Pattern Recognition for Micro Workpieces Manufacturing
Reconocimiento de Patrones para la Fabricación de Microobjetos

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Abstract

Two neural classifiers were developed for image recognition: PCNC (Permutation Coding Neural Classifier) and LIRA (Limited Receptive Area) neural classifiers. These neural classifiers are multipurpose neural classifiers. We applied them in micromechanics. Information about shape and texture of the micro workpiece can be used to improve precision of both assembly and manufacturing processes. The proposed neural classifiers were tested off-line in the both tasks.

Keywords: Computer vision, neural network, shape recognition, texture recognition, micromechanics.

Resumen

Dos clasificadores neuronales fueron desarrollados para el reconocimiento de imágenes: PCNC (clasificador neuronal con codificación con permutaciones) y LIRA (clasificador neuronal con área de recepción limitada). Estos clasificadores neuronales son clasificadores de diferentes aplicaciones. Nosotros usamos ellos en micromecánica. La información sobre la forma y textura del micro objeto se puede utilizar para mejorar la precisión de los procesos de ensamble y de fabricación. Los redes neuronales propuestos fueron probados fuera de línea en ambos tareas.

Palabras clave: Visión computacional, redes neuronales, reconocimiento de forma, reconocimiento de textura, micromecánica.

1 Introduction

A computer vision system permits one to provide the feedback that can be used to increase the precision of the manufacturing and assembly processes [Baidyk, et al., 2004; Kussul, et al., 2002]. The structure of the computer vision system which consists of a camera and a computer is presented in Fig. 1. Such systems can be used in low cost micromachine tools [Baidyk, et al., 2004; Kussul, et al., 2002].

A method of sequential generations was proposed to create such microequipment [Kussul, et al., 1996; Kussul, et al., 2002; Kussul, Baidyk, Ruiz-Huerta, et al., 2006]. According to this method the microequipment of each generation has the sizes smaller than the sizes of the equipment of previous generations. This approach allows us to use low cost components for each microequipment generation and to create the microfactories capable to produce the low cost microdevices.

To preserve a high precision of the microequipment it is necessary to use adaptive algorithms of micro workpiece production. The algorithms based on the contact sensors were tested and showed good results [Kussul, et al., 2002]. The neural network based vision system provides much more extensive possibilities to improve the manufacture and assembly processes [Baidyk, et al., 2004]. Specific projects on creation of a microfactory based on miniature micromachine tools were started in several counties including Japan [Okazaki, et al., 2000] and Switzerland [Bleuler, et al., 2000]. One of the main problems of such microfactories is the problem of their automation on the basis of vision systems. There are different approaches to construction of a computer vision system for this purpose [Baidyk, et al., 2008, Baidyk, et al., 2004; Wu, et al., 2001; Lee, et al., 2001, Kim and Cho, 1999].
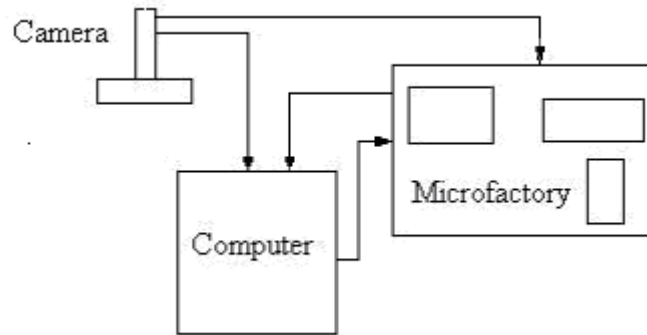
Fig. 1. The structure of the computer vision system

In this paper we propose two neural networks for computer vision system and present preliminary results of their off-line testing in two recognition tasks. These two systems differ in the type of neural classifier. The first system is based on the Permutation Coding Neural Classfier (PCNC) and the second one is based on the Limited Receptive Area (LIRA) neural classifier.

We developed these neural classifiers and tested them in handwritten recognition task and face recognition task. The comparison of these neural classifiers was made with other methods of recognition, for example, with Support Vector Machine [Vapnik, 1995; Vapnik, et al., 2006]. The results of this comparison were published in our publications (for example, [Baidyk, et al., 2004; Kussul, et al., 2006; Makeyev, et al., 2008]). This article is devoted to the adaptation of the developed methods to micromechanics.

The both neural classifiers were tested in other tasks of micromechanics, for example, in recognition of different work pieces and their positions [Toledo, et al., 2004; Toledo-Ramirez, et al., 2006]. Anabel Martín worked with shape recognition task [Martín, et al., 2006].

The task of shape recognition can have different methods to be resolved. As the shape features, it is possible to select the characteristic parts of the objects, protrusions and cavities, and term them primary features [Baidyk et al., 1999]. Below, we describe the algorithm of primary features extraction. The algorithm works with the binary image, i.e. the figure is represented on the image by the set of ones and on the background by the set of zeros. To extract primary features, it is necessary to create two additional figures: the first figure circumscribes the initial figure, and the second figure is inscribed to the initial figure. The primary features are a difference in the areas of the circumscribing figure and the initial one (in Fig.2, the initial figure of screw is presented in white and the circumscribing figure by dark-gray o deep-gray), and also a difference in the areas of the initial figure and the inscribed one (in the same figure, the inscribed figure is light gray in color).

The construction of the inscribed and circumscribing figures is achieved by scanning the image by a circle of a specific radius. The circle of a radius r is defined by the uniformly distributed points (for example, $r = 10$ pixels, $n = 28$, where n is a quantity of points). Fig.2 gives an example of several positions of this circle on the image of a screw. If the number of ones (points belonging to the initial figure) that fell into the circle is lower than the threshold P (experimentally established), then the circle center is excluded from the figure (Fig.2, case 1). Several such iterations lead to the truncation of all convex parts. The figure remains as if it is inscribed into the initial image. Then the areas of initial and inscribed figures are calculated. The difference between them is used as the first feature for shape recognition.

The extraction and the filling of cavities on the complex figure are done with the aid of the procedure of scanning by circle. The procedure must be repeated for the initial image. When a quantity of ones in the circle exceeds a certain threshold P, the center of the circle is included in the figure (Fig.2, case 2). Through several iterations, the initial image will be circumscribed by a certain figure whose points will fill its cavities. After calculating the areas of the initial and circumscribing figures and determining their difference, we will obtain the second feature for shape recognition. The processes of the truncation of protrusions and filling of cavities are invariant to the object position on the image.
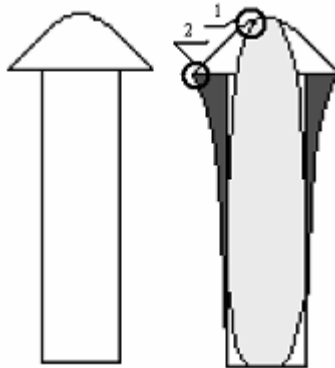
Fig. 2. Initial figure (screw), described and inscribed figures (deep-gray and light-gray)

The analysis of each protrusion and cavity of the figure can give additional information about the object shape. This method demands much time to realize it or demands especial device with parallel structure of information treatment. So we propose in this article another method of shape recognition.

In the first task of shape recognition of micro workpieces we tested our system on the image database which contains images of four classes of 3mm screws manufactured with different positions of the cutter: one class with correct position and other three with different incorrect positions. Incorrect cutter position leads to the incorrect shape of the screw. The system had to recognize the class of the image. This information can be then send to the microfactory and used to correct the cutter position.

In the second task of texture recognition of mechanically treated metal surfaces we tested our system on the image database which contains images of four texture types corresponding to metal surfaces after milling, polishing with sandpaper, turning with lathe and polishing with file. Due to the changes in viewpoint and illumination, the visual appearance of different surfaces can vary greatly, which makes their recognition difficult [Pietikäinen, et al., 2004]. Different lighting conditions and viewing angles affect the grayscale properties of an image due to such effects as shading, shadowing, local occlusions, etc. The real images of metal surfaces obtained in industrial applications have all these problems. Moreover, industrial environments pose some additional problems. For example, a metal surface can have dust on it.

Promising results were obtained in both mentioned tasks.

2 Micro Workpiece Shape Recognition Task

It is possible to use adaptive cutting process to increase the precision of micromachine tools[Kussul, et al, 2002]. Let us consider a lathe equipped with one TV camera (Fig.3).
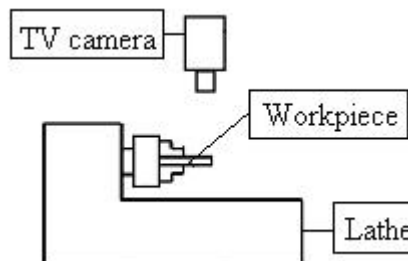

Fig. 3. Lathe equipped with TV camera

The images obtained by the TV camera can be used to evaluate the measurements of partially treated workpieces. Such evaluation can be used to make corrections to the cutting process, for example, to correct the position of the cutting tool relatively to the workpiece (Fig. 4). In this position TV camera can give useful information about the cutting process, for example, the chips formation, the contact of the cutter with the workpiece, etc. The images of workpieces are to be recognized with the image recognition system. We propose to create such recognition system on the basis of the neural network with permutation coding.
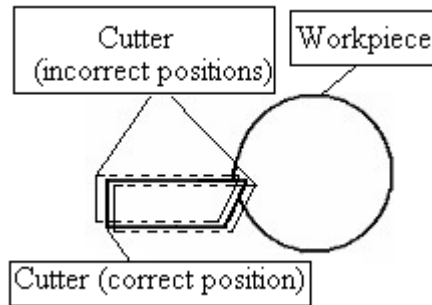
Fig. 4. Position of the cutting tool relatively to the workpiece

The task of shape recognition is well known [Grigorescu and Petkov, 2003]. In our case recognition of images of micro screw is based on the recognition of its shape or profile. The contours of the screw image are to be detected and this representation serves as input of the recognition system. The proposed vision system is based on the neural network with permutation coding technique described in [Kussul and Baidyk, 2003; Kussul, et al., 2004; Kussul, Baidyk, Wunsch, et al, 2006]. This type of neural networks showed good results in handwritten digit and face image recognition tasks. In this work we tested it in micromechanical applications.

2.1. Permutation coding neural classifier

A Permutation Coding Neural Classifier (PCNC) was developed as a general purpose image recognition system. It was tested on the MNIST image database of handwritten digits and ORL image database of faces, and showed good results [Kussul and Baidyk, 2003; Kussul, et al., 2004; Kussul, Baidyk, Wunsch, et al, 2006].

The structure of PCNC is presented in Fig. 5. The image is input to the feature extractor. The extracted features are applied to the encoder input. The encoder produces the output binary vector of large dimension, which is to be presented to the input of one-layer neural classifier. The classifier output represents the recognized class.
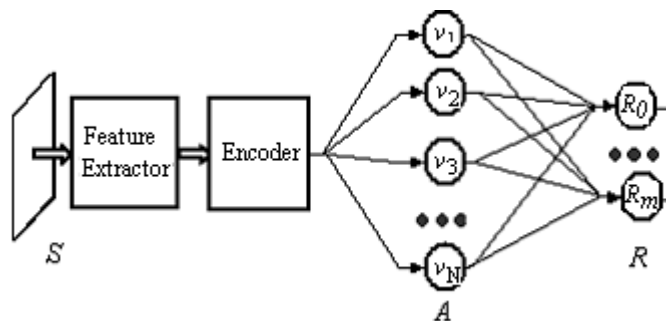
Fig. 5. Structure of the Permutation Coding Neural Classifier (PCNC)

2.1.1. Feature extractor

An initial image (Fig. 6) is to be input to the feature extractor. The feature extractor starts with selection of specific points on the image. Various methods of selection of specific points can be proposed. For example, contour points can be selected as specific points.
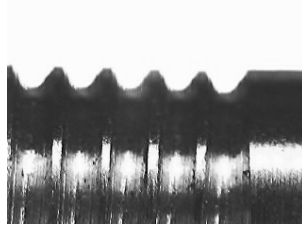

Fig. 6. Example of the initial image

We propose to select specific points in accordance with the following procedure. For each set of four neighboring pixels we calculate the following expressions:

$$d_1 = \left| br_{ij} - br_{i+1\,j+1} \right|,$$
$$d_2 = \left| br_{ij+1} - br_{i+1j} \right|, \tag{1}$$
$$\Delta = max(d_1, d_2),$$

where br_{ij} is the brightness of the pixel (i,j).

If $(\Delta > B)$, then pixel (i,j) is selected as specific point of the image, where B is the threshold for selection of specific points.

Each feature is extracted from the rectangle of size $h * w$, which is built around each specific point [Kussul, Baidyk, Wunsch, et al, 2006]. The p positive and the n negative points determine one feature. These points are randomly distributed in the rectangle $h * w$. Each point P_{rs} has the threshold T_{rs} that is randomly selected from the range:

$$T_{min} \leq T_{rs} \leq T_{max}, \tag{2}$$

where s stands for the feature number and r stands for the point number.

The positive point is active only if on the initial image it has brightness:

$$b_{rs} \geq T_{rs}. \tag{3}$$

The negative point is active only if on the initial image it has brightness:

$$b_{rs} \leq T_{rs}. \tag{4}$$

The feature under investigation exists in the rectangle if all its positive and negative points are active. In the opposite case the feature under investigation is absent in the rectangle.

2.1.2 Encoder

The encoder transforms the extracted features to the binary vector:

$$V = \{v_i\} \ (i = 1, \dots, N),$$

where $v_i = 0$ or 1. For each extracted feature F_s the encoder creates an auxiliary binary vector:

$$U = \{u_i\} \ (i = 1, \dots, N),$$

where $u_i = 0$ or 1.

A special random procedure is used to obtain the positions of ones in the vector U_s for each feature F_s. This procedure generates the list of the positions of ones for each feature and saves all such lists in the memory. We term vector U_s as the "mask" of the feature F_s. To create this vector it is necessary to take the positions from the list and to fill them with ones filling the rest of positions with zeros.

In the next stage of encoding process it is necessary to transform the auxiliary vector U to the new vector U^* which corresponds to the feature location in the image. This transformation is to be performed with permutations of components of vector U (Fig. 7).

The number of permutations depends on the feature location on the image. The permutations in horizontal (X) and vertical (Y) directions are different permutations. In Fig. 6 an example of permutation pattern for horizontal (X) direction is presented.
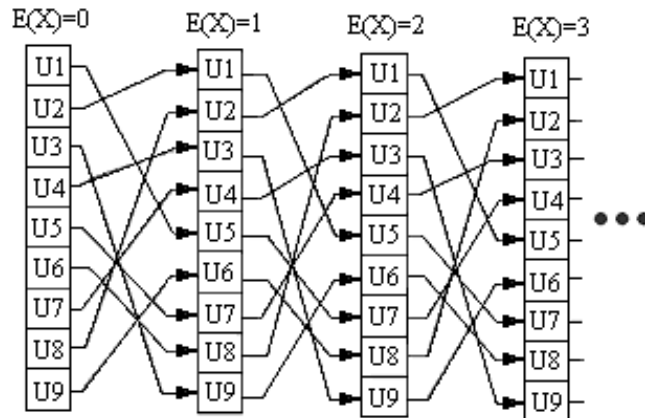

Fig. 7. Permutation pattern for horizontal (X) direction

Same feature can have different locations on the image. Such feature will have different binary code for each location. For two locations of the same feature the binary codes must be strongly correlated if the distance between the feature locations is small and must be weakly correlated if the distance is large. Such property can be obtained with the following procedure.

To code the feature F_s location on the image it is necessary to select the correlation distance D_c and calculate the following values:

$$
\begin{aligned}
&X = j \,/\, Dc, \\
&E(X) = (int)X, \\
&R(X) = j - E(X) \cdot Dc, \\
&Y = i \,/\, D_c,
\end{aligned}
\tag{5}
$$

$$E(Y) = (int)Y \qquad (6)$$
$$R(Y) = i - E(Y) \cdot D_c,$$

$$P_x = \frac{R(X) \cdot N}{D_c}, \qquad (7)$$

$$P_y = \frac{R(Y) \cdot N}{D_c}, \qquad (8)$$

where $E(X)$ is the integer part of X; $R(X)$ is the fraction part of X; i is the vertical coordinate of the detected feature; j is the horizontal coordinate of the detected feature, N is the number of neurons.

The original mask of the feature F_s is considered as a code of this feature located at the left top corner of the image. To shift the feature's location in the horizontal direction it is necessary to perform its permutations $E(X)$ times and to make an additional permutation for P_x components of the vector. After that, it is necessary to shift the code to the vertical direction performing its permutations $E(Y)$ times and an additional permutation for P_y components.

2.1.3. Neural classifier

The structure of the proposed recognition system is presented in Fig. 5. The system contains the sensor layer S, feature extractor, encoder, the associative neural layer A, and the reaction neural layer R. In the screw shape recognition task each neuron of the R-layer corresponds to one of the image classes. The sensor layer S corresponds to the initial image.

The associative neural layer contains "binary" neurons that have outputs equal to either zero or one. The output values of associative neurons represent the result of encoder's work. The neurons of the associative layer A are connected to the reaction layer R with trainable connections with weights w_{ji}. The excitations of the R-layer neurons are calculated in the following way:

$$E_i = \sum_{j=1}^{n} a_j * w_{ji} \qquad (9)$$

where E_i is the excitation of the i-th neuron of the R-layer; a_j is the excitation of the j-th neuron of A-layer; w_{ji} is the weight of the connection between the j-th neuron of the A-layer and the i-th neuron of the R-layer.

The winner neuron that has maximal excitation is selected after the calculation of excitations.

We use the following training procedure. Denote the winner neuron number as i_w, and the number of neuron that corresponds to the correct class of the input image as i_c. If $i_w = i_c$, then nothing is to be done. If $i_w \neq i_c$, then the weights are to be updated in the following way:

$$(\forall j)\left(w_{ji_c}(t+1) = w_{ji_c}(t) + a_j\right)$$
$$(\forall j)\left(w_{ji_w}(t+1) = w_{ji_w}(t) - a_j\right) \qquad (10)$$
$$\text{if } (w_{ji_w}(t+1) < 0) \quad w_{ji_w}(t+1) = 0,$$

where $w_{ji}(t)$ and $w_{ji}(t+1)$ are the weight of the connection between the j-neuron of the A-layer and i-neuron of the R-layer before and after reinforcement correspondingly.

2.2. Results

To test the proposed system in shape recognition of micromechanical workpieces we have produced 40 screws of

3mm diameter with the CNC-lathe Boxford. Ten screws were produced with correct position of the thread cutter. Thirty screws were produced with erroneous positions of the cutter. Ten of them had distance between the cutter and screw axis 0.1mm smaller than necessary. Ten screws were produced with the distance 0.1mm larger than necessary and the remaining ten with the distance 0.2mm larger than necessary. We created an image database of these screws with the resolution of 440x200 pixels using web camera Samsung mounted on an optical microscope.

Five randomly selected images from each group of screws were used for the neural classifier training and the other five were used for the neural classifier testing.

The mean recognition rate of 92.5% was obtained for window $h * w$ width $w = 25$, height $h = 25$, 3 positive and 3 negative points for each specific point, threshold used in selection of specific points $B = 60$ and the total number of associative neurons $N = 64000$.

This task was solved with another neural classifier: LIRA [Martín, et al., 2006]. It was obtained 98.9% of the recognition rate. This LIRA neural classifier we will describe in the next section.

3 Mechanically treated metal surface texture recognition task

3.1. Task description

Texture recognition systems are widely used for industrial inspection in cases when the texture of a surface defines its quality and therefore affects the durability of the product, for example, in textile industry for inspection of fabric [Chan and Pang, 2000], in electronic industry for inspection of the surfaces of magnetic disks [Hepplewhite and Stonham, 1994], etc. Texture recognition is also used when it is necessary to distinguish automatically different types of textures, for example, in decorative and construction industry for classification of polished granite and ceramic titles [Sanchez-Yanez, et al., 2003].

In this paper we propose a texture recognition system based on the Limited Receptive Area (LIRA) [Baidyk, et al, 2004] neural classifier for recognition of mechanically treated metal surfaces. The proposed texture recognition system may be applied in systems that have to recognize position and orientation of complex work pieces in the task of assembly of micromechanical devices as well as in surface quality inspection systems. Four types of metal surfaces after mechanical treatment were used to test the texture recognition system.

Different lighting conditions and viewing angles affect the grayscale properties of an image due to such effects as shading, shadowing, local occlusions, etc. The real images of metal surfaces obtained in industrial applications have all these problems. Moreover, industrial environments pose some additional problems. For example, a metal surface can have dust on it.

Texture recognition of metal surfaces provides an important tool for automation of micromechanical device assembly [Kussul, et al, 2002]. The assembly process requires recognition of the position and orientation of the components to be assembled [Baidyk, et al, 2004]. It is useful to identify the surface texture of a component to recognize its position and orientation. For example, a shaft may have two polished cylinder surfaces for bearings, one of them milled with grooves for a dowel joint, and another surface turned with the lathe. It is easier to obtain the orientation of the shaft if both types of the surface textures can be recognized automatically.

The only work on texture classification of mechanically treated metal surfaces known to us is published by [Brenner, et al., 1991]. The authors propose to use a vibration-induced tactile sensor that they call Dynamic Touch Sensor (DTS) in combination with one-layer Rosenblatt perceptron [Rosenblatt, 1962]. The DTS produces signals based on the vibration induced by a sensor needle sliding across a metal surface with fixed velocity and pressure. The motion path of the sensor is an arc of approximately 100 degrees. Such motion path permits to capture information about surface in two dimensions in one sweep; however, the 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. Surface roughness is a measure of the average height of the surface irregularities given in microinches. Six types of surfaces and six values of surface roughness were used in testing. Obtained recognition rate 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.

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 micro inch. In addition, our approach does not require a complex mechanical sensor and is robust to changes in texture position and orientation [Makeyev, et al., 2008].

3.2. Limited receptive area (LIRA) neural classifier

The structure of the LIRA neural classifier is presented in Fig. 8. LIRA neural classifier differs from the PCNC neural classifier in the coding procedure that is performed by the set of connections between the *S*-layer and *A*-layer and not by separate feature extractor and encoder.

As in case of the PCNC neural classifier the *S*-layer of the LIRA neural classifier corresponds to the input image. The associative neural layer *A* and the reaction neural layer *R* are the same as in the PCNC neural classifier. The training rules for connections between the layers *A* and *R* and the recognition procedure are also the same [Makeyev, et al., 2008].
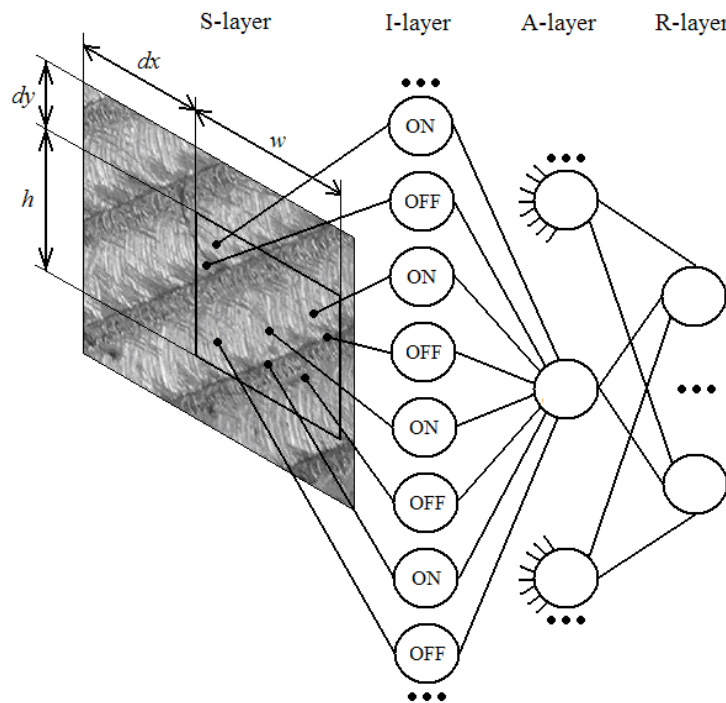

Fig. 8. Structure of the Limited Receptive Area (LIRA) neural classifier

The coding procedure used in the LIRA neural classifier is the following. We connect an A-layer neuron to S-layer neurons through the neurons of the intermediate neural layer *I* (Fig. 8). The input of each *I*-layer neuron is connected to one neuron of the *S*-layer and the output is connected to the input of one neuron of the *A*-layer. All the *I*-layer neurons connected to one *A*-layer neuron form the group of this *A*-layer neuron. There are two types of *I*-layer neurons: ON-neurons and OFF-neurons. The output of an ON-neuron *i* is equal to 1 if its input value is larger than the threshold θ_i and is equal to 0 in the opposite case. The output of an OFF-neuron *j* is equal to 1 if its input value is smaller than the threshold θ_j and is equal to 0 in the opposite case. For example, in Fig. 8 the group of eight *I*-layer neurons, four ON-neurons and four OFF-neurons, corresponds to one *A*-layer neuron. The thresholds θ_i and θ_j are selected randomly from the range $[0, b_{max}]$, where b_{max} is maximal brightness of the image pixels. The *i*-th

neuron of the *A*-layer is active ($a_i = 1$) only if outputs of all the neurons of its *I*-layer group are equal to 1 and is non-active ($a_i = 0$) in the opposite case. ON- and OFF-neurons of the *I*-layer in the structure of the LIRA neural classifier correspond to positive and negative points in the structure of the PCNC neural classifier.

The procedure for setting connections between the *S*-layer and a group of *I*-layer neurons is the following. The input of each *I*-layer neuron of one *A*-layer neuron group is connected to one neuron of the *S*-layer randomly selected not from the entire *S*-layer, but from the window *h*w* that is located in the *S*-layer (Fig. 8). The distances *dx* and *dy* are random numbers selected from the ranges: *dx* from [0, $W_S - w$) and *dy* from [0, $H_S - h$), where W_S and H_S stand for width and height of the *S*-layer. The procedure of random selection of connections starts with the selection of the upper left corner of the window $h * w$ in which all connections that correspond to one associative neuron are located.

The following formulas are used:

$$dx_i = random_i(W_S - w),$$
$$dy_i = random_i(H_S - h), \tag{11}$$

where *i* is the position of a neuron in associative layer *A*, $random_i(z)$ is a random number that is uniformly distributed in the range [0, *z*). After that position of each connection within the window $h * w$ is defined by the pair of numbers:

$$x_{ij} = random_{ij}(w),$$
$$y_{ij} = random_{ij}(h), \tag{12}$$

where *j* is the number of the connection with the *S*-layer.

Absolute coordinates of a connection to the *S*-layer are defined as:

$$X_{ij} = x_{ij} + dx_i,$$
$$Y_{ij} = y_{ij} + dy_i. \tag{13}$$

Detailed description of the LIRA neural classifier is presented in [Baidyk, et al, 2004].

3.3. Results

To test our texture recognition system we created our own image database of metal surface images. Four texture classes correspond to metal surfaces after milling, polishing with sandpaper, turning with lathe and polishing with file (Fig. 9). Twenty grayscale images with resolution of 220x220 pixels were taken for each class. We randomly divided these 20 images into the training and test sets. Fig. 9 illustrates the fact that different lighting conditions greatly affect the grayscale properties of images. The textures may also be arbitrarily oriented and not centered perfectly. Metal surfaces may have minor defects and be covered with dust. All these image properties correspond to the conditions of a real industrial environment and make the texture recognition task more complicated.

Images that correspond to each of four classes were randomly divided in half into the training and test sets.

The mean recognition rate of 99.8% was obtained for window $h * w$ width *w* = 10, height *h* = 10, three ON-neurons and five OFF-neurons in the *I*-layer neuron group and the total number of associative neurons N = 512000.

We made these experiments with computer equipped with AMD Athlon 64 x2 4400+ dual core processor and 2.00 GB of RAM.

The amount of time needed for one run of classifier coding, training and recognition is approximated 1 min 40 s (65 s for coding, 34 s for training and 1 s for recognition) for all images of database.
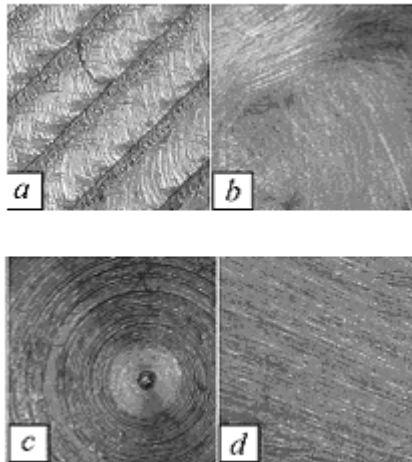
Fig. 9. Examples of metal surfaces after (columns): a) milling, b) polishing with sandpaper,
c) turning with lathe, d) polishing with file

4 Conclusion

This paper continues the series of publications on automation of micro manufacturing and micro assembly processes [Baidyk, et al., 2004; Kussul, et al., 2002].

Neural network based computer vision systems are proposed and tested in micro workpiece shape recognition and mechanically treated metal surface texture recognition. In the task of micro assembly such systems can be used to recognize position and orientation of complex micro workpieces. In the task of micro manufacturing such systems can be used to evaluate the measurements of partially treated workpieces. Such evaluations can be used to make corrections to the manufacturing process.

Promising results were obtained during the off-line testing of both systems.

5 Acknowledgment

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