Improved Neural Classifier for Microscrew Shape Recognition[1]

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Abstract—We propose a neural network based vision system for attending micropieces manufacturing process in micromechanics. The system permits us to recognize the shape of micropieces (screws of 3 mm diameter) in order to get information for controlling and improving the manufacturing process. The neural classifier used for the shape recognition task is termed Limited Receptive Area Grayscale (LIRA Grayscale). The developed vision system has a recognition rate of 98.90%. This work is motivated by the idea of obtaining an automated control system for micromachines. This paper contains a detailed description of the model and learning rules, and discusses future perspectives.

Key words: shape recognition, LIRA neural classifier, micromechanics, manufacturing process.

1. INTRODUCTION

Shape recognition is a major problem in image understanding and computer vision. In the area of micromechanics, shape recognition is an important task that is related to many microfactory processes such as microdevice assembly task [1], micropiece manufacturing process [2], among others [3, 4].

The microfactory concept was proposed in Japan in 1990 at the Mechanical Engineering Laboratory (MEL) with the developing of a desktop machining microfactory [5]. The microfactory consists of machine tools such as a lathe, a milling machine and a press machine; and assembly machines such as a transfer arm and a two-fingered hand. This portable microfactory has external dimensions of $625 \times 490 \times 380$ mm. The purpose of the microfactory concept is to build very small production units saving space and energy and characterized by a high level of flexibility.

In 1996, the Microequipment Technology (MET) was proposed [6]. In Mexico, scientists from the Center of Applied Sciences and Technological Development (CCADET) developed and applied this technology [7]. The main idea of this method is to create successive generations of microequipment, in which the microequipment sizes of each generation have smaller sizes than the ones of the previous generations. Each generation produces the micromachine tools of its next generation. This approach would allow to use low cost components for each microequipment generation and to create microfactories capable to produce low cost microdevices. The disadvantage of this microequipment is the poor precision of their processes. So we suggest the construction of microfactories composed with micromachine tools with automated control of their process in order to have autonomous and precision systems. Therefore, it is necessary to develop such control systems that improve its precision.

One of the main problems in such microfactories is the automation on the base of vision systems. There are different approaches to construct a computer vision system for these purposes [8–10].

One of the mechanical microcomponents produced by micromachine tools (i.e., microlathe) is the screw. These are necessary components to construct microequipment. The problem related on producing these micropieces is that some of these could have shape defects. These errors are related to the microscrew cutter tool position (Fig. 1). Because of the micromachine small size it is impossible to use ordinary instruments (on a large scale) for control processes. It is necessary to create a vision system that controls automatically the manufacturing process of these work pieces by means of a shape recognition process. High-quality micropieces will be achieved in this case.

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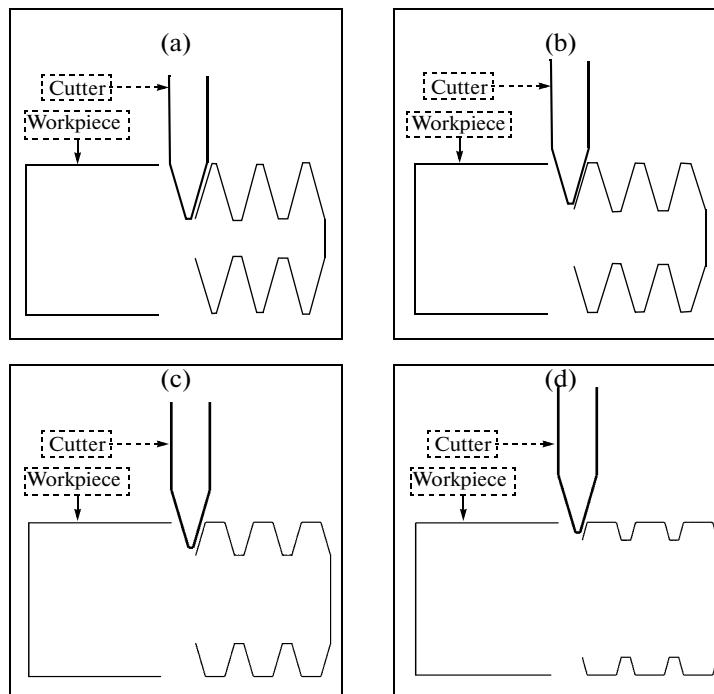
Fig. 1. The position of the cutting tool relatively to the work piece: (a) cutting tool located 0.1 mm below the correct position, (b) cutting tool located at the correct position, (c) cutting tool located 0.1 mm above the correct position, (d) cutting tool located 0.2 mm above the correct position.

Our purpose is to develop a vision system based on an artificial neuronal network (LIRA Grayscale) to attend microscrews manufacturing process. The system's target will be the recognition of the shape of the microwork pieces. Thus, the information obtained can be used to make the appropriate manufacturing corrections (i.e., relocate the cutter position) in case of error detection. The vision system proposed in this work can be used with micromachines tools of MET technology for improving their performance and precision.

2. NEURAL CLASSIFIER LIRA GRAYSCALE

Progress of neuroscience and information technologies give us opportunity to develop not only recognition system based on neural networks but makes possible actual implementation of old ideas to enable individual human being informational individuality with ability of autonomous existence ("life") in computers [11]. The artificial neural networks as one of the mechanisms can be realized with different methods, for example, through computer simulation [1−4], or neuro-holographic processing [12]. One of the interesting approaches is a vector presentation of associative memory [13]. We will describe the special type of neural classifiers [1, 14].

The neural classifier LIRA (Limited Receptive Area), based on Rosenblatt's perceptron principles, was tested on microdevice assembly tasks and handwritten digit recognition showing good results [1, 14]. We adapted LIRA for classifying microscrew grayscale images after the manufacturing process. The resulting neural network was termed LIRA Grayscale [14, 15].

2.1. Architecture

LIRA Grayscale consists of four layers: input layer (S), intermediate layer (I), associative layer (A) and output layer (R). The neural classifier architecture is presented in Fig. 2. The input layer neurons correspond to every image pixel having outputs in range [0, 255], where 0 and 255 indicate the minimum (black) and maximum (white) brightness pixel value. This layer has $W \times H$ neurons, where W and H correspond to the image width and height. The S-layer is connected to A-layer through I-layer by means of a random procedure we will describe later, and the resulting connections are non-trainable ones.
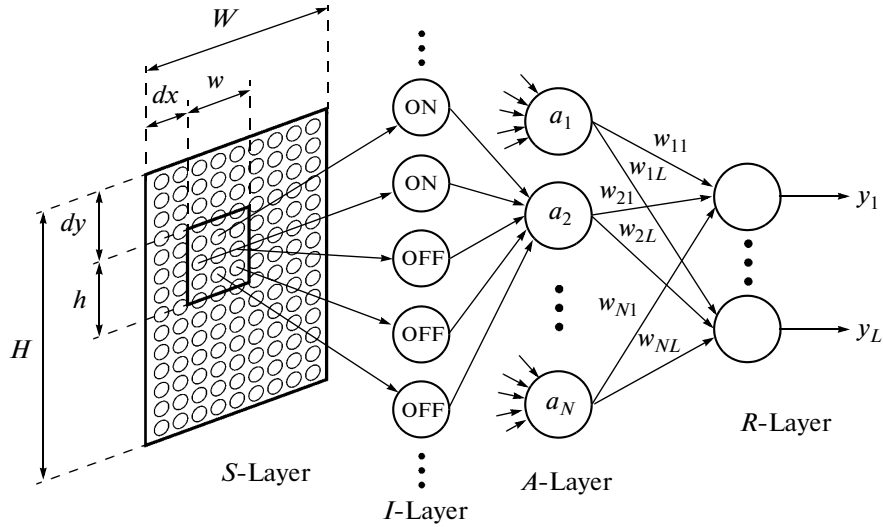
Fig. 2. LIRA Grayscale architecture.

The intermediate layer adapts LIRA Grayscale for handling grayscale images. This layer is located between S-layer and A-layer. The I-layer contains N groups of neurons, where N corresponds to the total number of neurons in the associative layer A. There are two types of neurons in I-layer: ON-neurons and OFF-neurons. According to the brain mechanisms for vision presented in [16], ON-neurons react with the presence of a stimulus and OFF-neurons with the absence of it. These neurons have two-state output values {0, 1}, where 1 indicates a neuron active state.

The associative layer corresponds to an image feature extractor containing neurons with two-state outputs {0, 1}. The A-layer is fully connected to R-layer, where the weights of these connections will be modified during the training process. The output layer consists of linear neurons and the number of neurons in this layer corresponds to the number of classes to recognize. The R-layer is the system's output.

2.2. Layer Interconnections and Neuron Activation

The procedure to connect the input layer S with the associative layer A through the I-layer is as follows. Let N be the number of associative neurons. For each associative neuron a_k, where $k = 1, ..., N$, we randomly select a rectangular area (called window) of $h \times w$ neurons in S-layer, as in Fig. 2. From this window we randomly choose m neurons (points) that will be randomly divided into two sets, one of p positive points and one of n negative points, where $p + n = m$. A positive point is defined as an S-layer neuron connected to an ON-neuron of I-layer and a negative point as an S-layer neuron connected to an OFF-neuron of I-layer. Every positive and negative point from this window will be connected to an ON-neuron and OFF-neuron of I-layer that has no previous connections, respectively, forming a new neurons group k in I-layer, and each one of these neurons in this group will have a threshold T_{mk} randomly selected from the range [0, 255]. This group k of m neurons of intermediate layer will be connected to the a_k neuron. This connection process will be done only once before training.

Let x_{ij} be an S-layer input neuron. The output of an ON-neuron will be equal to 1 (active state) if its input value is larger than a threshold T_{pk} and will be equal to 0 otherwise, i.e.,

$$\varphi_{on}(x_{ij}) = \begin{cases} 1, x_{ij} \geq T_{pk} \\ 0, x_{ij} < T_{pk}. \end{cases}$$

The output of an OFF-neuron will be equal to 1 (active state) if its input value is smaller than a threshold T_{nk} and will be equal to 0 otherwise, i.e.,

$$\varphi_{off}(x_{ij}) = \begin{cases} 1, x_{ij} \leq T_{nk} \\ 0, x_{ij} > T_{nk}. \end{cases}$$

An associative neuron will have output equal to 1 (active state) if all ON-neurons and OFF-neurons connected to it are active, otherwise the output will be 0. Each associative neuron acts like one image feature, which output shows if this feature exists or is absent in the image.

2.3. Learning Method

The neural network we propose uses a supervised learning method that implements a winner selection scheme. This scheme consists of applying to the simple rule of winner selection the following modification: let y_g be the winner neuron output, let y_c be its nearest competitor neuron output, if

$$\frac{y_g - y_c}{y_g} < T_e$$

the competitor is now considered the winner, where T_e is a constant termed the winner neuron superfluous excitation parameter. This modification was proposed in order to improve the recognition process, eliminating the possibilities of selecting a winner neuron by chance.

The learning process consists of three stages described next.

2.3.1. Initial phase. The training procedure begins with the presentation of the image to the neural network input layer. The image features are extracted and coded through I-layer and A-layer, respectively. The R-layer neuron output y_i is computed, as

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

where y_i is the output (excitation) of the i-th neuron of the R-layer, a_k is the output signal (0 or 1) of k-th neuron of A-layer, w_{ki} is the weight of the connection between k-th neuron of A-layer and i-th neuron of R-layer.

2.3.2. Winner selection scheme. After calculating all the outputs of R-layer neurons, the neuron output y_r, corresponding to the neuron real class, is modified by the factor $(1 - T_e)$, i.e.,

$$y_r = y_r(1 - T_e).$$

After this, the neuron having maximum excitation is selected as the winner neuron g.

2.3.3. Weights adaptation. Once we have obtained the winner neuron (recognized class by LIRA Grayscale), if the neuron r (real class neuron) is the same as the neuron g (winner class neuron), the connection weights remain unchanged; but if $r \neq g$ then

$$\forall k, w_{kr}(t + 1) = w_{kr}(t) + a_k$$

$$\forall k, w_{kg}(t + 1) = w_{kg}(t) - a_k$$

if $(w_{kg}(t + 1) < 0) \rightarrow w_{kg}(t + 1) = 0$

where $w_{ki}(t)$ is the connection weight between k-th neuron of A-layer and i-th neuron of R-layer before reinforcement, $w_{ki}(t + 1)$ is the same weight connection after reinforcement, a_k is the output signal of k-th neuron of A-layer.

This process will be repeated until a convergence criterion is reached, in our case, until the maximum number of training cycles (epochs) is attained or the recognition error equals zero. A test phase is then carried out, in which unknown test images are presented to the network to establish the extent to which the network has learned the task in hand.

2.4. Improvements in Learning Process

The image features extracted and coded in the first two layers are the same for every epoch of the training procedure. Therefore, in our experiments we performed the coding procedure only once and saved the lists of active associative neuron indexes for each image on the hard drive. Later, during the training procedure, we used not the images but the corresponding lists of active A-layer neurons. Due to this approach, the training process was accelerated approximately by an order of magnitude.

Reference [17] shows that the performance of the recognition systems can be improved by implementing distortions to the input image during training process. In our experiments we used different image transformations by combining horizontal and vertical displacements and rotations.
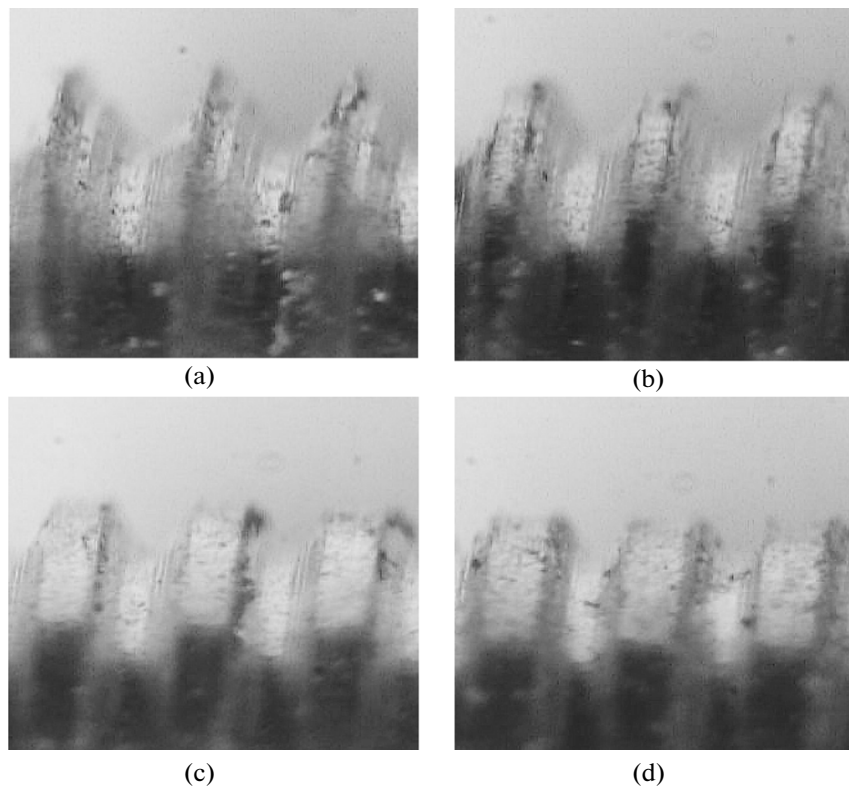
Fig. 3. Microscrew images: (a) class 0, (b) class 1, (c) class 2, (d) class 3.

3. RESULTS

To test the performance of the neural classifier LIRA Grayscale we create an image database with 440 grayscale images of 40 microscrews of 3 mm diameter (11 images in different positions per microscrew) with resolution of 320×280 in BMP format. We worked with four different microscrew classes; therefore we had 110 microscrew images per class.

In class 0 the microscrews were manufactured with a cutter position of 0.1 mm below the cutter correct position, for class 1 the microscrews were manufactured with the cutter correct position, for classes 2 and 3 the microscrews were manufactured with a cutter position of 0.1 mm and 0.2 mm above the correct one, respectively (see Fig. 3). The total number of images from the database was randomly divided to form the training and test sets for the neural classifier. We carried out preliminary experiments to estimate the neural classifier performance and for tuning its parameters. On the basis of these experiments we selected the best set of parameter values and carried out final experiments in order to obtain the maximal recognition rate. The following parameters were set: associative neurons $N = 512\,000$, the winner neuron superfluous excitation parameter T_e was set to 0.3, a window size of 20×20 with 4 positive and 3 negative points. To select the number of ON-neurons and OFF-neurons from I-layer corresponding to one associative neuron in A-layer we were based on that the active neuron number K in A-layer must be many times less than the whole associative neuron number N of this layer, i.e.,

$$K = c\sqrt{N},$$

where c is a constant experimentally selected from the range [1, 5]. This relation corresponds to neurophysiologic facts: the active neurons in the cerebral cortex is hundreds times smaller than the total number of neurons.

Three main experiments were done for evaluating the system. In order to obtain statistically reliable results we execute 30 runs for each experiment. Thus, the total number of images to recognize was calculated as the number of test images for one run multiplied by 30 and the recognition errors number was calculated as the sum of the misrecognized images per run.

Table 1. Recognition rates 6/4

Image distortions	Training images/Test images	Recognition errors number/Images to recognize	Recognition rate, %
0	264/176	88/5280	98.33
4	1320/176	86/5280	98.37
8	2376/176	84/5280	98.41

Table 2. Recognition rates 7/3

Image distortions	Training images/Test images	Recognition errors number/Images to recognize	Recognition rate, %
0	308/132	57/3960	98.56
4	1540/132	56/3960	98.59
8	2772/132	52/3960	98.69

Table 3. Recognition rates 8/2

Image distortions	Training images/Test images	Recognition errors number/Images to recognize	Recognition rate, %
0	352/88	34/2640	98.71
4	1760/88	33/2640	98.75
8	3168/88	29/2640	98.90

In the first experiment we chose images from six microscrews per class for training and the last four for testing, from a total of 10 microscrews per class (Table 1). Since we varied the image transformations number we had three different numbers of training images related with it (i.e., 0, 4, and 8). The second experiment consists of images from seven microscrews per class for training and three for testing (Table 2). In the last experiment we selected images from eight microscrews per class for training and the last two for testing (Table 3).

It can be seen that the training sample size is an important parameter because as the number of training images increases also the recognition rate increases. For example, in Table 1 with 264 training images it obtains 98.33% of recognition rate and in Table 3 with 352 training images it obtains 98.71%, this is 0.38% more exactitude.

On the other hand, image transformations help on increasing the recognition rate too. For example, in Table 2 as the number of image transformations increments, the recognition rate improves.

In addition, we compared our results with the classifier based on ensembles of extremely randomized decision trees for image classification [18] which was evaluated on different publicly available object recognition databases (MNIST, ORL, COIL-100, etc.) and had promising results. We tested this classifier the same way as ours and with 3168 training images and 88 test images it gave 44 recognition errors from a total of 2640 images to recognize, and therefore the recognition rate of 98.33%. The process time for this classifier was 10 minutes while LIRA Grayscale performed the same task in two minutes.

4. CONCLUSIONS

The neural classifier LIRA Grayscale for shape recognition of microscrew images for manufacturing process was developed. It was trained and tested with a database containing images of 40 microscrews of four classes, where every class is related to the definite cutter position. The recognition rate for the training phase was 100% and for the test phase, in the best case, the recognition rate was of 98.90%. These results are acceptable, nevertheless is necessary to improve the classification precision.

Finally, we want to notice that the major advantage of this neural classifier LIRA Grayscale is its universality. It was not constructed for a particular shape recognition problem but that can be adapted and be implemented in different image recognition problems.

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