LIRA neural network application for microcomponent measurement

Tatiana Baidyk, Ernst Kussul, and Miguel Hernández Acosta

Abstract— An automation of the production and assembly processes is one of the important tasks in micromechanics. To create totally automated micro factory it is necessary to develop a computer vision system that can replace an operator. Computer vision system may have several functions, for example, recognition of objects on the image of working area, recognition of mutual position of several components on the image, and measurement of component size, etc. We select one task, which is connected with the micromechanics area, - size measurement. The object of measurement is a micro piston. The micro pistons are the components of thermal micro motors that transform the heat energy from solar concentrator to electrical energy. The goal of this work is the development and research of the LIRA (Limited Receptive Area) neural classifier and its application to measure the micro piston size. To obtain the micro piston sizes it is necessary to recognize its boundaries in the image. We propose to use LIRA neural network to extract and classify piston boundaries. In this article we describe and analyze the preliminary results of LIRA application to micro piston boundaries recognition.

Keywords— Contour extraction, digital image, LIRA neural classifier, micropiston, object boundaries.

I. Introduction

IN the manufacturing some processes are controlled by an operator and others are automated. Those processes that involve an operator become more difficult to perform when the components reduce their sizes, especially if we speak about micro mechanical systems. That is why the micromechanical factories must be created as completely automated ones [1], [2]. For this purpose artificial intelligence methods can be used.

Some of the artificial intelligence (AI) methods, including neural networks, could be used to improve the automation system performance in manufacturing processes. However, the implementation of these AI methods in the industry is rather slow, because of the high cost of the experiments with the conventional manufacturing and AI systems. To lower the experiment cost in this field, we have developed a special micromechanical equipment, similar to conventional mechanical equipment, but of much smaller size and therefore of lower cost. This equipment could be used for evaluation of different AI methods in an easy and inexpensive way. The proved methods could be transferred to the industry through appropriate scaling. In this article we describe some AI method implementations to increase the microequipment efficiency and to do the microequipment work independent from operator. One of them uses computer vision system for microcomponent dimensioning.

The development of AI technologies opens an opportunity to use them not only for conventional applications (expert systems, intelligent data bases [3], technical diagnostics [4], [5] etc.), but also for total automation of mechanical manufacturing. Such AI methods as adaptive critic design [6], neural network based computer vision systems [7] – [10], etc. could be used to solve the automation problems. To check this opportunity up, it is necessary to create an experimental factory with fully automated manufacturing processes. This is a very difficult and expensive task.

To make very small mechanical microequipment, a new technology was proposed [2]. This technology is based on micromachine tools and microassembly devices, which can be produced as sequential generations of microequipment. Each generation should include equipment (machine-tools, manipulators, assembly devices, measuring instruments, etc.) sufficient for manufacturing an identical equipment set of smaller size. Each subsequent equipment generation could be produced by the preceding one. The equipment size of each subsequent generation is smaller than the corresponding size of preceding generation. We call this approach to mechanical microdevices manufacturing MicroEquipment Technology (MET) [2].

To create micromechanical factories, it is necessary to automate manufacturing and assembly processes [1], [2], including the process of size measuring of micro components. Due to inaccuracy of micro equipment the micro components can vary slightly in size. To realize the assembly process using these components it is important to obtain exact sizes of micro components.

To realize the process of micro components dimensioning, we propose to develop a computer vision system that is based on digital images processing with neural networks [11], [12], [13].

T. Baidyk is with the CCADET, UNAM , Circuito Exterior s/n, Ciudad Universitaria, 04510, Mexico city, D.F., Mexico (phone: 52 55 56228602; fax: 52 56 55500654; e-mail: tbaidyk@ unam.mx).

E. Kussul is with the CCADET, UNAM, 04510, Mexico city, D.F., Mexico. (ekussul@unam.mx).

M. Hernández Acosta is the post-graduate student at the CCADET, National Autonomous University of Mexico (UNAM).

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II. Neural Networks for Image Recognition

We have developed the LIRA (LImited Receptive Area classifier) neural classifier based on Rosenblatt's perceptron principles (Fig.1).

3-layer Rosenblatt perceptron contains sensor layer *S*, associative layer *A* and reaction layer *R*. Many investigations were dedicated to perceptrons with one neuron in layer *R* (*R*-layer) [14]. Such perceptron can recognize only two classes. If output of *R* neuron is higher than predetermined threshold *T*, the input image belongs to class 1. If it is lower than *T* the input image belongs to class 2. The sensor layer *S* (*S*-layer) contains two-state {–1, 1} elements. The element is set to 1 if it belongs to object image and set to –1, if it belongs to background.

Associative layer *A* (*A*-layer) contains neurons with 2-state {0, 1} outputs. Inputs of these neurons are connected with outputs of *S*-layer neurons with no modifiable connections. Each connection may have the weight 1 (positive connection); or the weight –1 (negative connection). Let the threshold of such neuron equals to number of its input connections. This neuron is active only in the case if all positive connections correspond to the object and negative connections correspond to background.

The neuron *R* is connected with all neurons of *A*-layer. The weights of these connections are changed during the perceptron training. The most popular training rule is increasing the weights between active neurons of *A*-layer and neuron *R* if the object belongs to class 1. If the object belongs to the class 2 corresponding weights are decreasing. It is known that such perceptron has fast convergence and can form nonlinear discriminating surfaces. The complexity of discriminating surface depends on the number of *A*-layer neurons.

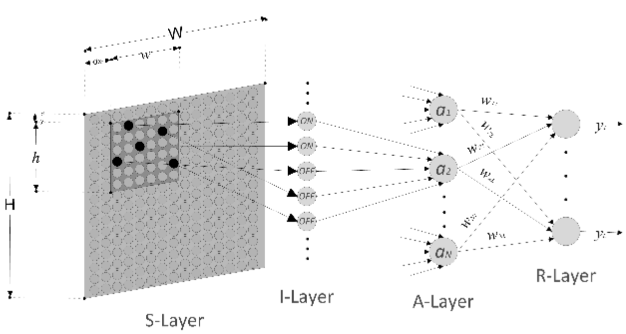


Fig.1. LIRA classifier structure

We created the LIRA neural classifier based on Rosenblatt perceptron (Fig.1). We have experience of LIRA neural classifier applications [15] - [17].

One of the tasks was handwritten digits recognition on MNIST database. The MNIST database contains 60,000 handwritten digits in the training set and 10,000 handwritten digits in the test set. Different classifiers proved on these data. To adapt Rosenblatt's perceptron for handwritten digit recognition problem we made some changes in perceptron structure, training and recognition algorithms.

Rosenblatt's perceptron contains three layers of neurons. The first layer *S* corresponds to retina. In technical terms it corresponds to input image. The second layer *A* called the associative layer corresponds to feature extraction subsystem. The third layer *R* corresponds to output of all the system. Each neuron of this layer corresponds to one of the output classes. In handwritten digit recognition task this layer contains 10 neurons corresponding to digits 0, …, 9. Connections between the layers *S* and *A* are established using a random procedure and cannot be changed by perceptron training. They have the weights 0 or 1. We introduced new *I*-layer (intermediate layer) to the LIRA structure.

Connections between layers *A* and *R* are established by the principle when each neuron of *A*-layer is connected with all neurons of *R*-layer. Initially the weights are set to 0. The weights are changed during the perceptron training. The rule of weights changing corresponds to the training algorithm. We used a training algorithm slightly different from the Rosenblatt's one. We have also modified the random procedure of *S*-connections establishment. Our latest modifications are related to the rule of winner selection in the output *R*-layer.

In this task we obtained with LIRA neural classifier 0,63% of errors that means that only 63 errors were obtained from 10000 images of test set [16]. The error number 63 corresponds to 99.37% of recognition rate.

The neural classifier LIRA we used in micromechanics to recognize mutual position of pin and hole in the task of microassembly.

The task of micromechanical device assembly requires the determination of the relative position of microcomponents (Fig.2). In the case of the pin-hole task it is necessary to determine the displacements *dX*, *dY*, *dZ* of the pin tip relative to the hole by using the images obtained with the aid of a TV camera.

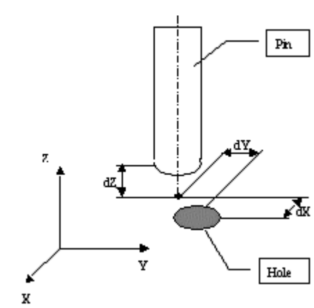


Fig.2. Mutual location of the pin and hole

It is possible to evaluate these displacements with a stereovision system, which resolves 3D problems. The stereovision system demands two TV cameras. To simplify the control system we propose the transformation of 3D into 2D images preserving all the information about mutual location of the pin and the hole. This approach makes it possible to use only one TV camera.

Four light sources are used to obtain pin shadows (Fig.3). Mutual location of these shadows and the hole contains all the information on displacements of the pin relative to the hole. The displacements in the horizontal plane *(dX, dY)* can be obtained directly by displacements of the shadows center points relative to the hole center. Vertical displacement of the pin may be obtained from the distance between the shadows. To calculate the displacements it is necessary to have all the shadows in one image.

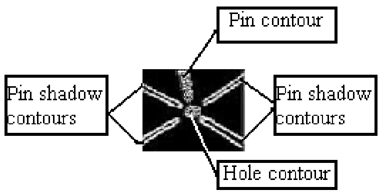


Fig.3. Input image for neural network

The experiments show that the computer vision system can recognize relative pin-hole position with a 0.1 mm tolerance. The neural classifier for this tolerance gives the correct recognition in 100% of cases in *X* and 86.7% cases in *Y*. The neural interpolator gives for axis *X* 100% and for axis *Y* – 99.86% [16].

Another task where we test the LIRA neural classifier was the shape recognition task [18] (Fig.4). The recognition rate of 96.88% was obtained.

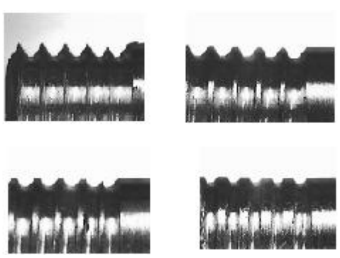


Fig.4. Screw shape recognition

So, the LIRA neural classifier was used in different task of image recognition and several examples of its applications were described.

III. Micropistons Image Database

The computer vision system can be used to make the size measurements of piston diameter. As an example, we selected a micro piston production for micro heat engines (as Stirling or Ericsson engines). These heat engines are used to transform heat energy to electric energy and are used, for example, in solar thermal power plants.

15 micro pistons were manufactured with a Sherline lathe, model 4410. The micro pistons were made with different diameters; from 8.0mm to 8.5mm, with a 0.1mm step. For every diameter we produced three pistons. Due to inaccuracy of the equipment we had variation in the same diameter. We took pictures of these pistons. Three pistons of the same diameter we grouped in one class.

The images were taken from 15 micro pistons with help of the Metallurgical Trinocular Microscope NJF-120. Our initial image database has 15 images. These images have a resolution of (1600x1200) pixels, in BMP format and RBG color model.

The images of the micro pistons are shown in Fig.5.

To adapt the LIRA neural classifier to measurement task we initiated from contour extraction of pistons on the images.

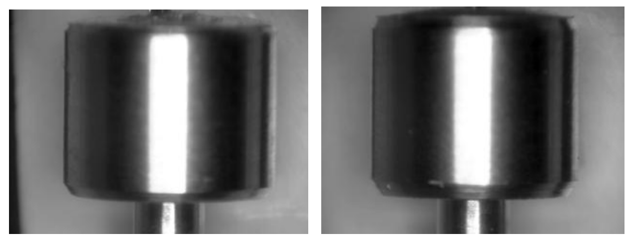


Fig.5. Digital images of micro pistons

In next paragraph we describe the methods of contour extraction, and in paragraph V we describe the structure and algorithms of LIRA neural classifier.

IV. Extraction of Contours

The main problem of the measuring on the base of digital images is to find the borders of the piece. To recognize the component and to distinguish it from background is one of the main tasks in image recognition.

The borders of the micro piston in the images are defined by significant brightness changes between neighbour pixels. Due to this fact it is possible to extract contours on the image. There are conventional gradient methods and filters for contours extraction, such as Sobel operator and Schwartz method, for example [19], [20]. In Fig.6 it is shown the contours extracted by Sobel operator (to see better the contours we inverted colors).

Fig.6. Micro piston image after
Sobel operator application

In Fig.7 the contours extracted by the Schwartz method are shown [20]. We present original images (Fig.7, a) and inverted images to see better extracted contours.

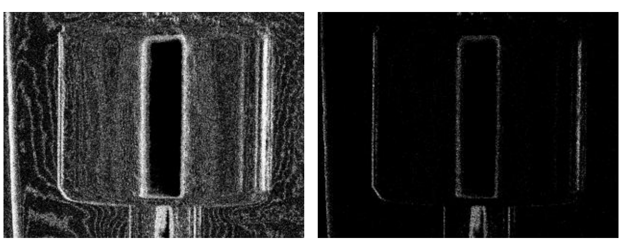
The principal disadvantage of these algorithms is that they extract many contours that made difficult distinguishing the object borders. Sometimes the number of contours is excessive for the object image analysis. It depends on the threshold constant that is an experimental constant.

a)

b)

Fig.7. Schwartz method applied on an micropiston image; a) original images; b) inverted images

We programmed and executed the both algorithms and applied them on our image data base of micro pistons (Fig.8). In Fig.8 two images are shown, on the first one the Schwartz method with C1 threshold constant, and the second image demonstrates the result of Schwartz method application with C4 threshold constant, which shows fewer contours in comparison with the first case.



a) b)

Fig.8. Contours extracted by: a) Schwartz method with C1 constant, b) Schwartz method with C4 constant

To obtain better results in border definition, it is necessary to use advanced methods for image recognition, such as adaptive systems, which can be trained using some image samples [15], [21]. The adaptive system developed for similar task is a LImited Receptive Area neural network (LIRA) [15] - [17].

LIRA neural classifier is neural network with supervised training. So it was necessary before apply this classifier to mark all images.

All 15 images were marked with red lines to demonstrate the micro piston border (Fig.9). This procedure is necessary for training the LIRA neural classifier.

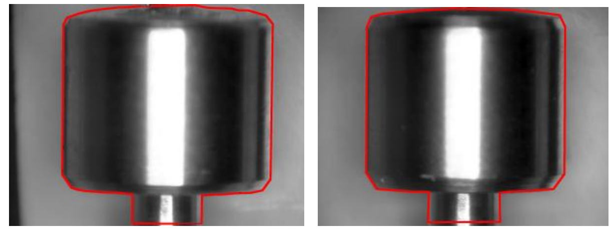


Fig.9. Marked border of micro pistons

In the next paragraph we describe the LIRA neural classifier.

V. LIRA Neural Classifier

Our investigation of LIRA neural classifier is focused on application it for obtaining the borders of the micro pistons. The objective is to recognize borders of micro pistons. After that, it is possible to measure diameter of the component.

The Limited Receptive Area (LIRA) neural classifier [22] is an artificial neural network based on Rosenblatt perceptron [14]. We realized several changes in the structure of neural network and in the algorithms to improve it.

The first layer is called *S*-layer and corresponds to the retina, in our task it is a sensor or an input image. The second one is named *A*-layer and includes the feature extraction subsystem. The last layer is known as *R*-layer and consists of the system's output, every single neuron of this layer corresponds to one of the output classes. The neural classifier LIRA has an additional layer, it is an intermediate layer between Layers *A* and *S*. The structure of LIRA classifier and its connections is shown in Fig.1.

There are two variants of LIRA classifier. The first one is LIRA-binary. It was developed for binary (black and white) images. The other variant is LIRA-grayscale [23]. It was developed for grayscale images at the input. We propose to use LIRA-grayscale in the task of recognition of micro-piece borders.

The connections between neural layers in LIRA-grayscale classifier are different. The layers *S* and *A* are connected through layer *I*, this connection is not trainable. Firstly, a rectangular window of (h x w) pixels is randomly defined in the *S*-layer (Fig.1); inside of this window, M pixels from the input image (every pixel corresponds to one neuron) are randomly selected. Each of those M neurons are connected to one neuron of the *I*-layer.

The *I*-layer has two types of neurons, *ON*-neurons and *OFF*-neurons, which are chosen to be connected with the *S*-layer by a random way. The *ON*-neuron is activated when its input is greater than a threshold, selected using random procedure; on the other hand, the *OFF*-neuron is activated when its input is less than another threshold, also selected with a random procedure. The outputs of neurons of I-layer are connected to *A*-layer.

The outputs of the *I*-layer are used as inputs to the *A*-layer. Each neuron of the *A*-layer will be active if all its inputs connected from the *I*-layer are activated.

The connections between the *A*-layer and *R*-layer are generated with the rule "all neurons are connected with all neurons". So every neuron from the *A*-layer is connected to each neuron of the *R*-layer and these connections have its respective weights. At the beginning, all the weights are set to zero. Each connection weight is modified during the training procedure. The weights are changed in accordance with Hebbian rule to have a better recognition rate in classes distinguishing.

Before application of LIRA-grayscale algorithm, we have to do some preliminary procedures with our images, as shown in Fig.10. The input image is converted to a grayscale image.

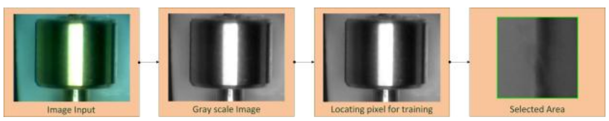


Fig.10. Stages before perform LIRA-grayscale algorithm

In our task we selected three classes to be recognized: background, borders, and object. So *R*-layer contains three neurons, each of them corresponds to one class. For each class we select several thousand points of interest. This means that in the image we will have several thousand samples of background, borders and object.

So we select a pixel of interest for analysis. Around that pixel the window of (*h* x *w*) pixels is selected. This window is used as *S*-layer in the LIRA neural classifier and it is presented in Fig.11.

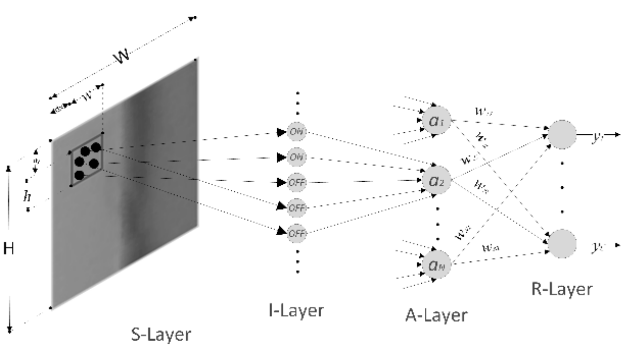


Fig.11. Window of (*h* x *w*) in LIRA structure

For LIRA neural classifier the training procedure is a supervised training. The training begins from the first image of the training set of images. The features of the image are extracted with help of the *I*-layer and they can be presented as a code (binary vector of *A*-layer). The excitations of all the neurons of *R*-layer are computed. The excitation of each neuron of *R*-layer is defined as:

$$y_i = \sum_{k=1}^{n} w_{ki} a_k \tag{1}$$

where y_i is the output of the *i*-th neuron of the *R*-layer, a_k is the output of *k*-th neuron from the *A*-layer, w_{ki} is the weight of the connection between *k*-th neuron of the *A*-layer and the *i*-th neuron of the *R*-layer.

The neural network response is the neuron of *R*-layer with maximum of excitation.

During the training process if the winner class corresponds to the correct class, nothing is done; but if they don't coincide, the weights are modified according to the following equations:

$$\begin{aligned} w_{kr}(t+1) &= w_{kr}(t) + a \\ w_{ku}(t+1) &= w_{ku}(t) - a \end{aligned} \tag{2}$$

where w_{ki} *(t)* and w_{ki} *(t+1)* are the weights of the connection between the *k*-th neuron of the *A*-layer and the *i*-th neuron of the *R*-layer before and after modification, *a* is the experimental constant.

To obtain better results in recognition and diminish the number of errors (when recognized class and true class does not coincide), the training process is iteratively repeated. A training iteration cycle is done when all the images from training set have been presented, and the number of errors is calculated. The end of iterations can be defined in following way: when number of errors becomes 0, or when we, from our experience, define the iteration number. In our case the number of iterations is predefined.

The program is written in C#, Visual Studio, Microsoft. The LIRA neural network implementation is presented in Fig.12. In the next paragraph we present preliminary results of LIRA investigation.

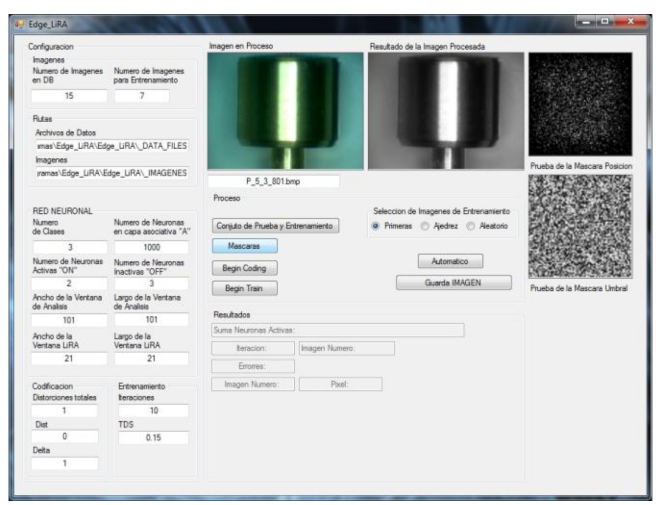


Fig.12. LIRA classifier realization

VI. Results of Investigation

Preliminary results were obtained for three classes: border pixels, background pixels and object pixels [24]. The LIRA neural classifier had the following parameters: three classes, 1024 neurons in *A*-layer, two ON-neurons and three OFF-neurons, $W = H = 101$ pixels, $w = h = 21$ pixels.

We divided the image database into two subsets, the training image set and testing image set. The training images are the first seven images and the rest of the image database are used to test the system. The number of training cycles was equal to 40.

The pixels number for each image is shown in Table 1.

Table 1
The pixels number for 15 images

Image	Number of border pixels	Total number of pixels
1	3177	9531
2	3026	9078
3	3015	9045
4	3021	9063
5	2937	8811
6	2999	8997
7	2990	8970
8	2976	8928
9	2986	8958
10	2949	8847
11	2997	8991
12	2953	8859
13	2910	8730
14	2953	8859
15	2970	8910

The total number of pixels included number of pixels for three classes: border, background and object.

The error rate is calculated as:

$$\%error = (100 * Errors)/TP, \quad (3)$$

where *Errors* is the number of pixels, that were not recognized correctly, *TP*=63495 is the total number of pixels that were analyzed in one cycle for seven images.

The results of experiment are presented in Fig.13.

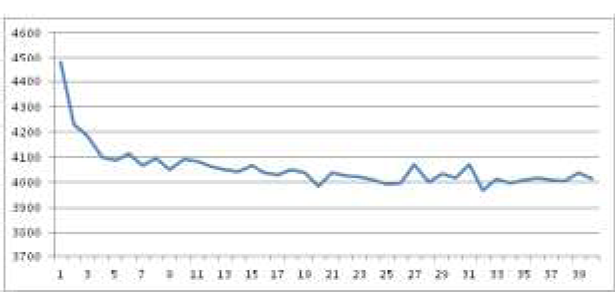


Fig.13. Training errors for 40 cycles

So, the training process shows the number error decreasing.

We test our system with different parameters. LIRA neural classifier had 1024 neurons in *A*-layer and 3 classes to be recognized for all experiments. In Table 2 we present the test parameters.

Table 2
Parameters for three experiments

Parameters	Experiments		
	1	2	3
w	51	51	21
h	51	51	21
Training Cycles	10	40	10
ON-neurons	2	2	2
OFF-neurons	3	3	3
W	151	151	101
H	151	151	101

In Fig.14, Fig.15 and Fig.16 the results of the first, second and third experiments are presented.

During the recognition process the system calculated the recognition errors. In Table 3 we present the obtained results. The recognition rate we calculated using equation (3) with *TP*=80052.

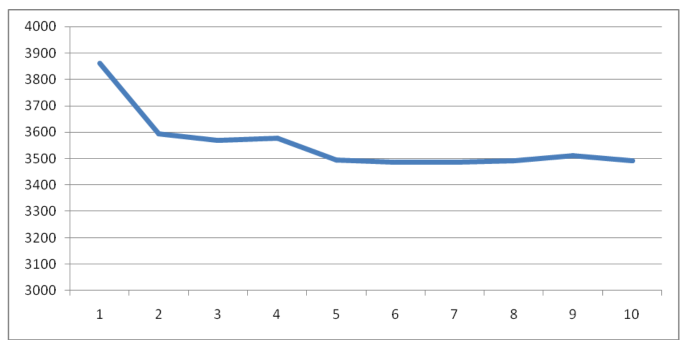


Fig.14. Training errors (experiment 1, Table 2)

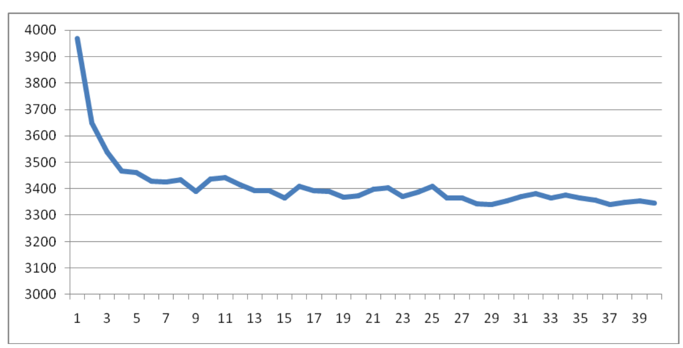


Fig.15. Training errors (experiment 2, Table 2)

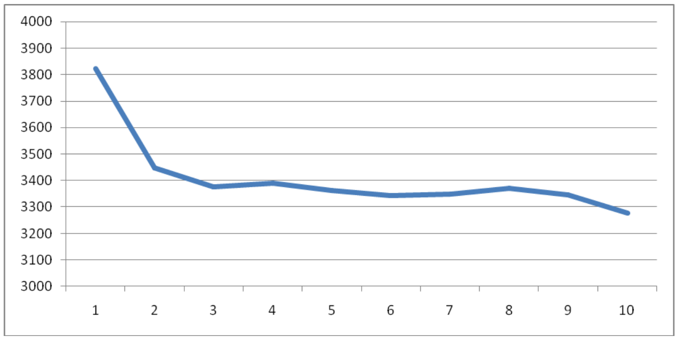


Fig.16. Training errors (experiment 3, Table 2)

Table 3
Recognition errors

Experiment	Recognition Errors	Recognition Errors (%)	Recognition Rate (%)
1	18677	23.33%	76.67
2	16966	21.19%	78.81
3	14212	17.75%	82.25

The next step will be the recognition test of piston borders.

VII. Conclusion

The problem of the micro components measurement is considered. For automatic measurements it is possible to use computer vision system. In this case the main problem is to recognize the borders of the object in the image. The problem is not trivial, because conventional algorithms of contour extraction give many “false” contours that not coincide with the object borders. We propose to use the LIRA neural classifier to resolve this problem. The preliminary results of experiments are given in this article. The results are promising.

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Tatiana Baidyk (Ph.D'83). From 1977 to 1995 she was with the Institute of Cybernetics of the Ukrainian Academy of Sciences. In 1994 T.Baidyk received D.Sci. in the area of neural networks. From 1995 to 1999 she was coordinator of the International Program of Education and Science in Ukraine, International Renaissance Foundation. From 1998 she was with the International Research and Training Center of UNESCO/IIP of Information Technologies and Systems as a leading researcher. From 2001 till now she has been Researcher in UNAM, Mexico.

She has about 200 publications, 3 books, 3 patents. Baidyk´s present research interests are neural networks, pattern recognition, control systems, and industrial applications.

Dr. Baidyk is a member of the Mexican Academy of Sciences and National System of Scientists.

Ernst Kussul (Ph.D.'67). From 1967 till 1998 he worked in the Institute of Cybernetics of Ukrainian Academy of Sciences. In 1982 he received the D. Sci. degree in artificial neural networks. From 1988 to 1998 he was Head of the Department of Neural Networks in the International Research and Training Center of UNESCO/IIP of Information Technologies and Systems. Since 1998 he is Researcher level "C" in UNAM, Mexico.

He is author and coauthor more than 200 publications, 4 books, 11 patents. His present research interests are micromechanics, mechatronics, neural networks, and pattern recognition.

Dr. Kussul is a member of IEEE. He is a member of the Mexican Academy of Sciences and National System of Scientists.

Miguel Hernández Acosta (B.'2005) was born in Zapopan, Jalisco Mexico in 1982. He received the B.S. degree in electronics and computer engineering from Center of Education in Industrial Technique (Mexico) in 2005. Now, he is studying at the National Autonomous University of Mexico (UNAM) for his M. Sc. Eng. He is interested in neural networks, computer vision and embedded systems.