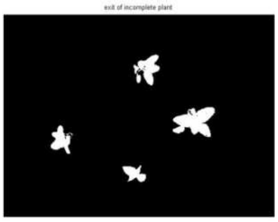

Fig12. Omission of incomplete plant from the edge of image

3. Selection of target plant

In the field images, presence of several plants in one image is unavoidable. Thus each plant was separately selected and processed by low label.

WEED CLASSIFICATION

Immediately after weed features were extracted they were compared using SVM and classified into broadleaf or grass weeds. Classified images were then labeled as grass or broad- leaf (Fig 13).

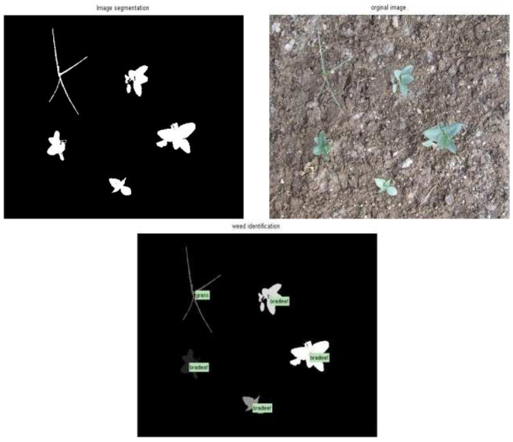

Fig13. Classification of weeds in two groups; grass and broadleaf

After determination of weed species by SVM, related poison was sprayed by sprayer.

RESULTS AND DISCUSSION

Image segmentation in laboratory

In assessment of image segmentation methods namely pixel wise, modified hue and NExG twenty images were randomly selected from laboratory images in different growth stages followed by manual modification until obtaining the best segmentation. In MATLAB application, algorithms of three automatic segmentation methods were written and the same images segmented manually were segmented by these methods. Each of segmented images was compared with manual segmented images pixel by pixel. During these comparison two measurement parameters, correct segmentation ratio (CSR) and incorrect segmentation ratio (ISR) were derived (formula 12).

$$CSR = \frac{P_0 \cap P_1}{P_0} \quad (12)$$

$$\mathrm{ISR} = \frac{\mathrm{P_0 \cup P_1 - P_0 \cap P_1}}{\mathrm{P_0}} \quad (13)$$

Where P_0 is the sum of pixels separated manually from background and P_1 is the sum of pixels separated automatically from background.

Table1. Calculation of CSR and ISR

Method	Pixel wise		NExG		Modified Hue	
Number of plant	CSR (%)	ISR (%)	CSR (%)	ISR (%)	CSR (%)	ISR (%)
1	100.00	0.11	97.94	3.68	99.32	1.17
2	100.00	0.29	96.09	14.53	90.20	9.94
3	99.72	0.33	93.06	12.91	96.11	8.77
4	99.89	0.11	80.55	22.51	96.55	7.48
5	97.53	2.47	84.10	21.25	95.05	8.85
6	88.48	11.76	90.05	61.74	82.46	22.32
7	98.80	0.12	97.02	5.57	98.19	2.57
8	99.94	0.23	95.51	5.78	97.90	2.73
9	99.10	0.12	75.70	25.25	69.20	31.91
10	99.97	0.03	64.66	36.36	72.48	28.67
11	97.53	0.13	77.28	24.34	70.99	31.08
12	98.94	1.06	86.41	14.75	85.15	15.69
13	100.00	2.47	65.82	34.35	81.19	19.48
14	100.00	0.12	95.53	6.12	78.62	22.15
15	100.00	0.33	99.73	4.25	84.85	16.76
16	87.82	12.18	74.93	37.91	81.99	18.54
17	97.88	2.60	92.11	15.04	96.47	6.25
18	93.40	20.00	81.10	22.00	85.00	36.00
19	98.00	10.40	96.40	10.30	96.40	30.00
20	99.50	8.30	96.00	4.30	99.40	16.30

For measurement of automatic methods of image segmentation, correlation value of CSR related to each method along with mean and SD values were calculated using Person's correlation coefficient and SPSS software. Results are indicated in tables 2 and 3.

Table2. Correlation value of CSR for image segmentation methods

Correlation				
Methods		NExG	Modified Hue	Pixel wise
NExG	Pearson Correlation Coefficient	1	0.652	0.193
	Significant Correlation	-	0.002**	0.416
	Number	20	20	20
Modified Hue	Pearson Correlation Coefficient	0.652	1	0.201
	Significant Correlation	0.002**	-	0.396
	Number	20	20	20
Pixel wise	Pearson Correlation Coefficient	0.193	0.201	1
	Significant Correlation	0.416	0.396	-
	Number	20	20	20

Table3. Mean and SD value for each of segmentation method in ISR and CSR parameters

Calculation of ISR				
		Pixel wise	NExG	Modified Hue
Number	Number	20	20	20
	Number of missing	0	0	0
Mean		3.65	19.14	16.38
(SD= Standard deviation)		5.69	14.81	10.77
Min		0.03	3.68	1.17
Max		20.00	61.74	36.00
Calculation of CSR				
		Pixel wise	NExG	Modified Hue
Number	Number	20	20	20
	Number of missing	0	0	0
Mean		97.82	86.99	87.87
(SD= Standard deviation)		3.65	10.88	10.01
Min		87.82	64.66	69.20
Max		100.00	99.73	99.40

Now regarding analysis performed on parameters CSR and ISR it can be concluded that: 1. In correlation assay, decision criterion or assay level is regarded to be 0.01. Based on table 2 p-value for NExG and modified hue methods are 0.002 indicative of a relationship between the said methods. However P-value between NExG and modified hue with pixel wise method was equaled to 0.416 and 0.396 respectively indicating that significant difference in CSR was observed between pixel wise method and two other segmentation methods. 2. Regarding table 3 pixel wise methods had a high mean CSR (97.8%) and a low mean ISR (3.6%) compared to other methods. Also for pixel wise method CSR ranged from 87.8- 100% and ISR varied from 0.03% -20%. Therefore algorithms of modified hue and NExG methods are not able to segment image of high quality. It is due to inability of the said method to do thresholding of target image when image brightness is not homogeneous. Another problem related to the said algorithms is that these methods change a three-dimensional matrix (RGB) to a one-dimensional vector. It leads to loss of information on hue and space, which is required for plant segmentation.

WEED IDENTIFICATION IN LABORATORY

Seven geometrical features such as ATL, PTB, ELG, CMP, LHW, LTP and ASP were extracted from images using 100 laboratory images including 50 images of broad- leaf weeds and 50 images of grass weeds. By use of MRMR method, geometrical features were prioritized based on their influences on accuracy of weed classification. Results are presented in table 4.

Table 4. results related to analysis of features by MRMR

Order of Features	K=1	K=0.5	K=0
1	ATL	ATL	ATL
2	CMP	CMP	CMP
3	ELG	ELG	ELG
4	LHW	LHW	PTB
5	ASP	LTP	ASP

To measure variations in accuracy of weed classification. With reduced number of geometrical features, two identification algorithms containing 3 and 7 features were made. Accuracy of weed classification was determined by 10- fold cross validation assay. Image process time for both algorithms was also measured. Table 5 shows results.

Table5. Segmentation error by identification algorithm containing 3 and 7 features

Calculation of 7 Properties				
Replication	Cross Validation	Processing time (s)	Average Precision	(SD= Standard deviation)
1	82%	1.1544	81%	1
2	81%			
3	80%			
Calculation of 7 Properties				
Replication	Cross Validation	Processing time (s)	Average Precision	(SD= Standard deviation)
1	75%	1.0608	72.6%	2.5
2	73%			
3	70%			

Results showed that use of seven features for identification algorithm of weed species by SVM could increase accuracy of weed classification by 8%. Whereas increase in process time due to use of seven features was very low (0.09) and had not a significant influence on operation run as real time.

FIELD ASSAY

There were 458 plants in 100 images taken in 15 and 16 July. In most images there were some plants from different species. Results related to weed classification by SVM are written in table 6. Classification accuracy is obtained by formula 14.

$$\text{Accuracy (\%)} = \left(1 - \frac{The\ number\ of\ shrubs\ identified\ incorrectly}{Total\ shrubs}\right) \times 100 \qquad (14)$$

Table6. Results of weed classification accuracy by SVM in the field assay

Mine of time (s/Image)	Classification of Accuracy (%)	Number of plants	Number of figures	Weed species	Date
2.17	65.09	150	50	Broadleaf	6th July Automatically
		78		Grass	
1.16	93.04	103	50	Broadleaf	7th July Manually
		127		Grass	

According to table 6 the accuracy that achieved by spraying the photographs are obtained automatically in corn, the least CV, and about 65% with an average processing time is 2.17 seconds, which is the most important factor because it is uncontrollable in the field test conditions. Factors such as wind, moisture, temperature and even the time of image acquisition can influence apparent features of plants. Among the other factors that could affect the accuracy of SVM is the image quality. For taking laboratory images, positions of camera and plant were fixed and camera showed no vibration while for taking field image, camera was mobile and had vibrations since land was uneven. When factors influencing accuracy of SVM are controlled during manual image acquisition, accuracy of SVM is reached to about 93% with mean process time of 1.16s. Therefore use of canopy for controlling sunlight radiation intensity and use of more technological cameras of higher quality and resolution insensitive to camera vibration can increase accuracy of SVM.

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