DETECTION OF HARMFUL INSECTS BASED ON GRAY-LEVEL CO-OCCURRENCE MATRIX (GLCM) IN RURAL AREAS MEHDI EBADI MANAA, RAAID N. AL-ABAEDY, WESSAM ABBAS HAMED

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ABSTRACT
There are many types of insects that affect agricultural fields. These harmful insects should be classified in a smart implementation for the rural fields. The main point to detect depends on their texture color. These textures are different from one insect to another. We propose a new hybrid method based on Gray Level Co-occurrence Matrix (GLCM) to detect the harmful insects in agricultural fields. The main idea shows that a tested image is composed of different texture regions of the insect and this will help to extract feature value. This paper consists of three steps: the first step extracts texture features using GLCM in four directions which are 0, 90, 180 and 270 degrees from the gray image. The second step trains the neural network depending on texture features in a large number of variety insect's images. The third step tests the unknown insect's image to classify it whether harmful or not. The purpose of this study helps rural farmers to detect the harmful insects and classify them to take care of their crops.

KEY WORDS
Insects' recognition, Gray Level Co-occurrence Matrix (GLCM) and Texture features.

1 INTRODUCTION

There are many efforts that need to be achieved to help the farmers in the rural areas. The technology tool has been used in this area to help people to achieve their work smoothly and in an easy way. Achievement of agricultural development in the 21st century depends on the wide use of information and communication technology. Most efforts in rural areas have been concerned in the training courses using ICT [1]. Supporting rural work using different technologies is a good way to increase their skills in agricultural fields. Based on this, we need to build a good tool that recognizes the insects in the agricultural field based on the insects' texture color.

There are different fields in image processing help to detect the object. This paper introduces a new hybrid of insect's recognition which is part of image processing using Gray level co-occurrence matrix (GLCM). This helps people in agricultural field to know more information about the harmful insects. This paper uses the combination of the GLCM algorithm and neural network. The neural network inputs depend on the extraction of texture features in different directions based on GLCM of different image patterns. These patterns have high variability of reflecting texture features. Therefore, using image texture features is a good way to recognize the harmful insect.

This paper aims at recognizing the harmful insects and identifying them to the farmers to take the right action based on computer tool. The structure of this paper consists of three steps: extracting the texture features from gray images and applying the GLCM algorithm in four directions. The second step trains the neural network according to the available images of insect's features and finally detecting the unknown insect whether harmful or not.

2. RELATED WORKS

Many research efforts in combining insect math morphology with computer technology start at the beginning of 1990s. Albrecht and Kailadraw wing venation pattern of Elachistidae on grided A4-sized paper[2]. Applying image-based insect's recognition using GLCM and neural network is a new hybrid method in pattern image processing. Extracting texture features in an insect image that can be used for recognition such as energy, entropy and others texture features based on GLCM matrix, has a wide range of applications. Generally, these applications can be used in predicting and preventing plant diseases and insect pests.

Most of the times, image processing has been developed in a new technology. We need to consider texture images with high resolution. For example, ZHU and ZHANG (2010) used colour histogram and GLCM (Gray level co-occurrence matrix) in insect recognition. Region of interest (ROI) is first segmented out from the insect image using image pre-processing algorithm. Thus colour features that are represented by colour histograms are extracted from the ROI which can be used for coarse level matching. The matching is realized by comparing the correlation of the feature vectors with certain threshold [3]. Before this paper, many efforts were made to classify an insect image based on either neural network or GLCM matrix. Zhang, Huo and Ding (2008) adopted the classification of stored product insects. The existing classification methods cannot acquire excellent performance. AdaBoost, an adaptive boosting algorithm, may improve the classification accuracy of any given classifier. In this paper, AdaBoost is adopted to increase the performance of artificial neural network for stored product insect classification in comparison with standard neural network methods. Experiment results show that the new method is efficient. In addition, a significant improvement in classification accuracy is obtained [4].

According to the global optimization ability of the particle swarm optimization (PSO) and the superior classification performance of the support vector machines (SVM), Zhang & Mao (2009) proposed a method based on PSO and SVM to improve the classification accuracy with the appropriate feature subset. The single objective fitness function was designed to evaluate the feature subset by introducing the v-fold cross-validation training model accuracy and the number of the selected features [5]. The main role in classification should include high resolution images for reorganization due to high resolution pixels. This way enables to extract features with accuracy. On the other hand, Shen and Sarris (2008) proposed the Application of Texture Analysis in Land Cover Classification of High Resolution Image. Their paper deals with the land cover classification of high resolution Quick bird images using the texture feature analysis. In their research, the study area covers the wider region of the urbanized environment of China and Greece. Different textural features including Entropy and Asm (angular second moment) were extracted based on GLCM(Grey Level Co-occurrence Matrix) texture feature and used as the distinct feature value in classification procedures[6].

Some studies adopted the segmentation of high resolution images in Effective Feature Extraction by Trace Transform for Insect Footprint Recognition [7]. Footprint segments are extracted from scanned footprints and appropriate features are calculated for those segments (or cluster of segments) in order to discriminate species of insects. The selection or identification of such features is crucial for this classification process. This procedure has been adopted by Shin et al (2008). Another direction in this paper presents pattern texture features to train the neural network. Some studies developed the research on Insect Gait Pattern classification based on image feature extraction. They designed a centrifuge system which is based on high-speed image detecting of moving object to test insect's gait under different conditions. From the statistics of the result, analysis classification regulation of insects gait mode and the paper proposed an algorithm based on image feature extraction [8].

An application of machine vision, incorporating neural networks, which aims to fully automate real-time inspection in component identification process, is described by Commander and V. (2007) [9]. Their methodology adopted comprises two distinct stages:the segmentation of the component from the background content of the image and the segmentation of suspect defect areas inside the region itself.

3 POPOSED SYSTEM

We propose insect classification in agriculture field based on Gray level co-occurrence matrix (GLCM) and neural network. It is necessary to divide the proposed work to three Steps. The first step converts the color image to gray color (256 color). The second step includes extracting the texture features such as entropy, energy and other features. These features extracted based on GLCM algorithm in four directions to train the neural network. The final step is to test the unknown image to detect the insects' images whether harmful or not.

A. Image *acquisition* and preprocessing

Twenty species were selected as the objective insects of this research. The image acquisition system was composed of an image acquisition species for different insects selected from the internet. Fig.1 gives some of the acquired insect image samples.

Aleuroclave	*Ceratites*	*Rhynchopho*	*Pseudophilu*	*Oryctes*	*Batrachedr*

Fig. 1: SOME harmful insect's images

In the image preprocessing, we need to convert the high resolution image to a gray color. Based on this image, the Pseduocode in VB code to convert the color RGB image to gray image is shown in fig. 2 below:

```
For Y = 0 To ImageHigh – 1,     YY = High - 1 - Y
   For x = 0 To Width - 1
        gray_image(x, Y) = Myimage(x, Y).red
        gray_image(x, Y) = (gray_image(x, Y) + Myimage(x, Y).g)
        gray_image(x, Y) = (gray_image(x, Y) + Myimage(x, Y).b)
        gray_image(x, Y) = gray_image(x, Y) / 3
        Picture2.PSet (x, YY), RGB(gray_image(x, Y), gray_image(x, Y),
        gray_image(x, Y))
        Next x Next Y
```

Fig.2: Pseduo Code to convert RGB image to gray

B. GLCM-based texture feature extraction

Gray level co-occurrence matrix (GLCM) [10], one of the most known texture analysis methods, estimates image properties related to second-order statistics. Each entry (*i*,*j*) in GLCM corresponds to the number of occurrences of the pair of gray levels *i* and *j* which are a distance ***d*** apart in original image. The GLCM generated provides information of the relationship between gray-scaled pixel values of the image. Therefore, many texture features could be extracted from the GLCM. We can calculate the image texture features which found by Robert Haralick in the 1970s [11]. Haralick proposed 14 statistical features extracted from image. To reduce the computational complexity, only 5 most relevant features that are used in this paper such as Energy, Entropy, mean correlation and others. Table (1) shows these texture features equations.

“Tab. 1: TEXTURE Features by Robert Haralick”

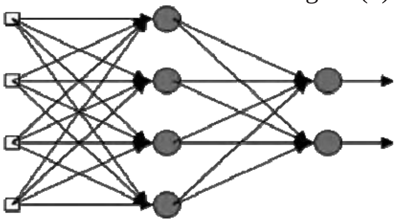
Energy	$\sum_{m=0}^{G-1}\sum_{n=0}^{G-1} P(m,n)^2$
Entropy	$\sum_{m=0}^{G-1}\sum_{n=0}^{G-1} p(m,n)\log p(m,n)$
Contrast	$\frac{1}{(G-1)^2}\sum_{m=0}^{G-1}\sum_{n=0}^{G-1}(m-n)^2\, p(m,n)$

Correlation	$\frac{\sum_{m=0}^{G-1}\sum_{n=0}^{G-1} mnp(m,n) - \mu_x \mu_y}{\sigma x \sigma y}$ *where* $\mu_x = \sum_{m=0}^{G-1} m \sum_{n=0}^{G-1} p(m,n)$ $\mu_y = \sum_{n=0}^{G-1} n \sum_{m=0}^{G-1} p(m,n)$ $\sigma_x = \sum_{m=0}^{G-1} (m-\mu_x)^2 \sum_{n=0}^{G-1} p(m,n)$ $\sigma_y = \sum_{n=0}^{G-1} (n-\mu_x)^2 \sum_{m=0}^{G-1} p(m,n)$
Homogeneity	$\sum_{m=0}^{G-1}\sum_{n=0}^{G-1} \frac{p(m,n)}{(1+\lvert m-n \rvert}$

Generating a GLCM, by using image matrix G x G, four directions can be focused on during the generation of the matrix. These directions are 0 degree (or horizontal) direction; 45 degrees direction; 90 degrees (or vertical) direction and 135 degrees direction. The direction and spatial distance from the reference pixel x will be defined such as 1 space for the horizontal direction that is to check the value of the adjacent pixel next to the reference pixels. Figure (2) shows the GLCM in different directions.

C.Backpropagation Neural Network

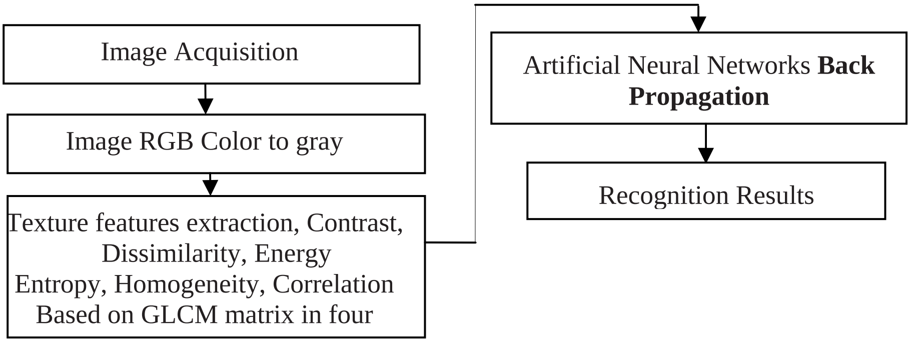
Back propagation, propagation of error, is a common method of teaching artificial neural networks. It was first described by Paul Werbos in 1974 [12]. The structure of multilayer BP network is shown in figure (3).



"Fig.3: MULTILAYER BP Network fully connected"

It wasn't used until 1986. It leads the renaissance in the field of artificial neural network research. It is a supervised learning method and is an implementation of the Delta rule. In this step, our back propagation network is represented by the following steps:

- Extract texture features based on GLCM matrix in different directions such as 0, 90, 180 and 270 degrees after converting the image to gray color as mentioned in steps one and two and train the back propagation neural based on extracted features in steps one and two for each direction.
- Classify the unknown image in trained network. If the image unknown, we train the neural again to include the features for new image. Figure (4). Shows the proposed system for the three steps.



"Fig.4: PROPOSED system using three steps"

4. EXPERIMENTAL RESULTS

In the first step of classification, we used 15 images out of 20 images for the training purpose and 5 images were used for testing purpose. In this level, accuracy is found to be 90% especially in correlation factor. In the Second level of classification, we used 13 images out of 20 images for the training purpose and 7 images for testing purpose. The accuracy in the second level is found between 70-80%. Below are given some results for different images and their extracting texture values in Table (2).

"Tab.2: TEXTURE Features for Contrast, Dissimilarity and Homogeneity"

Pattern Name	Contrast	Dissimilarity	Homogeneity	Energy	Entropy	Correlation
Image(1)	0.401412	0.49770	0.000656	0.000227	0.285005	0.891264
Image(2)	0.212272	0.28670	0.000983	0.000323	0.410021	0.983132
Image(3)	0.348910	0.39563	0.000609	0.000447	0.261166	0.947453
Image(4)	0.238856	0.33650	0.000772	0.000245	0.312132	0.963153
Pattern(k)	0.449092	0.47440	0.000872	0.000384	0.265215	0.831421

And the overall detection shows in table 3 below:

"Tab.3: Backpropgation Neural Network Detection percentage"

Overall Images		**Total of Features in four direction GLCM 0, 90, 180, 270**	**Correct percentage**	**False percentage**
Training Images	**Testing Images**			
15 images	5 images	300 features for 15 each image	90%	10%
13 images	7 images	260 features for each 13 images	70-80%	20-30%

5. FUTURE WORK AND ENHANCEMENT

In future work, we need to use the most modern neural networks instead of BP neural network due to its limitation issue in sample training. For example, we need to use SOM. We are looking forward to developing our system to include more images from different categories. So, we need to add more attributes to classify the insects and their texture features.

6. CONCLUSION

In conclusion, we have given a hybrid method which is very good for insect's detection in an agricultural fields based on extracting different texture features. GLCM matrix develops a new way for texture features, which relies on four directions, i.e., 0, 90, 80 and 270 for each image. This way enables us to compare and find the best matching for one image. As a result, we saw a correlation factor that is very important to match the image due to different values for each direction.

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