Investigation of Neural Classifiers for Recognition of Micro Components of Solar Concentrators

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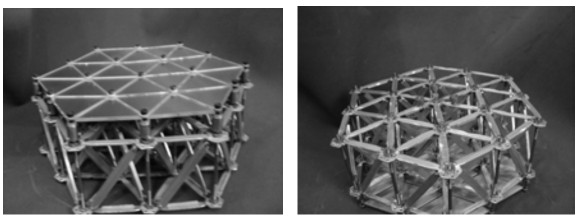
Abstract: - The aim of this article is to compare two neural classifiers applied to micro component recognition. These micro components can be used for the automation of production and assembly processes of solar concentrators. The image databases have been developed and include mixed and heaped-up micro work pieces. Two neural classifiers, the limited receptive area classifier (LIRA) and the permutation coding neural classifier (PCNC), were tested using these databases. Both methods have demonstrated good results. The LIRA neural classifier achieves a recognition rate of 90%, while the PCNC achieves 91%. Parameters of reliability, adjustability and other characteristics of the classifiers are compared. In the future, these algorithms can be used for the intelligent automation of renewable energy technology production. For example, we intend to use the algorithms for the assembly task of solar concentrators developed in our laboratory.

Key-Words: - Object recognition, computer vision, LIRA neural classifier, PCNC, solar concentrators, flat mirrors

1 Introduction

In recent years, we have developed and patented several prototypes of solar concentrators with flat mirrors in Spain, USA and Mexico [1]–[4]. One example of the solar concentrator prototype is presented in Fig. 1.



a b

Fig.1. Solar concentrator prototype: a) face side; b) rear side

The main feature of these concentrators is a large quantity of micro components such as screws and washers (Fig. 2). To reduce the cost of the production and assembly processes of these concentrators, it is necessary to develop an automatic process for their production.

Fig. 2. Screws and washers in the frame of a solar concentrator

In the last several decades, we have developed and tested several neural classifiers [5]–[7] to apply them to manufacturing and assembly tasks. In addition, three micro work piece databases were created to encourage the community to demonstrate, compare and improve their classifiers [8]. These three databases have different complexity levels for the recognition task as well as common characteristics, which are explained in the article.

In this research, we have adapted two neural classifiers called the LIRA and PCNC for the component recognition task. The LIRA neural classifier, which was adapted with the basic and second database of micro work pieces, is demonstrated [9]. Next, the PCNC was applied to the same pair of databases and obtained a better recognition rate than the LIRA [10]. In this paper, we describe the application of both classifiers to a third more complex database. We compare the current results for both classifiers. It was necessary to improve the algorithms and parameters of the neural classifiers. We analyze additional characteristics such as recognition and training times, stability and reliability of our neural classifiers.

This paper is organized as follows: Section 2 reviews the previous work with the classifiers in micro work piece recognition. Section 3 describes the LIRA neural classifier, while Section 4 describes the PCNC. In Section 5, we describe the databases used in the experiments. Section 6 is devoted to the experiments performed and the results obtained. The comparison of the LIRA and PCNC classifiers is presented in Section 7 followed by the conclusions in Section 8.

2 Previous Studies

In this section, the previous results obtained with the LIRA and the PCNC are reviewed. For each classifier, the results of the micro work piece recognition are presented.

2.1 LIRA neural classifier

For work piece recognition, the LIRA neural classifier was trained and tested in the recognition of a basic set with five classes [9]. Next, it was tested with the two simplest databases from our published sets. For the basic set with five classes, the best recognition rate was 94%. The recognition rate was examined for databases A and B from our published sets [9].

2.2 PCNC

The PCNC has been developed for different object recognition tasks [5], [6]. For the micro work piece recognition task, the PCNC was tested with the two simplest databases from the image database. The recognition rates were 96% and 97% for databases A and B, respectively [10]. In the following sections, we describe the LIRA and PCNC.

3 LIRA Neural Classifier

The LIRA neural classifier is based on the Rossenblatt Perceptron [11]. This classifier is called LIRA because of its way to process data from its input as randomly located subspaces.

3.1 Structure description

The LIRA neural classifier structure is presented in Fig. 3).

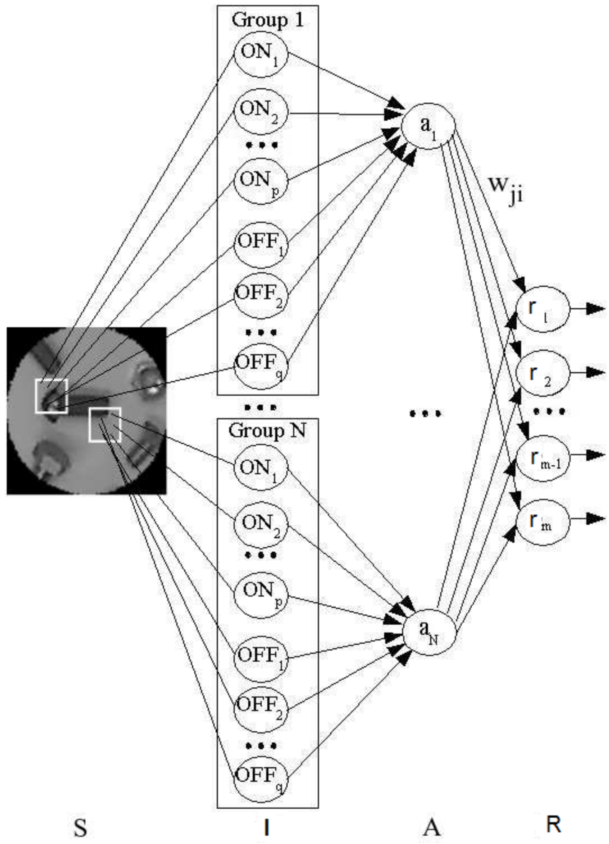


Fig. 3. Structure of the LIRA neural classifier

The LIRA has four layers:
– Input layer $S = s_1, s_2,..., s_{W \cdot H}$
– Group layer $I = i_1,..., i_N$
– Associative layer $A = a_1, a_2,..., a_N$
– Output layer $R = r_1, r_2,..., r_M$
where W and H are the width and the height of the input image, respectively. N is an internal parameter representing the number of groups in layer I as well as the number of neurons in layer A, and M is the number of output classes.

The S layer corresponds to the input image to be classified. The brightness of the pixel of the input corresponds to the excitation level of the corresponding neuron. The available brightness range is [0, B], where B is the maximum brightness of the image. The I group layer contains N neuron groups. Every group contains the same number of ON- and OFF-neurons, p and q, respectively, but with different positions.

An ON-neuron is defined as active if $x_{ij} > T_{ONij}$ while an OFF-neuron is active if $x_{ij} < T_{OFFij},$ where x_{ij} is the input of the corresponding neuron (j neuron in the i group). Each neuron has a constant threshold randomly selected at the initializing time. This threshold is within [0, B].

The a neurons from the A layer have $p + q$ inputs connected to the outputs of the corresponding group. These neurons have a binary response. It is active (1) if and only if all its inputs are active, otherwise it is inactive (0).

Finally, all a neurons are connected to each of the r neurons with the weighted connections. Each of these $N \cdot M$ connections has a weight to be adjusted during the training process. A detailed description of the LIRA neural classifier can be found in [7].

3.2 Training process
During the training process, the weights of the connections between the A and R layers are modified to obtain the correct output class.

The training process is as follows:

(i) All the weights w_{ji} should be set to constant.

(ii) An image from the training set is input to the classifier. The output of the A layer is calculated.

(iii) The true class corresponding to the image is read.

(iv) The r neuron with the highest output value, called the "winner", is detected. This neuron represents the current recognized class for the given image.

(v) The winner is compared with the true class. If they coincide, nothing is done. If not, it is necessary to decrease the weights of the winner (in this case the false class) and increase the weights of the correct class.

(vi) The process continues with all the images of the training set for a given number of cycles.

(vii) The process can be stopped by a fixed number of cycles or when a predefined error number is reached.

4 PCNC
The PCNC has been defined on the principles of the Random Local Descriptors [5], [6]. The PCNC takes advantage of a feature encoder and a neural network. The PCNC structure is explained briefly in the next section. The detailed description is presented in [7].

4.1 Structure description
The PCNC structure consists of three blocks called the feature extractor, feature encoder and neural classifier (Fig. 4). The feature extractor identifies many different features of the input image. They are coded and converted to a vector by the encoder. This vector is processed with the neural classifier to define the class of the presented input image.

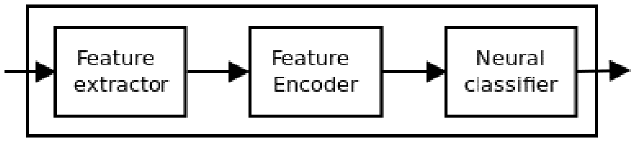


Fig. 4. PCNC main blocks

4.1.1 Feature extractor
The feature extraction permits us to select the most important characteristics of the input image to classify it.

For this purpose, we introduce specific points. The specific points can be defined as border points. For example, in [12] a Sobel operator is implemented to find the borders.

For every feature from F features we define a mask (S). The feature masks are defined as a square with size w. For each mask, positive p and negative n points are randomly selected within the square (Fig. 5).

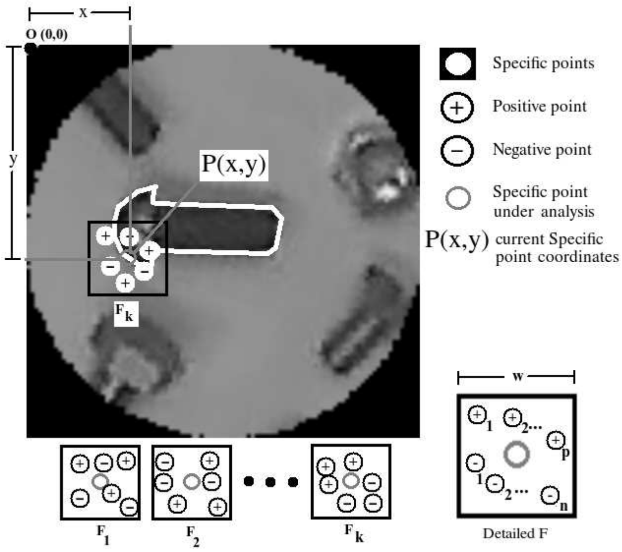


Fig. 5. Specific point and feature extraction

Positive and negative points are defined as ON- and OFF-neurons for LIRA neural classifier.

A feature F_i exists in a certain specific point only when all corresponding positive and negative points are active. Once all the specific points are analyzed, the available features are input to the feature encoder.

4.1.2 Feature encoder
The feature encoder transforms the detected features into a binary vector. This vector represents the encoded image. (In this paper, we will not describe the coding process in detail). In the results, we obtain the following important feature: this vector contains K elements with the value 1 where K is a

constant and should be chosen such that $K << N$. For each vector, the position of the elements with value 1 is randomly selected.

Two points containing the same feature are coded with correlated vectors. We obtain this property due to X and Y permutations of codes, where X and Y are coordinates of a specific point [7]. The resulting vector V represents the code of the image under process.

4.1.3 Neural classifier

The last component of the PCNC is a neural classifier. This classifier has two layers, the input layer and the output layer. The input layer has N neurons (Fig. 6). The output layer has as many neurons as the number of different classes that require detection.

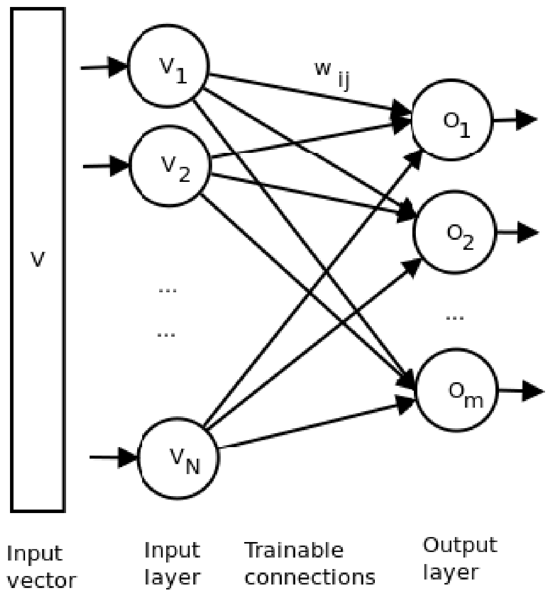


Fig. 6. PCNC structure

The layers are connected in the same way as the A and R layers of the LIRA neural classifier. Every connection has its weight that can be changed in the training process. Due to these similarities, the LIRA and PCNC require almost the same number of training cycles. In the following section, the image databases are described.

5 Databases

To investigate the LIRA and PCNC classifiers, three image databases of micro work pieces are created [8]. The databases have different levels of complexity..

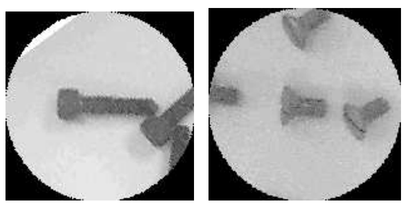
The micro work pieces are screws, washers and other similar objects. These objects are metallic, with colors ranging from black to gray and sizes between 14.2 and 4.2 mm. Some classes are similar to each other and have a circular cross section or flat shapes.

To create the image databases, we took several images from work pieces randomly located within a work area. The characteristics of these images are from real work conditions. The source images are gray-scale without special lighting and with different bright areas and shadows. One example of these images is shown in Fig. 7.

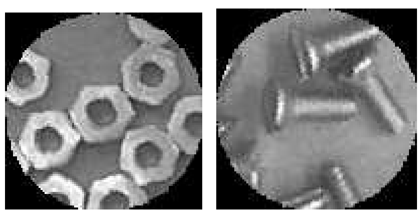
Fig. 7. Example of the initial image

Each image is normalized; this means that each sample has similar characteristics such as a centered class with a fixed orientation, squared and fixed dimensions, low resolution and a circular frame to facilitate rotation as shown in Fig. 8.

The image database includes three different databases with different levels of complexity. The first two image databases with isolated classes are called databases A and B. The experimental investigation with these two image databases are described in [9], [10]. The third database with all the mixed classes is called database D. Some examples from each set are shown in Fig. 8.



A



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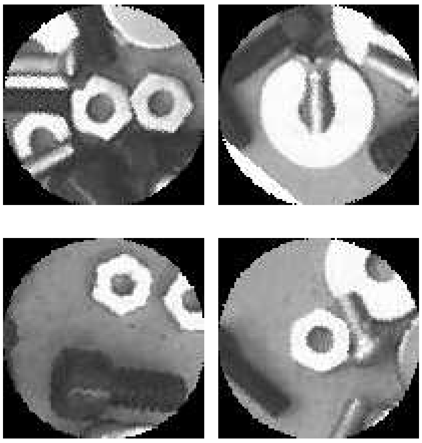

D

Fig. 8. Images from A, B and D databases

The properties of databases A, B and D are presented in Table 1.

Table 1.
Properties of the A, B and D databases

Image Database	Number of classes	Images per class	Total of images	Brief description
A	8	40	320	Isolated obj., one class per sample
B	7	78	546	Touching obj., one class per sample
D	7	55	385	Mixed and heaped up obj.

The databases were created using the specialized software *S*cissors. In this paper, we describe the LIRA and PCNC application to the complex database D. For this reason, this database is described in detail.

5.1 Description of database D

The image database D has been created with six types of micro work pieces. They are mixed and sometimes heaped up. The database has an additional class called “no micro work piece”. This allows the classifier to be trained with an empty class. Thus, in total we have seven classes.

The database has a high level of complexity due to its micro work piece density. The micro work pieces are, in some cases, occluded and have a little tilt in relation to the view plane. The database contains 55 images for each class; this implies 385 images in total. The image dimension is 100×100 pixels. In Fig. 8, some examples from this database are shown. In the following section, we analyze the results for database D with the LIRA and PCNC classifiers.

6 Experiments and Results

To find the best parameters of each classifier, we have performed several experiments. The PCNC and LIRA neural classifiers were implemented with special software written in C++. This software provides a common interface that allows classifier implementation.

The experiments are performed on an *Intel Pentium* TM4 processor, 2.80 GHz and 512 MB of RAM.

6.1 LIRA on image database D

The best parameters for the LIRA for the image database D were obtained from the knowledge of previous investigations. A best recognition rate of 90.47% was obtained. These parameters are as follows: the neuron number is N=200K, ON- and OFF-neurons are p=4, n=2, and the number of training cycles T=70. In the D database with 105 samples in the test set, ten samples were not recognized. Some recognized samples are shown in Fig. 9. In Fig. 10 the unrecognized samples are shown. These results show the ability of the LIRA to recognize partially occluded objects and lightly skewed ones (relative to the plane of vision).

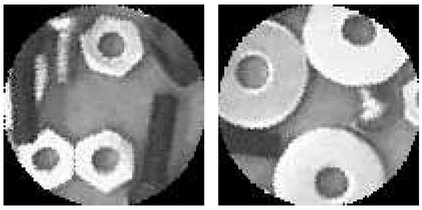

Fig. 9. Recognized samples from database D for LIRA

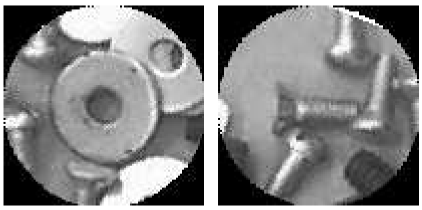

Fig. 10. Unrecognized samples from database D for LIRA.

6.2 PCNC on database D

The parameters of the PCNC are the following: neuron number N=400K, positive and negative points are p=4, n=3. The recognition rate of 91.43% was obtained for the PCNC after 30 training cycles. For the D database with heaped up and partially occluded objects, the PCNC was not able to recognize nine samples. Some recognized samples are shown in Fig. 11. The unrecognized samples are shown in Fig. 12. The nine errors were from four classes and the “no work piece” class resulted in six errors.

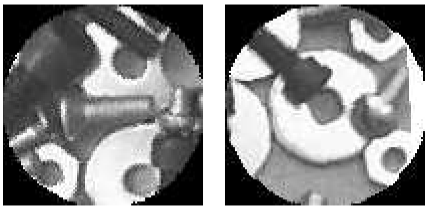

Fig. 11. Recognized samples from database D for the PCNC

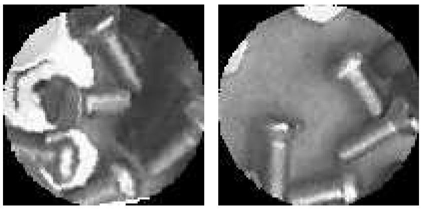

Fig. 12. Unrecognized samples from database D for the PCNC

Through the comparison of the unrecognized samples by both classifiers applied to database D, we observe that four samples could not be recognized by any classifier. Both classifiers were able to recognize partially occluded objects.

7 LIRA and PCNC Comparison

The aim of this section is to show, compare and discuss the advantages, disadvantages and differences between the described classifiers.

The most important parameters to be reviewed are, in order of importance, the recognition rate, the required classification time, stability, adjustability of parameters, training time and reliability.

7.1 Recognition rate and time

In Table 2, the recognition rates are presented for the LIRA and PCNC on database D as well as the previous results from databases A and B [9], [10].

Table 2.
Recognition rate for LIRA and PCNC

Database	Classifier	
	LIRA (%)	PCNC (%)
A	93.75	96.87
B	94.14	97.8
D	90.47	91.43

By comparing and analyzing these results, it can be shown that the PCNC performs better than the LIRA in all image databases. This advantage is small for the more complex image database D.

The recognition rate alone is not enough to analyze the neural classifier performance. It is necessary to also consider the resources such as the recognition time, training time, and time for codification. To better compare both classifiers, the same computer with the same conditions on the same image databases was used.

A comparison of the recognition time, the training time divided in the codification time and the training time for the classifiers on database A is presented in Table 3. This image database contains 160 images for the training set and 160 images for the test set.

Table 3.
Time for LIRA and PCNC classifiers on database A

Classifier	Time (s)			
	Training		Test	Rec/image
	Codification	Train. time		
LIRA	70	154	110	0.69
PCNC	198	148	222	1.39

The most important parameters related to the recognition time are the neuron number N for the LIRA and number of masks S and N for the PCNC. The differences in recognition time are connected with the coding phase while the training time (once the coding process is complete) is almost the same for similar structures with similar parameters.

The recognition time for one sample for both classifiers is compared for three image databases in Table 4.

Table 4.
Recognition time (seconds) of one sample for the LIRA and PCNC classifiers for databases A, B and D

Database	Classifier	
	LIRA (s)	PCNC (s)
A	0.53	1.44
B	0.5	1.36

D	0.54	2.35

The required time for the LIRA to classify one sample is approximately the same for each database. For the PCNC, this time increases for database D. The PCNC requires more than double the time for the recognition of databases A and B, and this difference is more than four times for database D. The recognition rates of the PCNC are higher than those of the LIRA. Therefore, for critical time applications, the LIRA should be selected.

7.2 Stability of instances creation

Due to the random nature of the connections inside the classifiers, each particular instance of the classifiers is unique. This implies that with the same parameters the probability for two LIRA or PCNC instances to be the same is zero. As a result, it is important to understand if these structures have stability with the same parameters or if the recognition rate and required time are conserved between instances. To show the stability, ten instances of each classifier were created, trained and tested with exactly the same parameters. Three databases were applied to each instance. An identical number of training cycles and training sets was used as well. The results are presented in Table 5 where the standard deviations of the recognition rate (σ%) from the experiments are shown.

Table 5.
Standard deviations obtained for ten instances of the LIRA and PCNC classifiers

Database	Classifiers	
	LIRA (σ%)	PCNC (σ%)
A	3.14	2.24
B	1.02	1.58
D	1.48	3.75

It can be observed that the worst value is obtained by the PCNC for the image database D. The worst value for the LIRA is similar. In fact, for the three analyzed databases, the LIRA was more stable but the unique valid conclusion is that the recognition rate can vary up to 4% between two identical parameter instances for both classifiers.

7.3 Adjustment of parameters

To analyze the influence of each parameter on the classifiers, many experiments were performed changing one parameter at a time and measuring the resulting recognition rate. Because a new instance of the classifier is created each time a parameter is changed, the results are inevitably polluted by the influence of the stability of instance creation discussed in the previous section. On the other hand, it can be observed that for image sets with similar characteristics, such as the dimension, a set of parameters experimentally obtained can be used to achieve a better recognition rate.

7.4 Training cycles

The number of required training cycles and the time to perform them are important to compare. According to the experiments, the LIRA neural classifier required between 30 and 70 training cycles to achieve its best recognition rate while the PCNC required between 15 and 30 training cycles. This implies that the PCNC can be trained with half the number cycles required for the LIRA. The fact that the PCNC takes more than double the time to encode the images from the training set does not benefit it because this coding process is completed once for each image and the time for the ensuing training cycles for both classifiers are almost the same as shown in Table 3.

7.5 Reliability of training cycles

Once a particular instance of a classifier is created, it is important to determine its reliability to recognize classes and the effectiveness of the training process. To determine this, the same instance of each classifier was trained and tested ten times with three databases. The variable element in this process was the training and tests sets being chosen randomly from the image databases each time. The results resuming the standard deviation of the recognition rates (σ%) for each trial are shown in Table 6. The PCNC has a lower variability than the LIRA in all tests, indicating that the PCNC has better reliability to ensure a given recognition rate.

Table 6.
Standard deviation for recognition rates for ten experiments for every classifier and database

Database	Classifiers	
	LIRA (σ%)	PCNC (σ%)
A	3.4	1.45
B	2.15	0.92
D	3.37	2.12

8 Future Applications

The frame structure of solar concentrators presented in Fig. 1 and Fig. 2 is highly complicated and contains many components. In this article, we describe a new approach for the manufacturing of the support frame of a solar concentrator with plane mirrors. The main idea of the new approach is using the parabolic dish reference surface as a mold for the support frame of the solar concentrator. One mold can be used to manufacture many support frames for solar concentrators. For this reason, the mold can be made much more precisely than individual support frames [13]. We used the parabolic dish of a TV antenna as a mold for the support frame of the concentrators as the reference surface for a solar concentrator prototype. If the solar concentrator has a relatively small size, it is possible to construct the support frame from two or three layers of fiberglass tissue filled with epoxy resin. The support frame is molded on the convex side of the parabolic dish antenna. After the epoxy resin hardens, small flat mirrors are glued on the concave face of the support frame (Fig. 13).

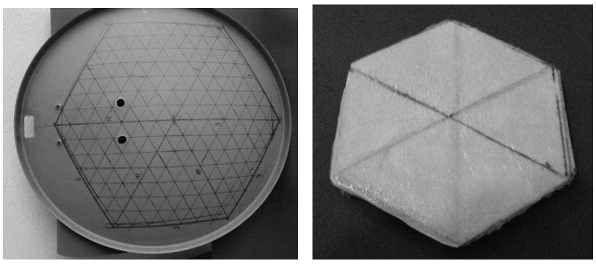

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Fig. 13. a)Parabolic dish of a TV antenna as a mold for the support frame. b) Back (convex) side of the parabolic concentrator

The main idea for the new solar concentrator manufacturing method is to use flat mirrors as components of the support frame structure. For this purpose, three special distant stems (Fig. 14) are glued on each vertex of the triangular mirrors.

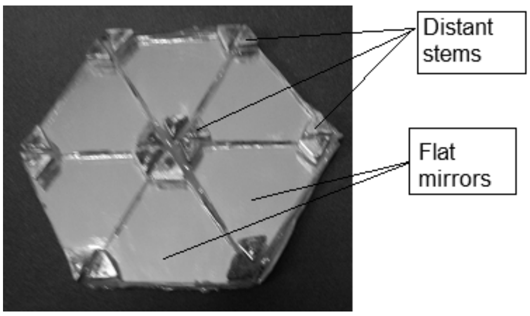

Fig. 14. New solar concentrator prototype

These distant stems permit us to place the triangular mirrors on the convex side of the parabolic surface in such a way that the reflected surface of the mirror is oriented toward the convex surface. The mirrors are glued to each other to approximate the parabolic dish surface in the new concentrator.

A new proposal is how to make the distant stems. We propose to use rings as shown in Fig. 15.

Fig. 15. New distant stems

The position of these distant stems on triangular mirrors is demonstrated in Fig. 16.

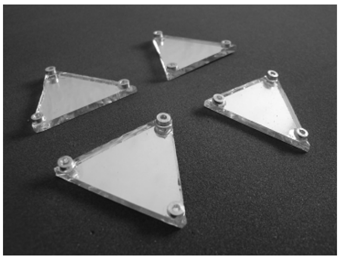

Fig. 16. Flat mirrors with distant stems

In Fig. 17 we show the assembly of a solar concentrator.

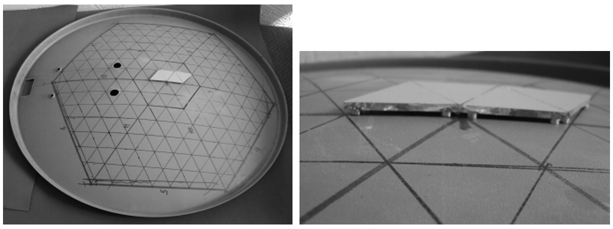

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Fig. 17. Assembly of parabolic solar concentrator from flat mirrors with distant stems

In this case the computer vision system is simpler. The recognition of micro components as presented in Fig. 15 can be realized with LIRA or PCNC neural classifier.

9 Conclusions

he PCNC demonstrates a better recognition rate than the LIRA for the three image databases. This advantage is less than 1% for the more complex image database D. The required time for the PCNC is approximately twice the required time for the LIRA for the same task. Both classifiers were analyzed with the described databases. We conclude that the PCNC is better for such applications where reliability is more important than time, for example, for object manipulation. However, the LIRA neural classifier is more suitable than the PCNC for such applications where time is most important, for example, within a production line or for massive classification. Regarding the comparison of the characteristics between the classifiers, the LIRA has greater stability than the PCNC for a given structure. The adjustability of parameters was similar for both classifiers. The number of required training cycles was more than double for the LIRA but this fact is compensated by the higher recognition time required by the PCNC. Concerning the reliability of the training process, the PCNC is more stable than the LIRA.

Acknowledgement
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