Developing a Machine Vision System to Detect Weeds from Potato Plant

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ABSTRACT

Potato is one of the widely used products all over the world that has numerous nutritional properties. Similar to other crops, different weeds grow along with potatoes in agricultural fields. These weeds reduce the performance of crops due to competing with them to absorb water, light, and nutrients from soil. Accordingly, in this study, a machine vision system with the hybrid artificial neural network-ant colony algorithm (ANN-ACO) classifier was developed for a site-specific spraying considering the weed type. Potato plant and three weed types including *Chenopodium album*, *Polygonum aviculare* L., and *Secale cereale* L. were used in this study. A digital camera (SAMSUNG WB151F (CCD, 14.2 MP, 30f/s) was placed in the center of the video acquisition system. The distance between plants and the digital camera was fixed at 40 cm. For video acquisition, only lamps of white LED with a light intensity of 327 lux were selected. For filming in order to evaluate the proposed system, a 4-hectare area of Agria potato fields in Kermanshah-Iran (longitude: 7.03°E; latitude: 4.22°N) was selected. Employing the Gamma test, among 31 features, 5 features (Luminance and Hue corresponding to YIQ color space, Autocorrelation, Contrast, and Correlation) were selected. The correct classification accuracy for testing and training data using three classifiers of the hybrid ANN-ACO, radial basis function (RBF) artificial neural network, and Discriminant analysis (DA) was 99.6% and 98.13%, 97.24% and 91.23%, and 69.8% and 70.8%, respectively. The results show that the accuracy of DA statistical method is much lower than that of the hybrid ANN-ACO classifier. Consequently, the results of the present study can be used in machine vision system for the optimum spraying of herbicides.

Keywords: Classification; Machine vision; Gamma test; Precision farming; Site-specific spraying

Patates Bitkisinde Yabani Otları Belirlemek için Yapay Görme Sisteminin Geliştirilmesi

ÖZET

Patates, tüm dünyada yaygın olarak kullanılan ürünlerden birisi olup sayısız besleyici özelliklere sahiptir. Tarım arazilerinde diğer bitkilerde olduğu gibi patateslerle birlikte farklı yabani otlar da yetişmektedir. Bu yabani otlar; su, ışık

ve topraktaki besin maddeleri için ana ürünle rekabete girerek bitkilerin büyüme performansını düşürürler. Bu nedenle çalışmada, yabani ot tipini göz önüne alarak bölgeye özel püskürtme yapan, yapay sinir ağı-karınca koloni algoritması (ANN-ACO)'ndan oluşan hibrit sınıflandırıcıya sahip bir yapay görme sistemi geliştirilmiştir. Bu çalışmada patates bitkisi ile *Chenopodium album*, *Polygonum aviculare* L. ve *Secale cereale* L. olmak üzere üç yabancı ot çeşidi kullanılmıştır. Video çekim sisteminin merkezine bir dijital kamera (SAMSUNG, WB151F (CCD, 14,2 MP, 30f/s) yerleştirilmiştir. Bitkiler ve dijital kamera arasındaki mesafe 40 cm olarak sabitlenmiştir. Video çekimi için yalnızca 327 lux ışık yoğunluğundaki beyaz LED lambaları seçilmiştir. Önerilen sistemi değerlendirmek üzere filme almak için Kermanshah-Iran'da (boylam: 7.03°E, enlem: 4.22°N), bir Agria patates tarlasının 4 hektarlık alanı seçilmiştir. Gamma testi uygulanarak, 31 özellik arasından 5 özellik (YIQ renk uzayına karşılık gelen parlaklık ve renk tonu, Otomatik korelasyon, Kontrast ve Korelasyon) seçilmiştir. Hibrit ANN-ACO, radyal esas fonksiyonlu (RBF) yapay sinir ağı ve Diskriminant analizi (DA) içeren üç sınıflandırıcı kullanılarak yapılan test ve eğitme verileri için düzgün sınıflandırma doğruluğu değerleri sırasıyla % 99.6 ve % 98.13, % 97.24 ve % 91.23, % 69.8 ve % 70.8'dir. Sonuçlar, DA istatiksel yönteminin doğruluğunun, hibrit ANN-ACO sınıflandırıcısından çok daha düşük olduğunu göstermiştir. Sonuç olarak, sunulan çalışmanın sonuçları herbisitlerin en uygun şekilde püskürtülebilmesi için yapay görme sisteminde kullanılabilir.

Anahtar Kelimeler: Sınıflandırma; Yapay görme; Gamma testi; Hassas tarım; Bölgeye özel püskürtme

1. Introduction

The number and type of weeds increase in agricultural fields proportional to the increase in the area under cultivation of crops and crop diversity (Mursalin et al 2013). These weeds deteriorate the performance of crops due to competing with them to absorb water, light, and soil nutrients. Among the most important methods recently applied methods by farmers for weed exclusion weeds are the manual and mechanical methods and the use of herbicides. The time-consuming weeds control operations and presence of weeds and crops together are the most significant limitations of manual and mechanical methods, respectively (Mursalin et al 2013). Owing to the mentioned limitations, herbicides have been currently used in weeds exclusion. However, the use of herbicides as traditional uniform distribution in the whole of the agricultural field has led to groundwater pollution, crops poisoning, and environmental pollution (Mursalin et al 2013). Applying precision agriculture technology and herbicides with variable rates will provide the possibility of cutting down the costs and preventing these problems (Bossu et al 2008). The machine vision systems are among the technologies that can be used for this purpose. These systems usually have two main parts: 1) video acquisition, pre-processing, and features extraction and 2) the analysis and classification of extracted features.

Generally, researchers have recently focused on identifying weeds using static images of the agricultural fields or greenhouses (Zhao et al 2009). The classification of different weed types and crops using computer vision and artificial neural networks has been considered among researchers (Zhao et al 2009). In this regard, Zhao et al (2009) classified three weed types, namely *Stellaria media*, *Celosia arentia*, and *Cephalanoplossetosum*, by applying the color principal component analysis (PCA). Their proposed method consists of two stages: 1) imaging of these three weed types in the laboratory (250 color images) and 2) dimensionality reduction using color PCA and classification. In the first step, the properties of three-dimensional color tensor were used to produce a vector space dimensionality reduction, and then the color PCA was utilized in dimensionality reduction. In the second step, the minimum Euclidean distance classifier was applied to recognize different weeds. The results showed that the accuracy of color PCA method is 4.4% higher than that of the conventional PCA that is 80.8%. Because this research was a laboratory-based work and, it did not yield practical results in the real conditions of agricultural fields. Mursalin et al (2013) classified five weed types including *Capsicum*, *Burcucumber*, *Cogongrass*, *Marsh herb*, and *Pigweed* using three Naïve Bayes, SVM, and C4.5 classifiers. They captured 400 images (80

images for every weed type) using a digital camera fixed 40 cm above ground and perpendicular to it. After pre-processing, nine features, namely Area, Perimeter, Convex Perimeter, Convex Area, Thickness, Solidity, Convexity, Form Factor, and Elongatedness were extracted from the weeds. The results indicated that Naïve Bayes classifier had the highest accuracy (99.3%) among these classifiers. Although the obtained accuracy was high for this database, it would not be achieved in weeds online identification in agricultural fields for two reasons: 1) a low number of samples in the database and 2) presence of frames with incomplete weeds and blurry frames in the provided videos.

Several researchers such as Bossu et al (2008) and Liu et al (2014) conducted some investigations to detect plant rows and weeds between these rows. Most of these systems used color characteristics to detect crop rows, assuming all plants between two neighboring rows as weeds. Montalvo et al (2013) demonstrated that automatic plant identification in agricultural fields based on imaging sensors is a big challenge. They proposed an automated expert system to identify weeds from corn in cornfields. The database utilized in their study consists of 230 images taken from the field in natural light conditions. Their proposed expert system has three stages: 1) the computation of vegetation indices and the use of the first threshold, 2) selecting black pixels and applying the second threshold, and 3) morphological operations and identification of masked and unmasked plants. In their research, the classification accuracy was achieved 89.9% using support vector machine. In this method, the plants placed between two corn rows were classified as the weed; thus, if the aim of weed recognition is spraying proportional to the type of weeds, this method is not practical. The major limitation of this method for weeds online identification is the small database size to train classification algorithm. Chowdhury et al (2015) presented a new texture feature based on the stable expert system to identify roadside vegetation. The database included 110 images in natural light conditions. From this database, 60 images corresponded to dense grass and the remaining 50 images with sparse grass.

The proposed system included five steps of image pre-processing, feature extraction, training with classification, classification, and validation; and eventually statistical analysis to classify these two weed types. Applying the co-occurrence of binary pattern method, the extracted texture features corresponded to the images of vegetation. In the step of training and classification, three classifiers were exploited to combine the multiple decisions. These classifiers are supported vector machine, feed forward back-propagation neural network, and nearest neighbor. The overall classification accuracy after applying these three classifications was 92.72%. Complete training is one of the main conditions for the success of each classification algorithm. In their study, only 90 images for training and 20 images for testing were used to identify weeds in the field by the algorithm that would face significant challenges.

Wavelets were also utilized in the field of classification and segmentation by some researchers. For example, Chen et al (2011) presented a new method, using Gabor wavelets and lie group structure of region covariance to classify broadleaf weed images on Riemannian manifolds. In their study, 320 images were used from four different weed types, namely *Oxaliscorniculata* L., *Duchesneaindica (Andrews) Focke*, *Herba Glechomae* L., and *Ixerischinensis (Thunb.) Nakai* for analys. The images were captured under natural light conditions by a digital camera. The distance between the ground and the digital camera was fixed at 50 cm, and the viewing angle of the lens was approximately adjusted horizontally. The optimal multiresolution Gabor wavelets were employed to decompose images into texture features, and lie group structure of region covariance was used to extract the filtered image features on Riemannian manifolds. K-nearest neighbor method was applied to classify four above-mentioned weed types. The results showed that the total accuracy classification is 93.13%. Video camera must be used for the majority of weeds online recognition in the agriculture field. Although the machine vision algorithm must be able to recognize several weeds in each frame, there was only one object in every frame in their research. Consequently, the method proposed in their study

was not practical in online recognition application. As pointed out in this section, a great number of researchers have focused on the application of image processing for weeds classification, which is not practical in online identification based on the aforementioned reasons. In this regard, videos are analyzed to recognize weeds online identification using machine vision.

The aim of the current research is developing a machine vision system to classify potato plant and three weed types of *Chenopodium album*, *Polygonum aviculare* L., and *Secale cereale* L. based on video processing and the hybrid neural networks-ant colony (ANN-ACO) classifier.

2. Material and Methods

To design a machine vision system, several steps are necessary. Two parts in each machine vision system are most important; i.e., segmentation and classification. Hence, it is essential to find the suitable color space and threshold related to segmentation and suitable classifier related to classification. The methodology applied in this work is as follows:

1) collect the required data to train machine vision system; 2) find the best color space to segmentation; 3) extract different features from each object; 4) select effective features among extraction features to train of the classifier; and 5) apply different classifiers to select the best classifiers. After these steps, a machine vision system is proposed based on video processing to classify potato plant and three weed types of *Chenopodium album*, *Polygonum aviculare* L., and *Secale cereale* L.

2.1. Video acquisition

In the present research, some videos were taken from one Agria potato fields with four hectares area in controlled light conditions in Kermanshah–

Iran (longitude: 7.03°E; latitude: 4.22°N). This field had three different weed types, tabulated with their corresponding names and varieties in Table 1. Figure 1 demonstrates images of potato plants and these three weed types. A chamber was designed and manufactured for video recordings with a speed of 0.145 ms^{-1} (Figure 2). The chamber light was provided by white LEDs with a light intensity of 327 lux. Videos were taken using SAMSUNG WB151F (CCD, 14.2 MP, 30f/s) camera. A computer with hardware of Intel Core i3 CFI i3 330M 2.13 GHz, RAM-4GB and 32 Bit equipped with MATLAB 2014 (a) and Microsoft office 2013 was used for analyzing. The distance between the camera and the plants was fixed as 40 cm. A tripod attached to the chassis along with rubber wheels was used to prevent the camera from shaking. Since the camera is moving in the field and each moment new details of plants are detected, the frames have to be analyzed individually.

2.2. Pre-processing and segmentation

In the first stage of pre-processing and analysis of the taken films, they must be converted to their frames. This task was performed by a code written in Matlab software. The camera utilized in this study captured 30 frames per second, and videos were converted to their constructive frames for image analysis. The first and the most important step for image analysis is segmentation, which is generally divided into two parts. The first part associated with the background separation from green plants while the second part is related to separation parts of plants from each other. After surveying the different color models such as RGB, HSV, HIS, YIQ, CMY, and YCbCr, the RGB model were selected for the first part of segmentation. The main cause for selecting the RGB model is that after the first part of segmentation in RGB color space, the image noise

Table 1- Three different weed types in potato fields

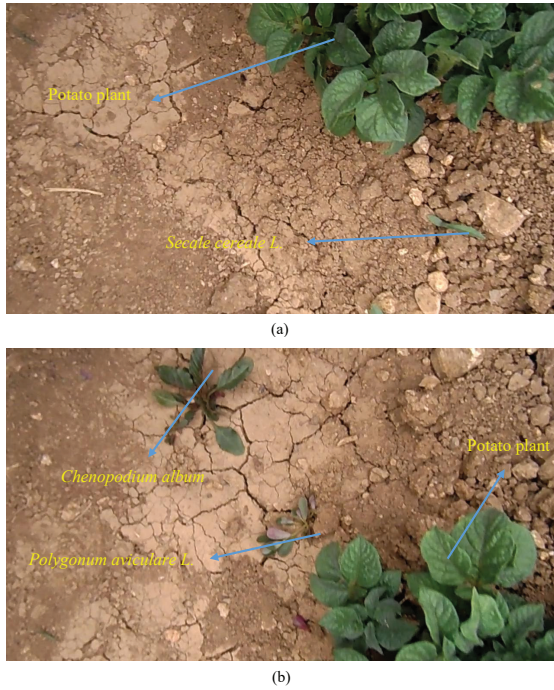| Name	Weeds		
English name	Knot weed	Rye	Common lambsquarters
Scientific name	*Polygonum aviculare* L.	*Secale cereale* L.	Chenopodium album

(a)

(b)

Figure 1- Different weeds types and potato plant; (a), *Secale cereale* **L. and potato plant; (b),** *Polygonum aviculare* **L.,** *Chenopodium album* **and potato plant**
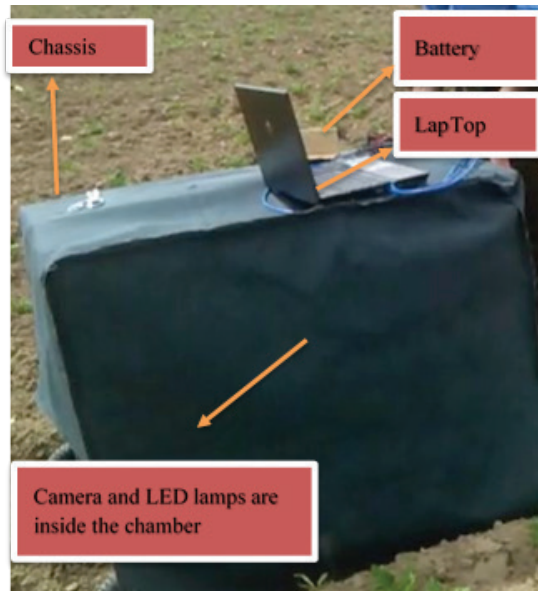
was less compared to that of other color spaces. Because frames may include several green plants corresponding to different species, each object (integrated pixels in each frame are called object) must be analyzed separately. For this reason, the Bounding Box was used. Figure 3 shows a sample of the first part of segmentation. At the top of the frame, the number of detected objects (which is 4 in this frame) is shown. Each object is identified by the coordinates of the center of mass (x and y). In order to extract the shape features, the segmented images must be converted into binary images. Figure 4 depicts the frame conversion steps to improved binary image. Figure 4 (a) demonstrates an extracted frame from a video. Besides, Figure 4 (b) illustrates the segmented image corresponding to this frame that was obtained by Equation 1. In fact, Equation 1 classifies a pixel as plant if its Green component is greater than its Red or Blue components.

$$R(i,j)G(i,j) \mid B(i,j)G(i,j) \tag{1}$$

The binary image in Figure 4 (c) presents several noises and holes, which must be removed by morphological processing. The morphological filter
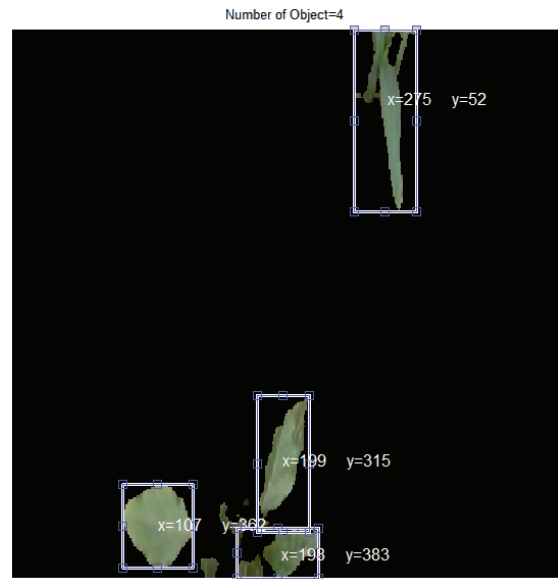

Figure 2- The specific chamber used for video recordings

Figure 3- The second part of segmentation of green plants in a frame

(a)

$$R(i,j) \leq G(i,j) \mid B(i,j) \leq G(i,j)$$

(b)

Convert segmented image to binary image
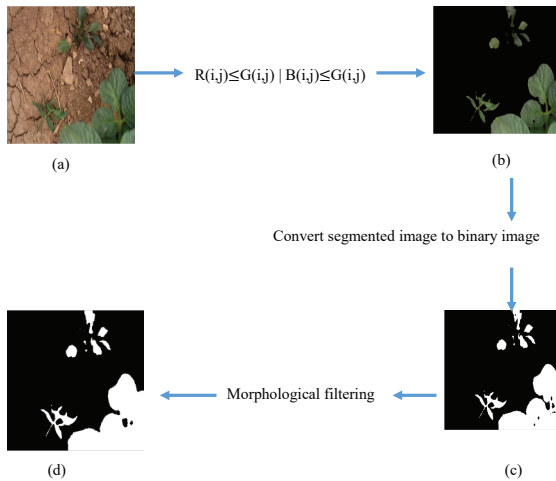
Morphological filtering

(d)

(c)

Figure 4- The proposed algorithm to convert color image to binary image; (a), original image; (b), segmented image; (c), binary image; (d), improved binary image

employed in this study was Closing. The Closing filter is a combination of two Dilation and Erosion operations that soften the contours of the object. This operation also leads to a connection between thin broken components and thin holes filling smaller than a structural member (Gonzalez et al 2004). Figure 4 (d) shows the improved binary image. After pre-processing operations on all frames, 3376 objects were extracted from the film taken. A total of 3376 objects corresponding to a 60-seconds video taken in the potato field were divided into two sets; training data with 2361 objects (all taken in 40 seconds) and testing data with 1015 objects (all taken in 20 seconds). Because the number of samples was not similar for all classes, all samples from each class were divided into two groups randomly: 1) training data (70% of all samples) and 2) testing data (30% of all samples). Thus, in the final training and testing data, there were 70% and 30% of samples related to each class.

2.3. Extracting features

Feature extraction is one of the most important tasks in machine vision. For this reason, 31 features were extracted from texture features based on the gray level co-occurrence matrix (GLCM), texture descriptors based on the histogram, color features, moment invariants, and shape features.

2.3.1. Texture features based on the gray level co-occurrence matrix (GLCM)

The gray level co-occurrence matrix includes information about the position of pixels with similar grayscale values. In this study, 10 features corresponding to the gray level co-occurrence matrix were extracted. Auto-correlation, contrast, correlation, difference entropy, difference variance, mean correlation 1, mean correlation 2, inverse difference, normalized inverse difference, and normalized inverse difference moment were textural extracting features. The gray level co-occurrence matrix must be normalized before introducing these features (Marques 2011).

2.3.2. Texture descriptors based on histogram

One of the most important methods to describe an area is the use of texture descriptors based on the histogram. Due to the textural difference among potato plants, *Secale cereale* L., *Polygonum aviculare* L., and *Chenopodium album*, these descriptors may be useful for classifying these four plant types. For this reason, two homogeneity and entropy features were used in this study (Gonzalez et al 2004).

2.3.3. Color features

The color models are used to determine color specifications in a standard, which is usually acceptable, method. In this study, three color spaces of YCbCr, HIS, and YIQ were utilized to extract their components (Gonzalez et al 2004).

YCbCr color model: This color model is used in digital images. In this space, the information of luminance is saved in Y, Cb, and Cr, which are the blue and red chroma components (Gonzalez et al 2004).

HSI color model: HIS color model was formed by applying Hue, Saturation, and Intensity components.

YIQ color model: YIQ color model consists of three Luminance, Hue, and Saturation components.

2.3.4. Moment invariants

Moment invariants are two-dimensional moments from the (p+q) degree that is applied to f(x,y) images with the dimensions of M×N. These moments are insensitive to transfer, congruency, reflection, and rotation. For this reason, moment invariants were employed in the present study. In the agricultural field, the leaves of potato plants and weeds have different sizes and orientations; therefore, moment invariants may be useful for classification purposes.

2.3.5. Shape features

Considering the difference in forms of the potato leaves, *Secale cereale* L., *Polygonum aviculare* L., and *Chenopodium album* plants, shape features may be useful parameters for classification purposes. Hence, in this study, eight features of Eccentricity, Orientation, ConvexArea, FilledArea, EulerNumber, EquivDiameter, Solidity, and Extent were extracted.

2.4. Selecting effective features

Selecting effective features is the main step for classification, which was done using Gamma test in the present work. Because Gamma test is a simple form of error deviation, it is applied to determine optimal inputs. This test indicates the estimated error, using direct data (Noori et al 2011). In this study, SPSS software was applied to perform Gamma test (Table 2). The results show that five variables including Auto-correlation, Contrast, Correlation, Luminance, and Hue corresponding to YIQ color space have lower Gamma values, and thus they are used as the best classification inputs.

2.5. Classification

In the present investigation, three classification methods of Discriminant analysis using SPSS statistical software, radial basis function (RBF) artificial neural network, and the hybrid of artificial neural network-ant colony (ANN-ACO) were tested for classification.

Table 2- The result of Gamma test performed on extracted features

Feature	Gamma coefficient	Feature	Gamma coefficient
Autocorrelation	-0.001	H	0.518
Contrast	-0.0012	S	0.291
Correlation	0.0015	I	-0.311
Difference variance	-0.234	Y	-0.0019
Difference entropy	-0.197	I	-0.0014
Mean correlation 1	-0.151	Q	-0.223
Mean correlation 2	0.137	Sixth moment invariant	0.186
Inverse difference	0.145	Seventh moment invariant	-0.018
Inverse difference normalized (INN)	0.18	Eccentricity	-0.002
Inverse difference moment normalized	0.231	Orientation	0.047
Homogeneity	0.085	ConvexArea	0.249
Entropy	0.05	FilledArea	0.234
Y	-0.281	EulerNumber	-0.71
Cb	-0.097	EquivDiameter	0.234
Cr	-0.305	Solidity	-0.338
Extent	-0.124		

2.5.1. The hybrid of artificial neural network-Ant Colony Algorithm

To optimize multilayer perceptron (MLP) artificial neural networks, five parameters, namely the number of neurons, the number of layers, transfer function, back-propagation network training function, and back-propagation weight/bias learning function must be optimized, which was done using ACO in this study (Sen & Mathur 2016). Table 3 also demonstrates the optimal values of MLP neural network. Figure 5 show the architecture of the ANN optimized using ACO and the criteria to stop learning process. Finally, Figure 6 presents a flow diagram for classification of four different types of plants using a video processing approach.

3. Results and Discussion

3.1. Image segmentation

Figure 7 presents the segmentation results of RGB, YIQ, and HSI models and Figure 7 (b) shows the results of YIQ model. As one can see, some parts of plants were considered as background in this segmentation. The HSI model results were shown in Figure 7 (c). Due to the high noise shown in the figure for this model, it would not have the ability of segmentation. Finally, the results of RGB model are given in Figure 7 (d). Evidently, this model had done segmentation thoroughly; therefore, the rest of the analysis would be based on this model. This program performs the first segmentation part

Table 3- The optimized value to classify using ANN-ACO

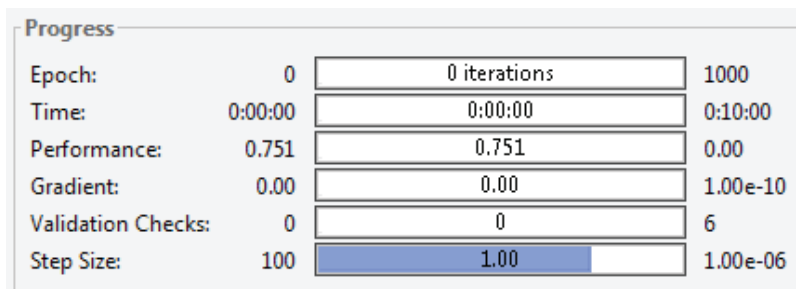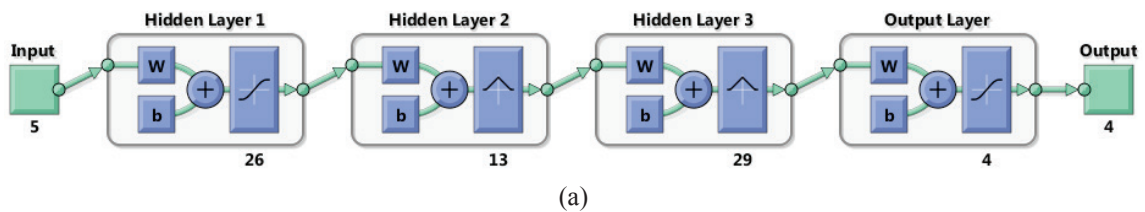|	
The number of neuron:	The first layer: 26, the second layer: 13, the third layer: 29
The number of layer:	3
Transfer function:	The first layer: tansig, the second layer: tribas, the third layer: tribas
Backpropagation network training function:	Trainlm
Backpropagation weight/bias learning function:	Learngdm

(a)

(b)

Figure 5- (a), architecture of optimized ANN using ACO and (b), the criteria to stop learning process
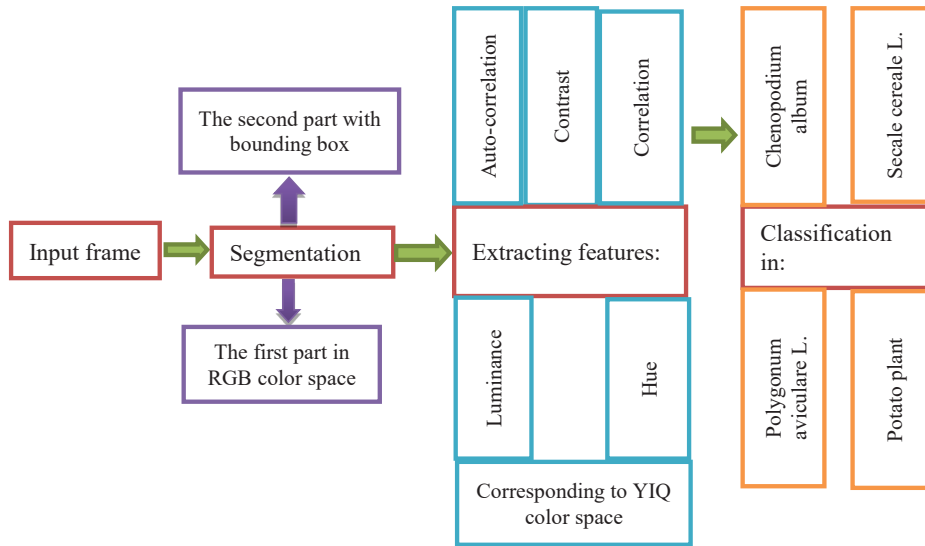
Figure 6- A flow diagram for classification four different types of plants
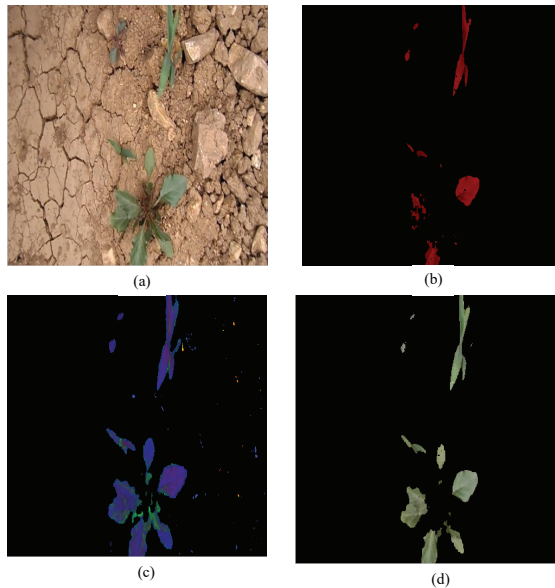

Figure 7- The different color models to segment; (a), original image; (b), YIQ color model; (c), HSI color model, and (d), RGB color model

using Equation 1; thus, it removes the parts pixel number less than 250 and considers the remaining parts as objects. Since the camera was moving in the agricultural field, each frame would present only a part of the plant. To reduce computing time and avoid possible errors, only the objects with pixel numbers higher than 250 were selected.

3.2. Classifying using the hybrid artificial neural network-Ant Colony Algorithm (ANN-ACO)

Figure 8 illustrates a comparison between the actual data and the predicted data, using the artificial neural network (ANN). The horizontal and vertical axes were consistent with the number of samples and the number of classes respectively. In this figure, the blue circles and the red stars correspond to actual data and the predicted data, respectively. Clearly, in most cases circles and stars had similar coordinates, implying that the ANN is trained correctly. Figure 8 (b) shows a magnified portion of Figure 8 (a). This finding proves that *Secale cereale* L. weed had more differences with other classes regarding Auto-correlation, Contrast, Correlation, Luminance, and Hue corresponding to YIQ color space features. Table 4 and Figure 9 present the classification of the testing data using the hybrid ANN-ACO. Each class was shown by a special color at the bottom of the diagram in Figure 9. This diagram demonstrates
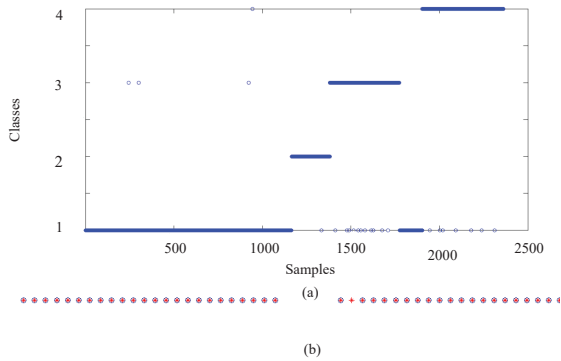
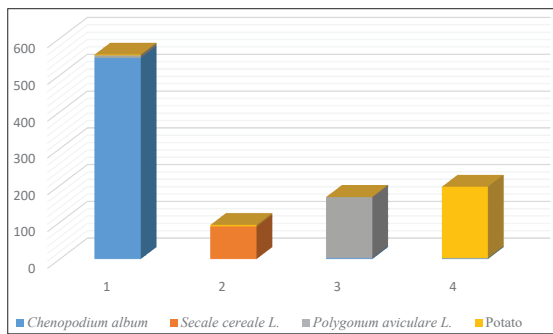**Figure 8- Comparison between real data and estimated data by ANN-ACO**

Figure 9- Classification of test data by ANN-ACO

that 547 samples corresponding with *Chenopodium album* were correctly classified while nine samples (seven samples as *Polygonum aviculare* L. and two samples as potato plant) are misclassified. The second diagram has only two colors: orange and yellow. The orange color matches *Secale cereale* L. plant (89 samples) that was classified accurately while the yellow color corresponds with potato

plant (four samples) that was misclassified as *Secale cereale* L.. The third diagram represents *Polygonum aviculare* L. class. As it is evident, there are only two blue and yellow colors in this diagram, except for the gray color that matches *Polygonum aviculare* L. class. The blue color signifies *Chenopodium album* in which seven samples were misclassified as *Polygonum aviculare* L.. Moreover, one sample of potato plant was misclassified in this class. Ultimately, out 169 *Polygonum aviculare* L. samples, 166 ones were classified correctly. In the fourth diagram, which corresponds to potato plant class, there are three misclassified samples among 197 plants. Among these three samples, two samples represent *Chenopodium album* and one sample signifies *Polygonum aviculare* L.. Furthermore, in the testing data, all types of plants were incorrectly classified as *Secale cereale* L.. This finding proves that *Secale cereale* L. weed had more differences with other classes regarding Auto-correlation, Contrast, Correlation, Luminance, and Hue corresponding to YIQ color space features. Figure 10 shows the classification results of the hybrid ANN-ACO in six different frames. In this figure, Ch, pot, S, and polrefer to *Chenopodium* album, a potato plant, *Secale cereal*e L., and *Polygonum aviculare* L., respectively.

3.3. The classification using Radial Basis Function (RBF)

In addition to the hybrid ANN-ACO classifier, RBF neural network was also used to classify potato plant and three weed types, including *Chenopodium album*, *Polygonum aviculare* L., and *Secale cereale* L. based on the video processing applied in this research.

Table 4- The classification results related to testing data using ANN-ACO classifier. 1) *Polygonum aviculare* **L.; 2)** *Secale cereale* **L., 3)** *Chenopodium album*, **and 4) potato plant**

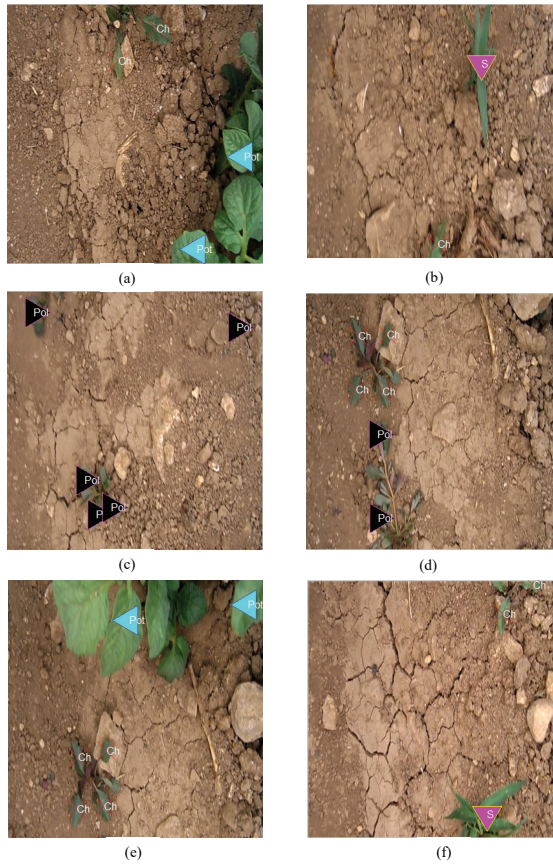| Classes	1	2	3	4	All data	The percentage of incorrect classification (%)	The percentage of general classification (%)
1	547	0	7	2	556	1.62	
2	0	89	0	4	93	4.31	98.13
3	3	0	166	0	169	1.77	
4	2	0	1	194	197	1.52	

Figure 10- Identification of potato plant and three different weed types; (a), potato plant and *Chenopodium album*; (b), *Secale cereale* L. and *Chenopodium album*; (c), *Polygonum aviculare* L.; (d), *Chenopodium album* and *Polygonum aviculare* L.; (e), potato plant and *Chenopodium album*; (f), *Secale cereale* L. and *Chenopodium album*

Figure 11 indicates the testing data classification results using RBF. There are four classes shown as four diagrams in this figure. Each class in this figure is marked by a specific color. The first diagram corresponds to *Chenopodium album* class. There are different colors in this diagram, which means that the samples of other classes were misclassified in this class. Moreover, 33 samples were classified as *Chenopodium album* incorrectly. From these 33 samples, two samples correspond to *Secale cereale*

L., 23 samples to *Polygonum aviculare* L., and eight samples to potato plant. The second diagram, which corresponds to *Secale cereale* L. class, show that the samples of *Chenopodium album* (12 samples) and *Polygonum aviculare* L. (one sample) were misclassified in this class. In addition, 22 samples were misclassified in *Polygonum aviculare* L. class. Among these 22 samples, 20 samples were corresponding to *Chenopodium album*, 1 sample to *Secale cereale* L., and the remaining one sample to potato plant. Finally, 15 samples correspond with *Chenopodium album*, two samples with *Secale cereale* L., and three samples to *Polygonum aviculare* L. were misclassified in potato plant class. By comparing the last two sections, it can be concluded that the various methods of artificial intelligence with same inputs provide different results, therefore, selecting an effective method for classification is of high significance.
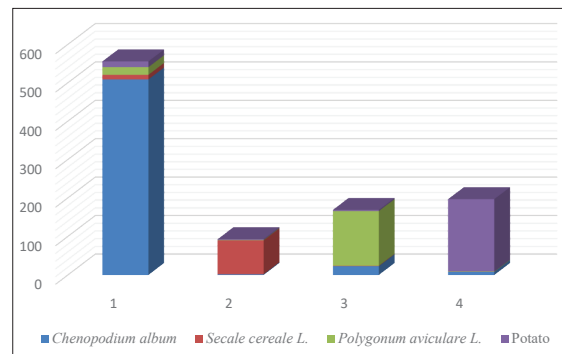

Figure 11- Classification of test data by RBF neural network classifier

3.4. Classification using discriminant analysis statistical method

Discriminant analysis statistical method was also applied to classify potato plant and *Chenopodium album, Polygonum aviculare* L. and *Secale cereale* L. in this research. This statistical method conducted to detect the accuracy performance of the hybrid ANN-ACO. Figure 12 illustrates the results of testing classification using Discriminant analysis method. The first diagram is the combination of four colors, implying that the data corresponding to *Chenopodium album* were misclassified using

Discriminant analysis method; as 31.7% of all samples corresponding to *Chenopodium album* were misclassified. The second diagram indicates that 10.7% of all samples were misclassified as *Secale cereale* L. weed. The third diagram shows that only 0.7% of all data were misclassified as *Polygonum aviculare* L. weed. Finally, the fourth diagram reveals that 83.8% of potato plant samples were classified correctly. The overall classification accuracy of testing data was 70.8%. The results confirmed that the accuracy of Discriminant analysis statistical method was lower than that of artificial intelligence methods. In most cases, statistical methods assume that the data have a normal distribution, and the truth or falsity of the results depends on this initial assumption. In contrast, machine-learning methods do not use any assumptions about data, and this is the case led to the differences between these two methods. Hence, as the results indicated, Discriminant analysis statistical is not a suitable method to classify the data used in this study.
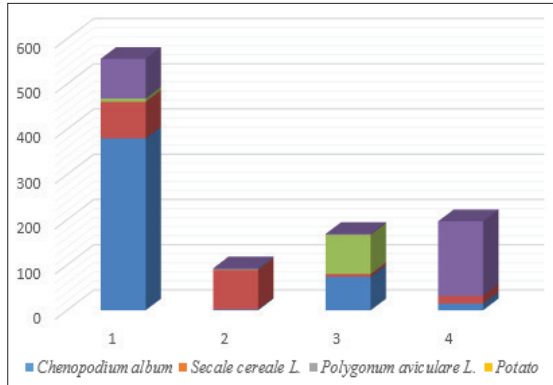

Figure 12- Classification of testing data by Discriminant analysis classifier

3.5. The performance comparison of two ANN-ACO and RBF classifiers

In general, classifiers were evaluated using three criteria of sensitivity, specificity, and accuracy was applied, where sensitivity is a fraction of the samples that are correctly classified; specificity is a fraction of the samples that are classified by the

system; and accuracy is the total classification rate of the classifier. These three criteria are calculated using Equations 2-4 (Liu et al 2015).

$$Sensitivity = \frac{TP}{TP+FN} \qquad (2)$$

$$Specificity = \frac{TN}{FP+TN} \qquad (3)$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad (4)$$

Where; TP is the number of studied class samples correctly identified as studied class; TN is the number of other classes samples correctly identified as other classes; FN is the number of studied class samples incorrectly identified as other classes; and FP is the number of other classes samples incorrectly identified as studied class (Wisaeng 2013). Table 5 presents the results corresponding to these three criteria. The table also demonstrates that the sensitivity of all classified classes using ANN-ACO is over 90%. For example, the sensitivity of *Chenopodium album* is 99.77%, suggesting that the system has correctly identified *Chenopodium album* weeds by 99.77%. The accuracy of ANN-ACO classifier for all classes is over 99.6%. For instance, the accuracy of *Secale cereale* L. is 99.96%, denoting that this classifier system has correctly classified other plants in addition to *Secale cereale* L. weeds. The criterion of specificity for all classes is over 99.2%. *Secale cereale* L. weed has the highest value of specificity, namely 100%; implying that the classification system did not classify any samples in this class incorrectly. The results shown in Table 5 prove the superiority ANN-ACO to RBF. For example, the accuracy corresponding to *Polygonum aviculare* L. in RBF classifier is 98.41%, whereas in ANN-ACO classifier it is 99.76%, being 1.38% more than RBF classifier. As previously mentioned, the database is the same for both classifiers, and this difference is only due to classifiers classification method. The classifier is of the main parts of machine vision system, especially for classifying weeds and crops to the optimal spraying of herbicides. As stated earlier, there is no possibility of direct comparison

of the employed method in this study with those of other researchers. However, Table 6 compares the correct classification rate of the present study and those of two other studies. In the first study (Hlaing & Khaing 2014), the authors classified four weed types, including Rape plant, Lanchon, Pigweed, and Kyautkut using Area Thresholding Algorithm. As shown in Table 6, from 35 samples, six samples were misclassified; therefore, the correct classification rate of the system was 82.85%. The second study is consistent with the study by Arribas et al (2011) who identified sunflower from non-sunflower,

using the generalized softmax perceptron (GSP) neural network. This classifier system misclassified 25 samples from 192 samples, thus the correct classification rate of the system being 85%. By comparing the above-mentioned results and the results of the present study, the superiority of the method applied in this study is demonstrated. Hence, by employing this method, the possibility of making a machine vision system to real-time detection of *Chenopodium album*, *Polygonum aviculare* L., and *Secale cereale* L. weeds in potato agricultural field is raised up.

Table 5- Criteria of confusion matrix performance

Class	RBF			The hybrid ANN-ACO		
	Sensitivity	Accuracy	Specificity	Sensitivity	Accuracy	Specificity
Chenopodium album	99.30	97.37	96.03	99.77	99.66	99.61
Secale cereale L.	96.31	99.57	99.05	99.54	99.96	100
Polygonum aviculare L.	92.37	98.41	98.12	99.49	99.79	99.24
Potato plant	96.07	99.09	99.13	99.12	99.74	99.56

Table 6- A comparison between correct classification rate of present study and those of two other studies

Method	The number of samples	The number of misclassified samples	Accuracy rate (%)
Proposed model	1015 (testing data)	19	98.128
Hlaing & Khaing (2014)	35	6	82.85
Arribas et al (2011)	192	29	85

4. Conclusions

A novel method based on machine vision was applied to classify potato plant and three weed types of *Chenopodium album*, *Polygonum aviculare* L., and *Secalec ereale* L.. In order to survey the performance of the proposed classification method, a novel classifier known as the hybrid artificial neural network-Ant Colony (ANN-ACO) was presented. The findings confirmed that this classifier had the highest classification accuracy. In this work, the low computation speed in some moment was observed. Such a low speed is due to the excessive computations required to classify the weeds.

Since the Matlab is not a compiled programming environment, the algorithm can be recorded using a compiled programming language like C for raising the speed of computations.

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