# Limited receptive area neural classifier based image recognition in micromechanics and agriculture

Tatiana Baidyk, Ernst Kussul, Oleksandr Makeyev, and Alejandro Vega

***Abstract*—**Two multi-purpose image recognition systems based on neural classification are proposed. First application is an image recognition based adaptive control system for micromechanics where the limited receptive area (LIRA) neural classifier is proposed for texture recognition of mechanically treated metal surfaces. The performance of the proposed classifier was tested on image database of 80 images of four texture types corresponding to metal surfaces after milling, polishing with sandpaper, turning with lathe and polishing with file. The promising recognition rate of 99.8% was obtained for image database divided in half into training and validation sets. The second application is agriculture, where vast amounts of pesticides are used against the insects. In order to decrease the required amount of pesticides it is necessary to locate the precise form distribution of the insects and larvae. In this case the use of pesticides will be local. In order to automate the task of recognition of larvae we propose to use a web-camera based computer vision system. We tested the proposed system on image database of larvae of different forms, sizes and colors, distributed in different amounts and positions and containing 79 images. The main idea was to recognize the difference between the textures corresponding to the larvae and real world background. Recognition rate of 90.36% was obtained with only 10 images used for training and the rest of the image database used for validation suggesting high potential of the proposed approach. In this article we present the structure and the algorithms of recognition with LIRA neural classifier, and results of its application in both tasks.

***Keywords*—**agriculture, image recognition, larvae, LIRA, micromechanics, neural classifier.

## I. Introduction

VAST amounts of pesticides are used against the insects in agriculture [1], [2]; for example, Dichloro-Diphenyl-Trichloroethane (DDT) has been used in Mexico for more than 50 years. It is now prohibited in United States, Canada and Europe for being a cause of cancer. In order to decrease the required amount of pesticides it is necessary to locate the precise form distribution of the insects and larvae.

This task is very important not just for the farm production but also for the monitoring of forests. The forest health also demands efforts to fight the threats of different types of insects and larvae [3], for example, Emerald Ash Borer (EAR, Agrilus Planipennis Fairmaire) [4]. This species-invader was found in the north of the United States and Canada in June of 2002. The ash trees in Ontario, Canada and, to a larger extent, central regions of US have been exhibiting a range of bad tree health conditions, including the fall of leaves of the crown, generalized diseases of the leafs and droughts. These symptoms of the declination of the ashes were caused by EAR. The larvae of this species have been living in branches as small as 1.1 centimeters in diameter due to a small size of EAR larva ranging from 26 to 32 millimeters in length. The estimations of damage caused by EAR are the following: it has killed hundreds of thousands of ash trees in the county of Essex, Ontario, and 8 to 10 million ash trees in state of Michigan, US. The loss of the trees included ornamental, rural trees and ones of the forests.

We will investigate the problem of larvae recognition. For example, butterfly larvae (worm form). Larvae are numerous; more than 11.000 species exist in North America, 5.000 species in the east of the United States [3]. The majority of the larvae feed on plants. A great variety of the larvae exist in plants, and many of them are serious parasitic insects. The larvae are most common of all the forms of the insects found in the foliage of the forests and ornamental trees.

The larvae have a great variety of forms, colors and sizes. Some species are hairy, others with little hair; some are monotonous, others are multicolored; some have smooth bodies, others have one or many tubercles, bristles, spines, and/or horn-like projections.

This paper is organized as follows: Section 2 presents the background on classification and recognition of larvae. Section 3 provides a detailed description of the LIRA neural classifier. Section 4 presents a detailed description of the dataset that were used to validate the proposed approach. Image preprocessing techniques used for recognition of larvae

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T. Baidyk is with Center of Applied Sciences and Technological Development, National Autonomous University of Mexico (UNAM), Ciudad Universitaria, Circuito Exterior s/n, MEXICO (corresponding author: 52 55 56-22-86-02 ext.1206; e-mail: tbaidyk@servidor.unam.mx).

E. Kussul is with Center of Applied Sciences and Technological Development, National Autonomous University of Mexico (UNAM), Ciudad Universitaria, Circuito Exterior s/n, MEXICO, (ekussul@servidor.unam.mx).

O. Makeyev is with Department of Electrical and Computer Engineering, Clarkson University, Potsdam, NY 13699, USA, (makeyevo@clarkson.edu)

A. Vega is with Center of Applied Sciences and Technological Development, National Autonomous University of Mexico (UNAM), Ciudad Universitaria, Circuito Exterior s/n, MEXICO, (alexandro_veg@yahoo.com).

images are presented in Section 5 followed by recognition results for both tasks presented in Sections 6 and 7 correspondingly. Discussion and conclusions are presented in Section 8 and 9 respectively.

## II. State of the Art

Different methods are used for the classification and recognition of larvae. Recognition techniques based on the chromatography and pattern gas have been used to develop a potential method to classify the Anastrepha larvae [5]. The test data consisted of 148 chromatograms of the extracts obtained from three diverse species of the larvae. This method is developed for laboratory conditions and cannot be used, for example, for real world agricultural applications.

Another method based on chemical stimulus [6] was developed for recognition of the larvae of bees, to better understand the sociobiology of these insects.

Our method will be based on computer vision with utilization of the limited receptive area (LIRA) neural classifier.

## III. Limited Receptive Area (LIRA) Neural Classifier

The limited receptive area (LIRA) neural classifier is based on the principles of Rosenblatt perceptron [7]. This classifier was tested with high recognition rates in tasks of micro assembly, texture recognition and recognition of hand-written digits [8] - [11]. LIRA was also adapted to classify micro screws images [13], [14]. The resulting neural network was denoted LIRA Grayscale [9]. The general structure of this classifier will be described below.

### *A. Structure*

The neural classifier LIRA Grayscale consists of four layers: input sensor layer (*S*), intermediate layer (*I*), associative layer (*A*) and output reaction layer (*R*). All the neurons in these layers are connected as it is demonstrated in Fig. 1.

### *B. Connections Between Neural Layers*

The procedure to connect the input layer *S* with the associative layer *A* through intermediate layer *I* is the following one. The total number of associative neurons is *N*. For each associative neuron $a_k$, where $k = 1,\ldots, N$, the procedure randomly selects a rectangular area in layer *S* (defined like window) of $h \times w$ neurons, as shown in Fig. 1. *M* points (neurons) are randomly chosen out of this window. They will be divided in random way to *p* “positive” points and *n* “negative” points. Each positive point will be connected to one ON-neuron and each negative point will be connected to one OFF-neuron of layer *I*, respectively, where each of these points will have a $T_{mk}$ threshold randomly selected from the range [0, 255] that represents 256 intensities of gray. This group of *m* neurons in the intermediate layer will be connected to the neuron $a_k$ of associative layer.

An associative neurons will have outputs equal to 1 (active) if all the ON- and OFF-neurons of the group connected to it are in active state, otherwise their outputs will be equal to 0. Each associative neuron acts as a feature extracted from the image, whose output indicates if this feature is present or absent in the image.

### *C. Training Procedure*

Prior to starting the training procedure the weights of all connections between neurons of the layers *A* and *R* should be set to 0. As distinct from the Rosenblatt perceptron LIRA neural classifier has only non-negative connections between layers *A* and *R*.

First stage. The training procedure starts with the presentation of the first image of the training dataset to the LIRA neural classifier. Image is coded and reaction layer neuron excitations $E_i$ are computed. $E_i$ is defined as:

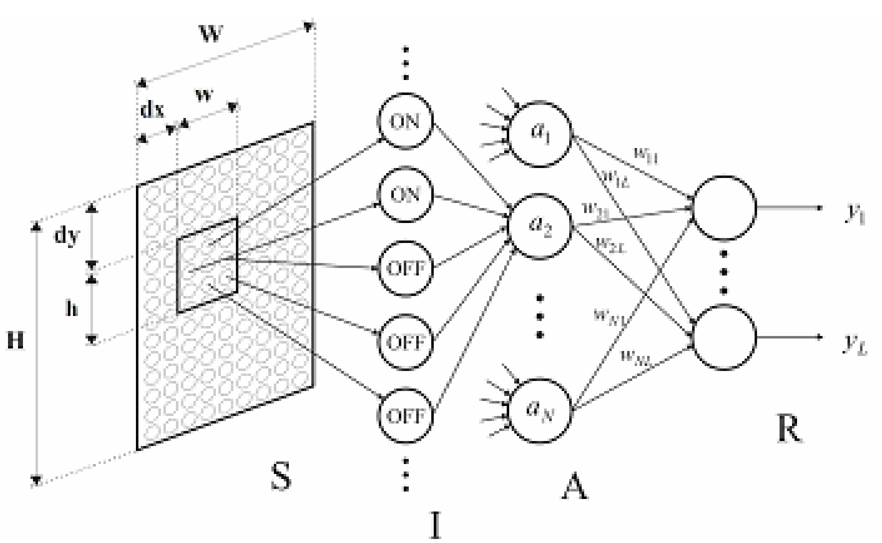


Fig. 1 Structure of the LIRA Grayscale neural classifier

$$E_i = \sum_{j=1}^{N} a_j \cdot w_{ji}, \tag{1}$$

where $E_i$ is the excitation of the i-th neuron of the layer $R$, $a_j$ is the output signal (0 or 1) of the $j$-th neuron of the layer $A$, $w_{ji}$ is the weight of the connection between the $j$-th neuron of the layer $A$ and the $i$-th neuron of the layer $R$.

Second stage. Robustness of the recognition is an important requirement that classifier must satisfy. After calculation of the neuron excitations of the layer $R$, the correct class $c$ of the image under recognition is read. The excitation $E_c$ of the corresponding neuron of the layer $R$ is recalculated according to the formula:

$$E_c{*} = E_c \cdot (1 - T_E), \tag{2}$$

where $0<T_e<1$ determines the reserve of excitation that neuron that corresponds to the correct class is required to have.

After that we select the neuron with the largest excitation and this winner neuron represents the recognized class.

Third stage. Let's denote the winner neuron number as $j$ keeping the number of the neuron that corresponds to the correct class denoted as $c$. If $j = c$ then nothing has to be done. Otherwise the following modification of weights has to be performed:

$$w_{ic}(t+1) = w_{ic}(t) + a_i, \tag{3}$$

$$w_{ij}(t+1) = w_{ij}(t) - a_i, \tag{4}$$

$$\text{if } \ (w_{ij}(t+1) < 0) \ \text{ then } \ w_{ij}(t+1) = 0, \tag{5}$$

where $w_{ij}(t)$ and $w_{ij}(t + 1)$ are the weights of the connection between the $i$-th neuron of the layer $A$ and the $j$-th neuron of the layer $R$ prior and after modification, $a_i$ is the output signal (0 or 1) of the $i$-th neuron of the layer $A$.

The training process is carried out iteratively. After all the images from the training dataset have been presented to the classifier the total number of training errors is calculated. If this number is larger than some predefined percentage of the total number of images then the next training cycle is carried out; otherwise training process is stopped. The training process is also stopped if the number of performed training cycles gets bigger than some predefined threshold value.

### *D. Validation Procedure*

It is known that performance of some recognition systems can be improved with implementation of distortions of the input image during the training process. In our experiments we used different combinations of horizontal, vertical and bias image shifts.

In LIRA neural classifier image distortions are used not only in training but also in validation process. There is an essential difference between implementation of distortions for training and validation. During the training process each distortion of the initial image is considered to be an independent new image. In the validation process it is necessary to introduce a rule of decision-making in order to make a decision about a class of the image under recognition based on the mutual information about this image and all of its distortions. The rule of decision-making that we have used consists in calculation of the layer $R$ neuron excitations for all the distortions sequentially:

$$E_i = \sum_{k=0}^{d} \sum_{j=1}^{N} a_{kj} \cdot w_{ji}, \tag{6}$$

where $E_i$ is the excitation of the $i$-th neuron of the layer $R$, $a_{kj}$ is the output signal (0 or 1) of the $j$-th neuron of the layer $A$ for the $k$-th distortion of the initial image, $w_{ji}$ is the connection weight between the $j$-th neuron of the layer $A$ and the $i$-th neuron of the layer $R$, $d$ is the number of applied distortions (case $k = 0$ corresponds to the initial image).

After that we select the neuron with the largest excitation. This winner neuron represents the recognized class.

## IV. LARVAE IMAGE DATABASE

We use the basic images from the Foliage Feeding Insects image base (www.forestryimages.org). We present some examples of the larvae images in Fig. 2 – 4.

Sizes of all images are equal to $W$ x $H$ = 768 x 512 pixels.


Fig. 2 Image Number: 0014123;
Luna moth; Image Citation:
Gerald J. Lenhard. www.forestryimages.org


Fig. 3 Image Number: 0355031;
Spiny Oakworm; Image Citation:
Robert L. Anderson, USDA Forest Service, www.forestryimages.org


Fig. 4 Image Number: 1435080;
Orangestriped Oakworm; Image Citation:
Clemson University - USDA Cooperative Extension Slide Series,
www.forestryimages.org

## V. Larvae Image Preprocessing

Examples of images shown in Fig. 2 – 4 demonstrate that recognition of larvae of different sizes, forms, colors and positions is not a trivial task [15], [16].

We performed preprocessing of these images marking the larvae with white color to have possibility of extracting the larvae from the image for the neural networks training phase (Fig. 5 – 7).

Database of marked images is prepared to initiate the works with neural networks. We initialized the works of programming of the LIRA neural classifier. We expect the LIRA neural classifier to be able to extract the larvae of any image background in the similar way this algorithm was applied for mechanically treated metal surface texture recognition in micromechanics.

## VI. Recognition of Textures in Micromechanics

The first application of LIRA neural classifier for texture recognition was in micromechanics [10], [11].

Texture recognition of metal surfaces is an important problem for automation of micromechanical assembly [8]. Assembly process requires recognition of position and orientation of the components to be assembled [8]. It may be important to identify the surface texture of a component to

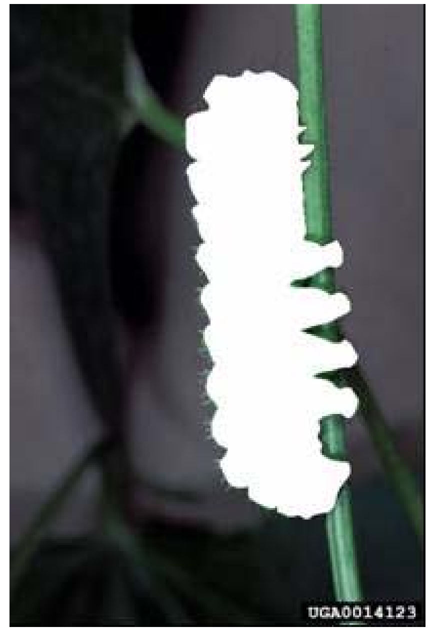


Fig. 5 Preprocessed larvae image

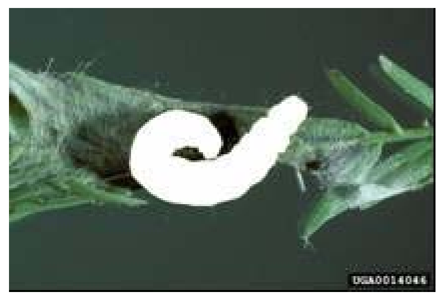


Fig. 6 Preprocessed larvae image

Fig. 7 Preprocessed larvae image

recognize its position and orientation. For example, shaft may have two polished cylinder surfaces for bearings, one of them milled with grooves, and another one turned with the lathe. Orientation of the shaft may be obtained easily if both types of the surface textures are recognized automatically.

While texture classification of mechanically treated metal surfaces is an important task the number of proposed approaches is limited [10], [11], [12]. In [12] authors propose to use a novel vibration-induced tactile sensor that they term

Dynamic Touch Sensor (DTS) combined with one-layer Rosenblatt perceptron. DTS produces signals based on the vibration induced by a sensor needle sliding across the metal surface with fixed velocity and pressure. The motion path of the sensor is a part of a circle of approximately 100 degrees since such motion path permits capturing information about surface in both directions in one sweep. However, system is very sensitive to the changes in texture position and orientation. Spectral energy of the sensor was used as an input to the neural classifier. Metal surfaces were characterized by two characteristics: surface type and surface roughness. In texture recognition system validation six types of surfaces and six values of surface roughness were used. Obtained recognition rates varied from 74.16% in recognition of two types of metal surfaces with roughness of 8 microinches to 100% in recognition of three types of metal surfaces with roughness of 250 microinches.

We worked with four texture classes that correspond to metal surfaces after: milling, polishing with sandpaper, turning with lathe and polishing with file (Fig. 8). 20 grayscale images of 220x220 pixels were taken for each class. It can be seen that different lighting conditions have a significant effect on the grayscale properties of the images. The textures are also arbitrarily oriented and are not centered perfectly. Some of the metal surfaces had minor defects and dust on them. All these image properties correspond to the conditions of the real industrial environment and make the texture recognition task more complicated.

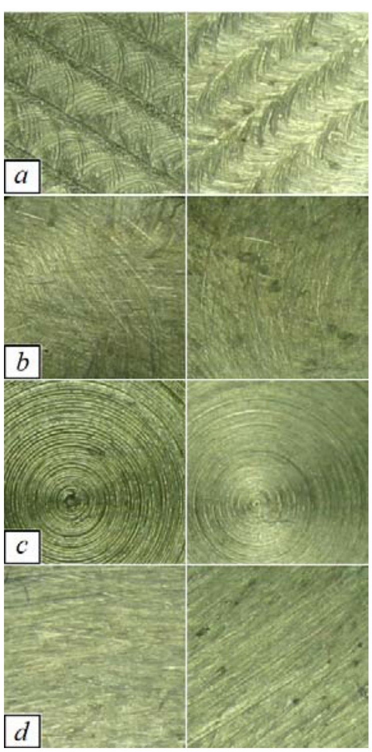

Fig. 8 Examples of metal surfaces after (rows): (a) milling, (b) polishing with sandpaper, (c) turning with lathe, and (d) polishing with file

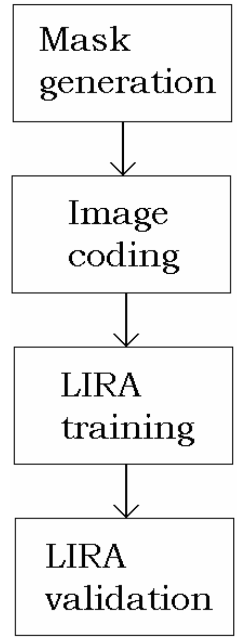

Fig. 9 Block-scheme of the image recognition system

At the first stage of our experiments we worked with texture recognition system based on the Random Subspace (RSC) neural classifier [10]. The best recognition rate of 79% was obtained in recognition of three classes of metal surfaces. The numbers of images in training and test sets were 3 and 17 correspondingly.

The use of the LIRA neural classifier in our texture recognition system resulted in recognition rate of 99.8% obtained in recognition of four classes of metal surfaces with image database divided in half into training and validation sets [11]. All experiments were performed on a Pentium 4, 3.06 GHz computer with 1.00 GB RAM.

In our experiments we achieved the recognition rate of 99.8% in recognition of four types of metal surfaces with roughness of the order of 1 microinch. Along with the fact that our approach doesn't require the use of a complex mechanical sensor and is robust to the changes in texture orientation and position this suggests superiority of the LIRA based approach.

We hope that LIRA neural classifier will be useful in texture recognition of different larvae types too [15], [16].

## VII. RECOGNITION OF TEXTURES IN AGRICULTURE

Implementation of larvae image recognition system includes four main blocks (Fig. 9).

The first block consists of the masks formation. This block corresponds to generation of ON- and OFF-neurons. With the help of random procedure we generate the coordinates of these neurons on the window that moves on the image. The number of ON- and OFF- neurons can be changed during the experiments with the LIRA neural classifier. Once the number of ON- and OFF- neurons is selected, the structure of the first layer of neural classifier is defined. All ON- and OFF-neurons present the mask of the current image.

This mask can be applied to every image of the image database. This process is called coding (block 2 in Fig. 9). For every image we can obtain the binary code of this image. This code is saved in the file and used instead of the repeated image coding. During the next steps (for example, blocks corresponding to training and validation of the LIRA neural classifier) we can work not with images, but with the binary codes of those images.

To prepare LIRA neural classifier to recognition of images from different classes, we must train the neural classifier first. This process corresponds to the third block of the Fig. 9. The training rule is the following. When we have an image at the input of the system, the system tries to recognize it. If the recognition is correct then nothing has to be done. If the recognition is incorrect then we increase the weights of the connections corresponding to the correct answer and decrease the weights of the connections corresponding to incorrect answer between layers *A* and *R* (Fig. 1).

We performed experiments with 79 images corresponding to different types of larvae.

The following parameters of the LIRA neural classifier were selected: number of neurons in *A* layer was equal to 32000 neurons (Fig. 1), the size of window $w$ x $h$ in the *S* layer was equal to 20 x 20 pixels, the step of the window movement was 10 pixels, in the *I* layer we generate two ON-neurons and three OFF-neurons, the number of windows for each image was 3750.

In the first stage of validation we used ten images for training of LIRA neural classifier. The number of training cycles was selected to be 150. The obtained recognition rate was 9.64% of errors.

In the second stage we changed the size of the scanned window from the size $w$ x $h$ = 20 x 20 to $w$ x $h$ = 200 x 200 pixels, and the step of the window movement to 100 pixels. In this stage of the validation the obtained error rate was 17.46%.

The second result of 17.46% is worse in comparison with the first result of 9.64% of errors because of the size of the scanned window. The second case validation was performed as a system test. The window with the size of 200 x 200 pixels gives a very rough representation of the texture which explains the lower recognition rate.

## VIII. Discussion

Obtained results suggest high efficiency and reliability of the proposed method, though tests on a larger database would be needed for a conclusive proof.

The number of extracted random features which is equal to the total number of associative neurons is a crucial parameter of the system. This number should be sufficiently large to create a detailed description of the image providing a basis for further classification. At the same time large number of associative neurons results in computational burden that may pose problems for real world consumer applications in micromechanics or agriculture. Separate assessment of possibility of real-time recognition with the highest recognition rate is needed for each application.

Structure of the LIRA neural classifier contains a large number of random features extracted from the image. It is clear that majority of these features is not useful for any class recognition. The idea of the training procedure is to increase the weights of the connections between the class specific features as much as possible and preserving the weights of the connections of non specific features to be as low as possible. The change of the weights during the training procedure occurs when the classifier makes an error of the recognition. Let us consider now our case of two classes for larvae recognition (larvae / background). In this case the training process is organized as following: small window scans the image sequentially line by line. When the window scans the background all non specific features rapidly increase the weights of their connections to the output neuron that presents the background class. If the window finds the boundary part of the larvae sequence all the non specific features decrease their weights to the output neuron that presents the background class and increase the weights of the connections to the output neuron that presents larvae class. The classifier begins to give the response “Larvae” for all windows of the following sequence. It means that the actual weight modification occurs mostly at the boundaries between the two classes at each stage of the training process. Step by step the width of these boundaries will increase and at the final stage of the training process practically all the images will be participating in the weight modification but to achieve this final stage it is sometimes necessary to perform a significant number of training cycles. At the first stage of such training process the number of errors increases. It usually starts to decrease when most of images have participated in the training process.

In Fig.10 the general scheme of the training process is presented.

The first row of the Fig. 10 shows the sequence of actual classes of the image database (two classes that corresponds to 0 and 1).

The second row shows the probability that the classifier will give the response “1” on the same sequence of the images. This line corresponds to the first stage of training. The training process occurs only if the classifier gives an erroneous response. This line shows that an erroneous response can be given in short period near the line of class change.

The third row shows the second stage of training process where training period is expanded.

The forth row corresponds the third training stage when the training process occurs for all images.

The final training stage corresponds to the end of the training process. As a rule the end of the training process is determined as the moment when the number of errors becomes less than some predefined value.

The completion of the training process requires significant amount of time. To avoid this situation and solve this problem

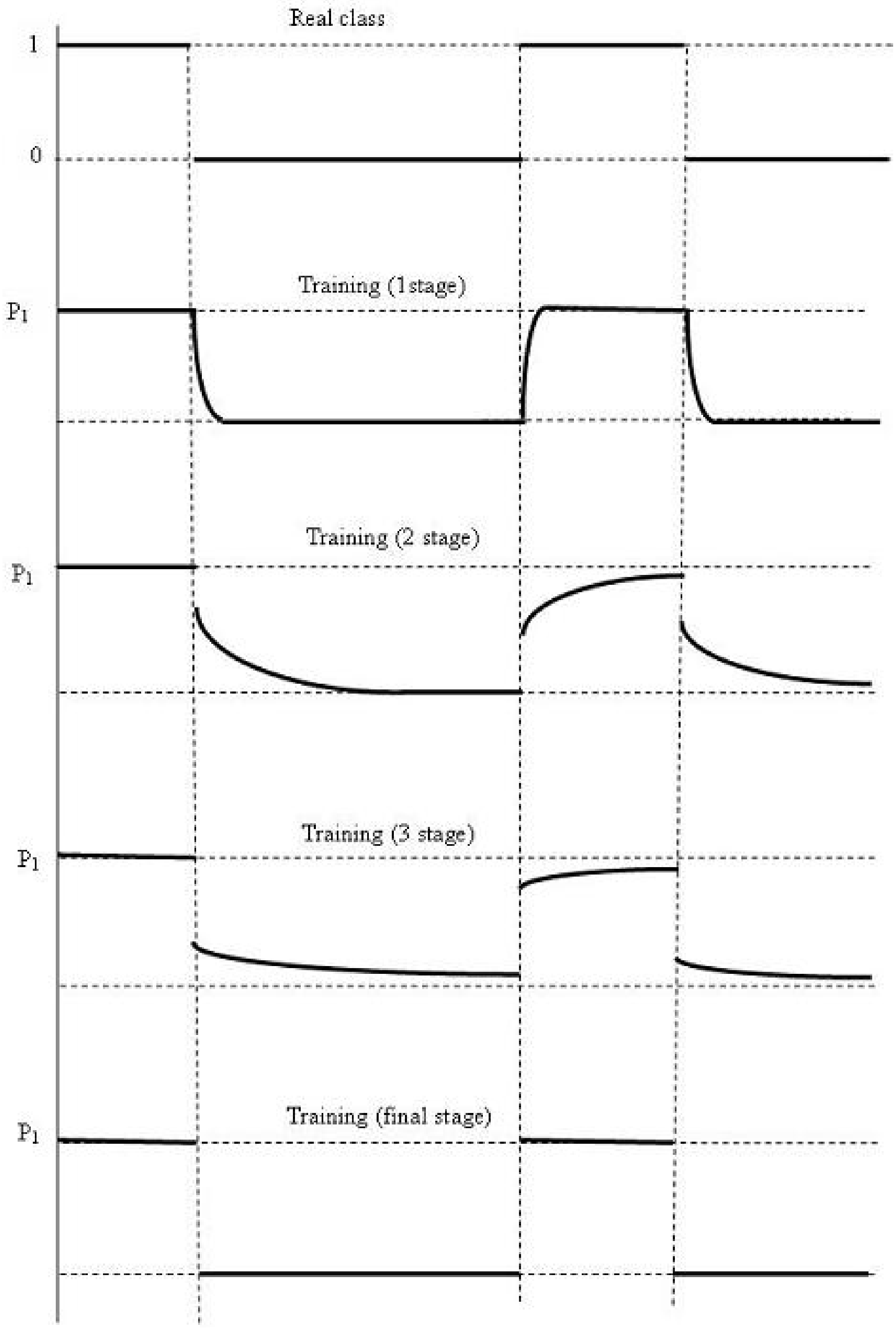


Fig. 9 Block-scheme of the image recognition system

it is necessary to create the sequence of training windows not in the scanned sequence but randomly permutated from initial sequence. This procedure can be very similar to permutation coding procedure [9], [17]. We plan to implement this new type of training in the near future.

## IX. Conclusions

Multi-purpose image recognition system based on the limited receptive area (LIRA) neural classifier is proposed for automated image recognition of larvae. Such recognition could potentially allow localizing the distribution and decrease the amount of pesticides needed to eliminate the insects.

We use an image database of larvae of different forms, sizes and colors, distributed in different amounts and positions in order to validate our classifier in recognition of textures corresponding to the larvae and real world background.

The best error rate obtained in larvae recognition was of 9.64% which corresponds to 90.36% recognition rate.

Performance of the similar multi-purpose image recognition system was also evaluated in texture recognition of mechanically treated metal surfaces after milling, polishing with sandpaper, turning with lathe and polishing with file. The promising recognition rate of 99.8% was obtained.

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