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# Image Recognition Systems with Permutative Coding

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**Abstract-** A feature extractor and neural classifier for image recognition system are proposed. They are based on the Permutative Coding technique which continues our investigations on neural networks. It permits us to obtain sufficiently general description of the image to be recognized. Different types of images were used to test the proposed image recognition system. It was tested on the handwritten digit recognition problem, the face recognition problem and the shape of microobjects recognition problem. The results of testing are very promising. The error rate for the MNIST database is 0.44% and for the ORL database is 0.1%

## I. INTRODUCTION

We have developed a new image recognition method for various applications. It is based on discovering specific points on the image, and extraction of local features of the image around these points. The extracted features are coded in binary form. The binary code of each feature contains the information about localization of this feature in the image, but the code is insensitive to small displacements of the feature in the image. The proposed method recognizes objects having small displacements in the image and small distortions. It could be applied to gray scale or color images. We proved this method on the handwritten digit recognition problem, the face recognition problem and the microobject shape recognition problem.

## II. SPECIAL AND GENERAL PURPOSE IMAGE RECOGNITION SYSTEMS

At present very good results are obtained using special recognition systems. Let us, for example, compare the best results obtained in handwritten digit recognition on the MNIST database and face recognition on the ORL database.

The MNIST data base contains 60,000 handwritten digits in the training set and 10,000 handwritten digits in the test set. There are different classifiers which have been applied in the task of handwriting recognition [1], [2], [3], [4], [5], [6], [7]. The best results were obtained with Boosted LeNet-4[distortions] [1], Shape Matching+3NN[3],[4], Classifier LIRA [5], [7], SVC-rbf\_grayscale [6].

The ORL database contains 400 photos of 40 persons (10 photos of each person). The photos differ in illumination, face expression and position. 5 photos of each person are used for training and the other 5 photos are used for testing of the recognition system. The best results were obtained on the ORL database with Wavelet+HMM [8], PDNN [9], SVM+PCA coefficients [10], Continuous n-tuple classifier [11], Ergodic HMM+DCT coefficients [12], Pseudo 2D HMM+DCT coefficients [13].

As can be seen almost all of the best recognition systems for the ORL database differ from the recognition systems for the MNIST database. Some of the systems use the same type of classifiers, for example SVM, multilayer neural networks, but the features extracted from the images in these cases are different.

The great variety of recognition systems takes a huge amount of human work for software development and complicates the development of special hardware which could ensure high speed and low cost image recognition. Therefore, it is necessary to search for more general methods which would give sufficiently good results in different recognition problems. There are general purpose recognition systems, for example, LeNet [1], [2], Neocognitron [14]-[17], Receptive Fields [18] but the recognition quality of such systems is lower than the quality of special systems. It is necessary to develop a general purpose recognition system having a quality comparable with the quality of specialized systems.

Some years ago we started to investigate a general purpose image recognition system. In this system we use the well known one-layer perceptron as a classifier. The center point of our investigations is the creation of a general purpose feature extractor. This feature extractor is based on the concept of random local descriptors (RLD). We consider the term "feature" and "descriptor" as synonyms. We intend to develop the method of RLD creation which could be successfully used for different types of images (handwriting, faces, vision-based automation, etc.)

### III. RANDOM LOCAL DESCRIPTORS

RLD are based on two known ideas. The idea of random descriptors of the images was proposed by Frank Rosenblatt. In his three-layered perceptron [19] each neuron of the associative layer plays the role of random descriptor of the image. Such a neuron is connected to points randomly selected on the retina (input image) and calculates a function from the brightness of these points. It is important to note that the connections of the neuron are not modifiable in the training process. Another idea of local descriptors is drawn from the discovery of Hubel and Wiesel [20], [21]. They have proved that in the visual cortex of animals there are local descriptors which correspond to local contour elements orientation, movements etc. The discovered local descriptor set is probably incomplete because in the experiments of Hubel and Wiesel only those descriptors or features were detected which were initially prepared to present to the animals. Probably not all the descriptors (features) which can be extracted by the visual cortex of the animals were investigated. The random descriptors of F.Rosenblatt could overcome this drawback. But the application of these descriptors to full size image decreases the effectiveness of the application.

We introduce RLDs which are similar to the descriptors of Rosenblatt but are applied to the local area of the image. In the first version of our recognition system each random detector was applied to its own local area, selected randomly in the image. This recognition system was named LIRA (Limited Receptive Area). LIRA was tested on the MNIST database and showed sufficiently good results - 55 errors [7]. One of the LIRA drawbacks is the sensitivity to image displacements. We compensated this with distortions of input images during the training process. But this method cannot be used for large displacements. For this reason we developed more sophisticated image recognition system.

The scheme of the general purpose image recognition system is shown in Fig.1. The base of this system is a multilayer neural network. The first layer  $S$  (sensor layer) corresponds to the input image. The second layer  $D_1$  contains RLD's of the lowest level. The layer  $D_2$  contains RLD's of the higher level. The associative layer  $A$  contains associative elements which could be represented by groups of neurons. The layer  $R$  contains the output neurons; each of these neurons corresponds to the image class under recognition.

The scheme of the RLD of the lowest level is presented in Fig.2.

Each RLD contains several neurons (the neurons with numbers 1-5 in Fig.2). All neurons of the RLD are connected to the local area of the  $S$ -layer (the rectangle with size  $H \times W$ ). The neurons number 2-5 serve for testing the pixels of the  $S$ -layer, randomly selected in the rectangle. These neurons we call simple neurons. There are two types of simple neurons: ON-neurons and OFF-neurons (similar to

ON- and OFF-neurons of natural neural networks). The outputs of simple neurons are "0" or "1".

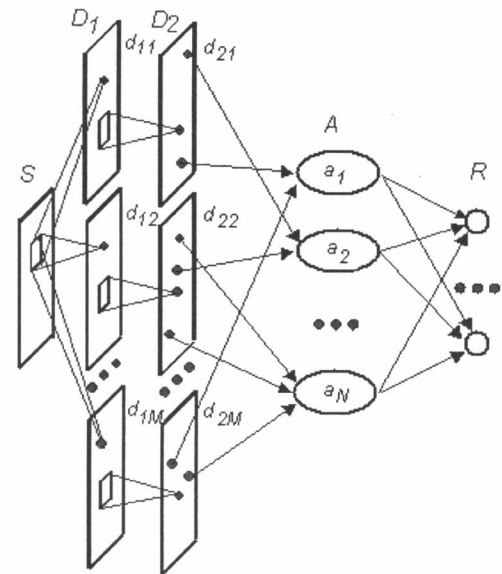


Fig.1. Structure of general purpose image recognition system

ON-neuron has the output "1" if the brightness  $b_i$  of the corresponding pixel is higher than the neuron threshold  $T_i$ :

$$b_i \geq T_i. \quad (1)$$

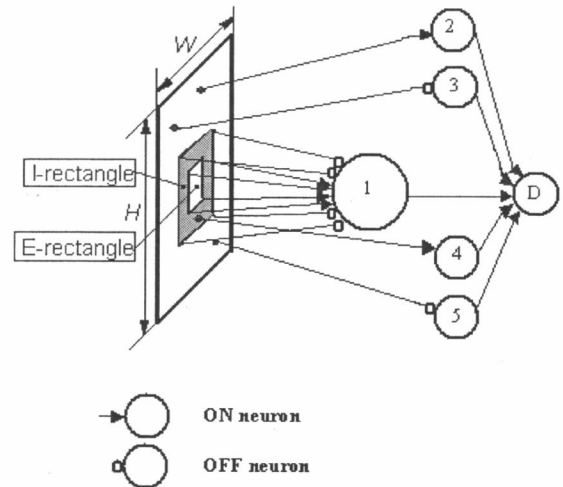


Fig.2. Scheme of the RLD of the lowest level

The OFF-neuron has the output "1" if the brightness  $b_i$  of the corresponding pixel is less than the neuron threshold  $T_i$ :

$$b_i < T_i. \quad (2)$$

In Fig.2 the neurons 2 and 4 are ON-neurons, the neurons 3 and 5 are the OFF-neurons. The thresholds  $T_i$  are randomly selected in the dynamic range of the input image brightness.

The neuron number 1 is the complex neuron. It has excitatory connections with all the pixels from the small rectangle (E-rectangle in Fig.2) located in the center of the rectangle of  $H \times W$  and inhibitory connections with the pixels located around the small rectangle (I-rectangle in Fig.2). Excitatory connections have the weights +1, and inhibitory connections have the weights -1. The weights of the connections could be different in different image recognition problems. These weights should be determined by the recognition system designer and are not modifiable during the training processes. In the simplest cases the neuron number 1 can extract the contour points. For this case the weights of excitatory connections must be inversely proportional to the area of the E-rectangle and inhibitory connections must be inversely proportional to the area of the I-rectangle. Another simple case corresponds to extracting the bright areas of the image. For this case the weights of the excitatory connections should be inversely proportional to the area of the E-rectangle and all the inhibitory connections should be "0". The first case we use for face recognition problems and micromechanical applications of the proposed system, the second case we use for handwritten digit recognition. The output of the neuron number 1 is "1" if the algebraic sum of the input signals is positive and the output is "0" if the sum is negative. We assume that the complex neurons will detect the most informative points of the image.

The neuron descriptor  $D$  has output "1" if all the neurons 1-5 have output "1". If at least one of these neurons has output "0", the output of neuron  $D$  is "0". The neuron  $D$  can be termed AND-neuron.

The neural layer  $D_1$  (Fig.1) consists of a huge number of planes  $d_{11}, d_{12}, \dots, d_{1M}$ . Each plane contains the number of AND-neurons equal to the pixel number of the input image. The plane  $d_{ij}$  preserves the topology of the input image, i.e. each neuron of plane  $d_{ij}$  corresponds to the pixel located in the center of the corresponding rectangle of  $W \times H$  (Fig.2). The topology of connections between the sensor layer and neurons 2-5 (Fig.2) is the same in the range of every plane  $d_{ij}$  (Fig.1). The topology of connections between the sensor layer and neuron number 1 is the same for all the neurons in all the planes of layer  $D_1$ . The aim of each plane is to detect the presence of one concrete feature in any place of the image. The number of planes corresponds to the number of extracted features (in our system each feature corresponds to one descriptor type). The huge number of features permits us to obtain a good description of the image under recognition. In the MNIST database we used 12,800 features; in the ORL database we used 200 features. To estimate the required number of features it is necessary to solve the problem of structure risk. It is difficult to obtain an

analytical solution of this problem for the complex recognition system. So we estimate the required number of features experimentally for each recognition problem.

Layer  $D_2$  (Fig.1) also contains  $M$  planes of neurons. Each neuron of the  $d_{2j}$  plane is connected to all the neurons of  $d_{1j}$  plane located within the rectangle. The output of each neuron is "1" if at least one of the connected  $d_{1j}$  neurons has the output "1". Such a neuron is termed an OR-neuron. The topology of the  $d_{2j}$  neurons corresponds to the topology of the  $d_{1j}$  neurons and to the topology of the  $S$  layer.

All neurons having output "1" we shall term the active neurons.

All the neurons of the associative layer  $A$  have trainable connections with each neuron of the layer  $R$ .

#### IV. COMPUTER SIMULATION

Direct implementation of the proposed image recognition system as a computer program has a high computational cost. To reduce the time of computation we use the following method. For each pixel of the input image we calculate the activity of complex neuron 1 (see Fig.2). If this neuron is active we make sequential calculations only for those elements of the neural network which are connected with this active neuron. In our work the number of active complex neurons is much less than the whole number of complex neurons (sparse code representation). We follow this principle also in other calculations up to the calculation of  $R$ -neurons excitations, i.e. we analyze only those connections which correspond to the active neurons  $D_1, D_2$  and the  $A$ -layer. This method reduces the calculation time by dozens or hundreds of times and makes it possible to simulate the proposed recognition system in real time. We term our system the Permutative Coding Neural Classifier (PCNC). PCNC is described in [22], [23].

#### V. RESULTS OBTAINED ON THE MNIST DATABASE

The MNIST database contains 60,000 samples in the training set and 10,000 samples in the test set. The results of these experiments are presented in Table 1. The values presented in this Table correspond to the number of errors in the recognition of 10,000 test samples. We made several runs with different structures. Each row in the Table corresponds to one of these runs. The first column of the Table (Run) enumerates the experiments. The second column contains the obtained results (Table 1).

Unrecognized digits of the best experiment (Table 1, line 3) are presented in Fig. 3.

TABLE 1  
RECOGNITION RESULTS  
(N = 512,000; S = 12,800)

Run	Recognition Error Number
1	56
2	50
3	44
Mean value	50
Mean value (%)	0.5

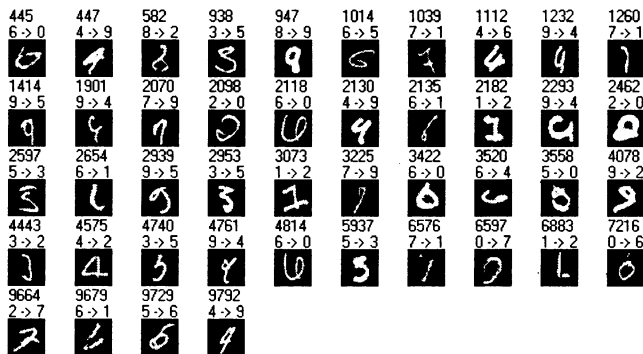


Fig. 3. An example of unrecognized handwritten digits.

Table 2 gives the possibility to compare our best result with those obtained with other authors.

TABLE 2  
RECOGNITION RATE OF DIFFERENT CLASSIFIERS

METHODS	% OF ERROR NUMBER	REF.	YEA R
Boosted LeNet-4 [distortions]	0.7	[1]	1994
Shape Matching + 3-NN	0.63	[3],[4]	2001
Classifier LIRA	0.63	[5]	2002
Classifier LIRA	0.55	[7]	2004
<b>Classifier with permutative coding</b>	<b>0.44</b>	This paper	2005
SVC-rbf grayscale	0.42	[6]	2002

## VI. RESULTS OBTAINED ON THE ORL DATABASE

The ORL data base contains 400 images of 40 persons (10 images of each person). Each image is full face.

The difference between 10 images of each person consists of shifts, head inclination, different face expression, presence or absence of glasses. As a rule the algorithms are tested on the ORL data base in the following manner: five images of one person are used for classifier training and

other five are used for testing. There are two modes to make this partition.

In the first mode they use the first five images for training and last five images for testing. In the second mode they select randomly five images for training and the rest of images are used for testing. The first mode was good for comparison of the classifiers until classifiers with almost 100% recognition rate appeared. If error percentage is less than 2-3% it is difficult to compare the classifiers using this mode.

The second mode permits to make many different experiments with the same data base and to obtain statistically reliable results. In our experiments we use 10 runs for each experiment. This method was used also in other works for estimation mean value of error rate [24]. They used 6 runs for each experiment. Their results are given in Table 3.

TABLE 3  
BEST PERFORMANCES ON 6 SIMULATIONS

Simulation	1	2	3	4	5	6
NOM	2	6	6	2	1	6

(NOM – number of misclassifications or errors).

It is also interesting to investigate the cases where less than five images are selected for training and the rest for testing. The data from such experiments are presented in [25]. Unfortunately the data are presented graphically and no table is given. We tried to restore the data from the graphics. The results are given in Table 4.

TABLE 4  
ERROR RATES FOR DIFFERENT NUMBER OF EACH PERSON'S IMAGE PRESENTED FOR TRAINING

Number of training/examine images	The best result from [25] (restored from graphics)	Our result
1/9	17.6	16.1
2/8	8.8	7.09
3/7	4.8	2.15
4/6	2.8	1.4
5/5	1.2	0.1

The note tr./ex. reflects how many images were used for training (tr.) and how much for examine (ex.). The comparison of results show that our classifier in most of the cases gives the best recognition rate.

The results of our experiments are presented in Table 5.

TABLE 5  
RECOGNITION RESULTS FOR ORL DATABASE

tr./ ex.	NOM										Total NOM	E <sub>ave</sub> (%)
	Run											
	1	2	3	4	5	6	7	8	9	10		
1/9	64	66	55	46	52	63	72	44	58	60	580	16.1
2/8	14	29	18	18	25	26	19	13	21	44	227	7.09
3/7	6	13	6	0	9	8	10	3	4	1	60	2.15
4/6	3	3	7	2	5	1	0	7	4	2	34	1.4
5/5	0	0	0	0	0	0	0	0	0	2	2	0.1

The comparison of our results with the results of other authors is given in Table 6.

TABLE 6  
COMPARATIVE RESULTS ON THE ORL DATABASE

Method	Error	Ref.	Year
PDNN	4.0%	[9]	1997
SVM + PCA coef.	3.0%	[10]	2001
Continuous n-tuple classifier	2.7%	[11]	1997
Ergodic HMM + DCT coef.	0.5%	[12]	1998
<b>Classifier with permutative coding</b>	<b>0.1%</b>	This paper	2005
Pseudo 2D HMM + DCT coef.	0%	[13]	1999
Wavelet + HMM	0%	[8]	2003

We mentioned above that different methods of specific points detection could be used. For face recognition we used the points of the contours. For this purpose the connections from the E-rectangle (Fig.2) must have positive weights, and the connections from the I-rectangle must have negative weights).

#### VII. RESULTS OBTAINED ON MICROOBJECT SHAPE RECOGNITION

A computer vision system permits one to provide the feedback, which increases the precision of the manufacturing process. It could be used in low cost micromachine tools and micromanipulators of microfactories which produce microdevices.

One of the main problems in microfactory creation is the problem of automation on the base of vision systems [26]-[28].

To examine the PCNC in recognition of the shape of micromechanical workpieces we have produced 40 screws of 3mm diameter with the CNC-lathe of the company "Boxford". Ten screws were produced with correct position of the thread cutting cutter (Fig. 5, b). Thirty screws were produced with erroneous positions of this cutter. Ten of them (Fig. 5, a) had the distance between the cutter and screw axis 0.1mm less than necessary. Ten screws (Fig. 5, c) were produced with the distance of 0.1mm larger than

necessary and the remaining ten (Fig. 5, d) with the distance 0.2mm larger than necessary. We made an image database from these screws using a Samsung Web-camera mounted on an optical microscope. Examples of the images are presented in Fig. 4.

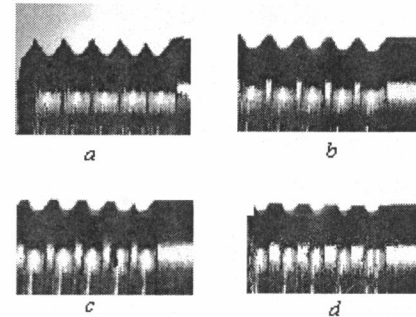


Fig. 4. Examples of initial images

An example of the specific points selected in the image is presented in Fig. 5.

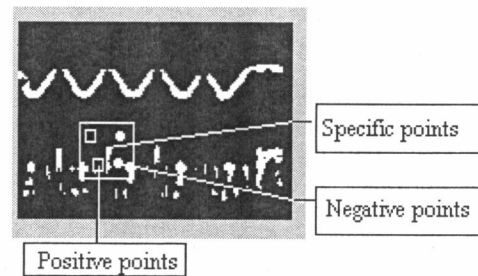


Fig. 5. Specific points selected on the contour image of screw

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

The experiments were made with different parameter  $B$  of specific point selection ( $B$  is the threshold for specific point selection). Four different runs were made for each value  $B$  to obtain statistically reliable results. Each run differs from others by the set of samples selected randomly for the neural classifier training and by the permutation scheme structure. For this reason we obtained different error rates in different runs. We obtained the following mean value: if  $B=20$ , the correct recognition was 85%; if  $B=40$ , the correct recognition was 88.75%; if  $B=60$ , the correct recognition was 92.5% [23].

#### VIII. DISCUSSION

A multipurpose image recognition system is developed. This system contains a feature extraction subsystem based on the permutative coding technique and one layer neural classifier. The main advantage of this system is effective recognition of different types of images. The system was tested on handwritten digit recognition, face recognition and microobject shape recognition problems. The large number

of features used by this system permits us to obtain good (complete) description of image properties and for this reason good recognition results could be achieved. All the features are based on random neural network structures and that is why they are applicable to a wide range of image types. The huge number of elements of the associative layer permits us to transform the initial image to the linearly separable space. In this space the one-layer neural classifier works effectively. So, the advantages of the one-layer classifier (simple training rules and fast convergence) make the system good for different application.

## IX. CONCLUSION

A new multipurpose image recognition system was developed. The system is based on the permutation coding technique. This technique decreases the sensitivity to the object displacements in the image. Tests of the classifier on the MNIST database show very good recognition rate 0.44% errors and 0.1% errors on ORL database. The system was also tested on microobject shape recognition problem and showed the promising results. In the future, faster recognition methods, which are insensitive to object rotation and scale change, will be developed.

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