Random Subspace Classifier for Recognition of Pests on Crops

Lucero Roldán-Serrato[1], Tetyana Baydyk[1], Ernst Kussul[1], Alberto Escalante-Estrada[2], Graciela Velasco-Herrera[1]

[1] Centro de Ciencias Aplicadas y Desarrollo Tecnológico, Universidad Nacional Autónoma de México, Circuito Exterior S/N, Ciudad Universitaria, AP 70-186, CP 04510, México D. F. México
[2]Postgrado en Botánica, Colegio de Postgraduados, México
tbaidyk@unam.mx

Abstract

The purpose of this work is to develop a recognition system of the Beetle Colorado Potato (Leptinotarsa decemlineata) pest. We work with images and we use them in the system based on neural networks. We use a collection of 25 images with different position of beetles, also with varying numbers of beetles. We calculate the brightness, contrast and contour orientation histograms for feature extraction of every image as input to the Random Subspace Classifier (RSC) neural classifier. We describe in this paper the structure, algorithms, and the initial results of the RSC classifier testing.

1. Introduction

The initial investigations for the detection and recognition of insects were developed in controlled environments (isolated chambers, laboratories and greenhouses) [1] - [7]. It was made in order to improve environmental conditions and to have a environmental stability that improve results of recognition technique implementation. The objective of these researches was to detect and to determine if the insect belongs to category or pest [8]. We need to have images that allow us to extract and obtain information, since the image acquisition to the application of algorithms for the automatic detection of patterns

The design and development of algorithms that work with images are important components in the methodology of image processing and computer vision. The computer vision systems in science and technology are based on extracting information from an image to solve a special task [9] – [10]. These systems are increasingly used in automation process in robotics, micromechanics, biomedical investigations, and etc. Computer vision technique has been shown to be consistent and economical inspection in the agriculture and crops quality measuring [6] - [11]. In Fig.1 we present one example of larvae recognition.

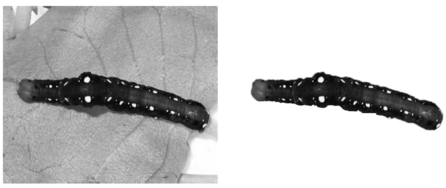

Figure 1: Image-based automatic recognition of larvae.

In recent decades some methods used in computer vision for detecting pests, insects and beetles were developed. Sometimes these methods are used to recognize pesticides that used against insects and larvae. For example, to obtain the number of harmful insects in a greenhouse the video processing algorithms were proposed. By making closed-circuit video the authors achieved sufficiently good results. The Bayesian neural networks for the detection of sterile fliers is another technique that was implemented [3]. The best result of recognition rate was obtained of 89.2%. The wavelet neural network (WNN) was developed and used to recognize the spectrum of pesticide on a crop [4].

The special techniques to detect sugar cotton pest in China was developed using the rough set with fuzzy C-means clustering [5]. The authors identify and diagnose the presence of pests in the crop using digital color image recognition. Their system had an efficiency of 85% of correct recognition. The techniques show good results in agriculture.

There is work to create algorithms that accept images with shape, texture and color varying [12].

In 2002 the United Nations Food and Agriculture Organization (FAO) highlighted the problems regarding food production, either water quality, soil quality and hence quality-culture in the use of pesticides. Therefore, we are interesting in two pests that devastate crops of potatoes and beans. These potatoes and beans have high productivity and high demand. They make up 85% of the total plant and fruit consumption [13].

In Mexico, the beans are one of the most important foods. The beans are extremely easy to grow. This plant has usually high productivity and low cost of farm work. The bean has a number of possible pests which cause various types of damage. A pest that can seriously damage the plants is the Mexican bean beetle MBB (*Epilachna varivestis*). MBB is a yellow or brown beetle, it has eight black spots on each wing. One of the techniques used to control the MBB is a manual selection and destruction of egg masses and adults beetles, removing or destroying the remains of plants after harvesting process [14] (Fig. 2).

Figure 2: Images of Mexican bean beetle on crops.

Potatoes have several different types of pests that can destroy plant leaves and tubers. The pests attack the potatoes and prevent its growth. One of the most common and most dangerous beetles is the Colorado potato beetle (CPB) (*Leptinotarsa decemlineata*). The CPB is mainly distributed in Europe and in the USA. This adult beetle is yellow or orange and his body is covered with 10 narrow black stripes. Many beetle populations have developed resistance to pesticides that have been widely used against them [15] (Fig.3).

Figure 3: Images of Colorado potato beetle on crops.

In this paper we propose a RSC neural classifier to recognize the Colorado potatoes beets. Any type of input images with MBB and CPB beetles of different shape or texture are acceptable.

2. Database and feature extraction

We have an image database of about 30 CPB samples and about 20 MBB samples. These images we have gotten from different websites. The images have dimensions of 250 x 180 pixels. Many insects use the technique of mimesis (imitation) to hide the foliage [16], [17]. However for the development of our system and due to the physiological characteristics of the Colorado beetle, this property does not affect our task of recognition. So it is possible to develop and to use a computer vision based on neural networks for localization and diagnosis of pests in potato crops.

Each image pretreatment was performed, changing the original image to grayscale. Then we have marked each image: put a white pixel to pixel containing only the beetle. After the marking process, each image is scanned with a window size of 20 x 20 to increase the number of samples for RSC classifier. For every window we realize the feature extraction specifically the calculation of three types of histograms. These are brightness, contrast and contour orientation histograms. We used these histograms as inputs for our RSC neural classifier. (Fig. 4).

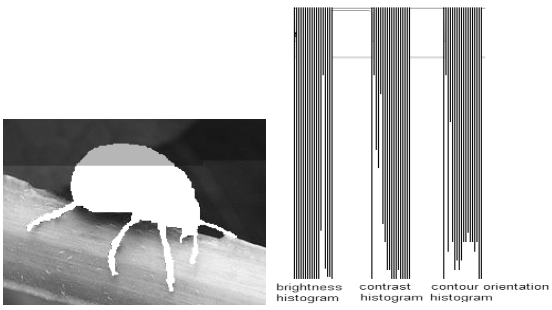

Figure 4: Feature extraction (three histograms)

To calculate the brightness histogram we analyze every pixel of the window that scanned the image. If we want to calculate the contrast histogram we need to analyze two neighboring pixels (in horizontal, vertical or diagonal direction). We can calculate the brightness difference of two pixels and after that to calculate the contrast histograms. For the third histogram of orientations of microcontours we need to analyze every four pixels of the window. For this purpose we used the Schwartz algorithm [18]. We show the results (three histograms) in Fig. 4 (contour orientation histogram is the third histogram) [18].

3. Random subspace classifier

The RSC is a multi-layer classifier. This classifier is based on Random Threshold Classifier (RTC) [19]. This classifier consists of an input layer, intermediate layers and output layer to demonstrate a system response (Fig.5).

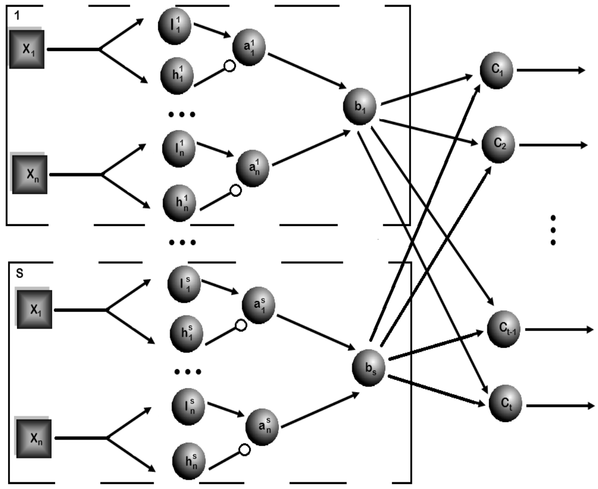

Figure 5: Structure of RSC classifier

The inputs are the parameters, for example the histograms of brightness, contrast, and orientations of microcontours ($X_1, X_2, .., X_n$). Every feature X has connections with two neurons with thresholds l y h, its subscript is which group belongs neurons ($1, 2, ..., n$), while the superscript refers to the features. l y h thresholds are randomly generated and have to satisfy the condition $l < h$. These neurons have excitatory and inhibitory connections with neuron of A layer (associative layer $a_1, ..., a_n$). The neurons are binary neurons. The states of the neurons can be 0 or 1, state 1 if it is active and 0 for inactive status. If all neurons a_i are active the b neuron is active. Every b neuron works as logical element “AND”.

Each neuron of B layer is connected with all neurons of C layer. Each connection has its own weight. During the training process these connections change their weights. For this training process we use the Hebb rule:

$$\omega_{jc}(t+1)=\omega_{jc}(t)+a_j \quad (1)$$
$$\omega_{ji}(t+1)=\omega_{ji}(t)-a_j \quad (2)$$

where $\omega(t)$ is the weight of the connection in moment t; i is the wrong class; c is the correct class; $\omega(t + 1)$ is the weight of the same connection in the moment (t+1).

In the training process if the classifier answer is correct we make no action. If the answer is incorrect we reduce the weights connected with the wrong neuron and increase the weights to the neuron corresponding to the correct answer (Fig. 5).

When the dimension of input space n (Fig.5) increases it is necessary to increase the gap between the thresholds of neurons *h* and *l*, so for large *n* many thresholds of neurons *h* achieve the higher limit of variable X_i and thresholds of *l* achieves lower limit of variable X_i. In this case the corresponding neuron always has output 1 and gives no information about the input data. This small number of chosen components of input vector we term random subspace of the input space.

4. Results of beetle recognition

For the beetles recognition task we have written the program in C ++ Builder 6. We divided the program in four sections:

-Mask generation. We mean the generation of the RSC structure with neurons that have the *l* and *h* thresholds. The initial structure of the RSC classifier and the selection of images for training set and recognition set.
-Coding. In this section, each image is scanned with a small window (*h* x *w*) in order to increase the sample number. For each window the program calculates its characteristics (histograms) and transfer to a binary vector.
-Training. This process begins from recognition of the input image for neural network training. During the training process the program realized the adjustment of weights. We determine the number of training iterations (cycle number).
-Recognition. The system works with images chosen for recognition and calculates the number of errors. The system gave us the recognition rate.

The Table1 shows the results of the beetle recognition. For the first steps we change the following parameters: the training cycle number and the scanning window size.

Table 1 Results for RSC neural classifier

Training cycle number	Window size	Recognition rate (%)
20	10	82
20	20	68
20	30	61
60	10	82
60	20	67
60	30	65

We have chosen 15 images for training and other 10 images for recognition. The best result is 82% and it was obtained for window size of (10 x 10) pixels. In comparison with RTC classifier when the best result was near 67.53 [19], with RSC we improve the results up to 82%. The time of training process depends on the computer where the program was run and also depends on the RSC parameters.

5. Discussion

We propose to apply RSC neural classifier for potato beetle recognition in the images. As inputs to the system we use three types of histograms: brightness histogram, contrast histogram and microcontour orientation histogram. Calculation of histograms gives the image features that can be used for the training process and recognition.

The image database is not uniform, since each image contains different number of beetles that can have any position and orientation. Sometimes the background varies too. So the images are very close to real situations and conditions.

The recognition rate of the RSC classifier depends on the size of window with which the image is scanned. For example, if we want to recognize the textures, we can choose the window size to represent this texture at the best way. If we want to recognize objects on the image, we need to prove that definite window size gives us the better results.

The RSC neural classifier is proposed for the beetle recognition task. Using special parameters, as window size, we obtained good results.

6. Conclusions

The RSC neural classifier is a neural classifier that can be used for the beetle recognition after the training process.
Feature extraction was performed through the calculations of histograms of brightness, contrast and microcontours for the 25 images. This information was coded and the codes were saved as binary vectors for every image.
We have obtained the best result of 82% for recognition of Colorado potato beetle.

We hope that this task is very important for whole the world. So, it is important to collaborate in resolving of the problem of pests detecting in potato and bean crops.

7. Acknowledgements

This work was partly supported by project PAPIIT IN102014 and by the CONACyT student grant.

8. References

[1] Chunli, L. and Mou, Y., “Application of Singular Value Decomposition in Pest Image Detection System”, *Intern. Conf. on Measuring Technology and Mechatronics Automation* (ICMTMA 2010), Vol.3, pp. 667-670.

[2] Blasco, J., et al, “Automatic sex detection of individuals of Ceratitis capitata by means of computer vision in a biofactory”, published online in Wiley Interscience: Pest Mananger 2009, Vol. 65, pp. 99-104.

[3] Bechar, I., et al, “On-line video recognition and counting of harmful insects”, *Intern. Conf. on Pattern Recognition 2010*, pp. 4068-4071.

[4] Gong, R., et al., “Fluorescence Spectrum Recognition of Pesticides Based on Wavelet Neural Network”, *Sixth Intern. Conf. on Natural Computation*: ICNC 2010, pp. 1248-1251

[5] Zhao, J., Liu, M., Yao, M., “Study on Image Recognition of Insect Pest of Sugarcane Cotton Aphis Based on Rough Set and Fuzzy C-means Clustering”, *Third Intern. Symposium on Intelligent Information Technology Application* 2009, pp. 553-555.

[6] Sang, R., et al, “Image-based Automatic Recognition of Larvae”, *Sixth Intern.l Symposium on Precision Engineering Measurements and Instrumentation: SPIE 2010*, pp. 11.

[7] Hongtao, Z., Bo, G., Yuxia, H., “Design and Realization of a Real-Time Detection Device for Insect Pests of Field Crops”, *Conf. on Electrical Power Systems and Computers 2011*, pp. 439–444.

[8] Kelemen, E., “Artificial Neural Networks and Artificial Evolution as Tools to Study Organization of Spatial Behavior in Rats”, *Advances in Artificial Life, 6th European Conf.: ECAL 2001*. Vol. 2159, pp. 236-241.

[9] Kussul, E., Baidyk, T., Wunsch, D.C., *Neural Networks and Micromechanics*, Springer Verlag, 2010.

[10] Sota, R. Y. *Computer Vision*, Nova Science Publishers Inc, N.Y 2011.

[11] Maren, A. J., Craig, T. H., Pap, R. M., *Handbook of Neural Computing Applications*, Editorial Academic Press, USA, 1990.

[12] Visión aplicada y elemento: http://gavab.escet.urjc.es/recursos/seminario_07.pdf (Access on Abril 2011)

[13] FAO. World agriculture: towards the years 2015 to 2030. Summary Report, United Nations Food and Agriculture, FAO 2002.

[14] Nichols, M. P; Kogan, M., *A bibliography of the Mexican bean beetle, Epilachna varivestis Mulsant (Coleoptera: Coccinellidae)*, Natural History Survey Division, 1972.

[15] Benkovskaya, G. V., Udalov, M. B., *Colorado Potato Beetles Investigations in South Urals*, Nova Science Publishers, 2010.

[16] Rodriguez Flores, M. A., Desarrollo de un sistema basado en un clasificador neuronal para reconocimiento de orugas, Facultad de Ingeniería, Tesis para obtener el título de Ingeniero en Computación, UNAM, 28.04.2010.

[17] Baidyk, T., Makeyev, O., Kussul, E., Rodríguez Flores, M.O., “Limited receptive area neural classifier for larvae recognition”, ed. by R.P. Soundararajan, in: *Pesticides – Advances in Chemical and Botanical Pesticides*, Chapt, 13, INTECH Pubisher, 2012.

[18] Schwartz, R., “Method and a circuit for determining a contour in an image”, Patent number**:** 4433912, issued Febr. 28, 1984.

[19] Baydyk, T., Kussul, E., Cabello, E., Conde, C., Colorado Beetles Recognition with Neural Networks, in *11th All-Ukraininan International Conference*, *UkrObraz 2012*, Kyiv, Ukraine, pp.121-123.