Neural classifier LIRA for recognition of micro work pieces and their positions in the processes of microassembly and micromanufacturing

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Abstract

The aim of the project is to design the technical vision system for automation of microassembly and micromanufacturing processes. One of the principal problems is connected with the recognition of work pieces and detection of their positions. For this purpose we use neural Random Subspace Classifier (RSC) called LIRA Gray Scale. This classifier was developed for wide range of image recognition tasks. Here we describe some results of application of LIRA to recognition of micro work pieces and their positions. Experimental results are reported.

1. Introduction

Micromanufacturing and microassembly processes automation is fundamental to achieve good performance of corresponding equipment [1] and [2]. In this processes it is very important to use computer vision methods. The paper contains the description of one method of micro work pieces recognition and their positions detection. The system is working with micro work pieces which are used in MicroEquipment Technology (MET). This technology is developing in the Micromechanics and Mechatronics Laboratory at "Centro de Ciencias Aplicadas y Desarrollo Tecnológico (CCADET) de la Universidad Nacional Autonoma de México (UNAM)" [3] and [4]. The final goal of these works is to create fully automated desktop microfactory for microdevices production on the base of mechanical methods [5] and [6]. The scheme of the proposed system is presented in Fig. 1. This system includes 2 cameras, one MET manipulator and 3 subsystems: manipulator control, technical vision and intelligent manipulation subsystem. In this paper we report the results of experiments with the part of the system which contains one camera and technical vision subsystem.

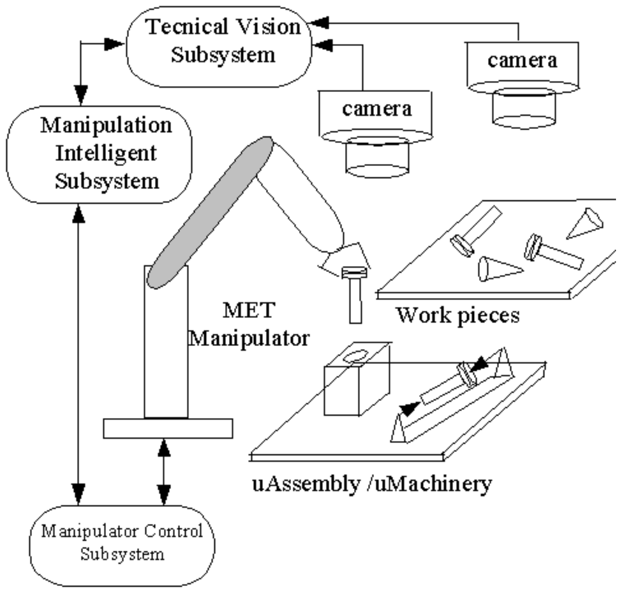

Figure 1: Automatic work piece handling system.

2. Recognition of work pieces and their position for microassembly and micromanufacturing

There are several techniques for work pieces recognition, some of them use flat images of work pieces [7], others use techniques for 3D objects [8]. In our work we use flat images of low resolution without hard illuminance conditions.

3. Neural classifier structure

The neural classifier which we use is a Random Subspace Classifier (RSC) based on modified Rossenblatt Perceptron [9]. We term this neural classifier as LImited Receptive Area gray scale or simply LIRA gray scale. This classifier has been proposed and proved in [10] with good results for small patterns recognition. Let us show the LIRA gray scale structure.

The LIRA gray scale neural classifier is an artificial neural network with four layers:

input (S) $S = s_1, s_2, ..., s_k$

groups (I) $Group = group_1, ..., group_N$

associative (A) $A = a_1, .a_2, ..., a_N$

output (R) $Y = y_1, y_2, ..., y_m$

S layer corresponds to the input image to be classified. In this layer, called retina, each neuron corresponds to the brightness of each pixel of the image to be processed, therefore the output range of these neurons is [0, B], where 0 equals to null brightness (black) and B equals to the highest brightness. This layer has $W \cdot H$ neurons, where W and H are respectively the width and the height of the image to be classified. The group layer or I layer contains N neuron groups, each $group_i$ has p ON-neurons and q OFF-neurons. Each ON-neuron is active if $x_{ij} > T_{ONij}$, each OFF-neuron is active if $x_{ij} < T_{OFFij}$, where x_{ij} is the input of the corresponding neuron, T_{ONij} is the ON-neuron threshold and T_{OFFij} is the OFF-neuron threshold. Each neuron threshold is randomly selected within [0, $B \cdot \eta$], where η is an experimental constant of the classifier to be select from $(0, 1]$. The neurons of the group are randomly connected with the neurons of S-layer located in a rectangular window $w \cdot h$ defined on S layer, see Fig. 2. Values dx and dy are selected randomly from $[0, W - w]$ and $[0, H - h]$ respectively. Parameters w and h are very important for performance of the neural classifier, and should be chosen experimentally. Connections between S layer and I layer don´t change their thresholds in the training process.

The A layer contains N neurons, each neuron has $p+q$ inputs connected to the outputs of corresponding group. An A-layer neuron is active if, and only if all its inputs are active, the neuron´s output equals 1 if it´s active and equals 0 if it isn´t. The connections between layers I and A cannot be modified by training process. All A layer neurons are connected to each R layer neuron. The weights of the connections are modified during the training process. The output from R layer neuron i is

$$y_i = \sum_{j=0}^{N} w_{ji} \cdot a_j, \qquad (1)$$

where w_{ij} is the connection weight between A layer neuron j and R layer neuron i and a_j is the neuron j output from the A layer.Image coding. When an image is assigned to the classifier input we calculate the activity of A layer neurons and present the activity as a binary vector $\vec{A}$. This calculation we term "image coding" and the vector $\vec{A}$ we term "image code". We store the image codes of training set on the hard drive for not to repeat the coding process in each training cycle.

4. Training process

At the start of training process we make every connection weight between the layers A and R equal to cero.

1. The process begins assigning an image to the classifier. The image is coded and the classifier´s outputs are calculated.

2. To make the training robust, after calculation of the R layer outputs, the correct class corresponding to the input image is read. Its output y_i is modified according to:

$$y_i = y_i \cdot (1 - T_E) \qquad (2)$$

where T_E is a constant termed "additional excitation of the winner neuron". After that, the neuron from layer R with the highest output value, called "the winner", is detected. This neuron represents the recognized class for the given input image.

3. Let y_w be the winner neuron´s output and y_c the output of the neuron which really represents the correct class. If $y_w = y_c$ nothing to be done.

If $y_w \neq y_c$, then

$$\begin{aligned} \forall j\ w_{ji_c}(t+1) &= w_{ji_c}(t) + a_j \\ \forall j\ w_{ji_w}(t+1) &= w_{ji_w}(t) - a_j \\ w_{ji_w}(t+1) < 0 &\Longrightarrow w_{ji_w}(t+1) = 0 \end{aligned} \qquad (3)$$

where $w_{ji}(t)$ is the corresponding weight of the connection between the A layer neuron j and the R layer neuron i before modification and $w_{ji}(t+1)$ after modification; a_j is the output value of A layer neuron j. The complete training process of the neural classifier is an iterative process. First of all each image from the training set is coded. It allows us to save computer time. After this, each training cycle deals with the image codes but not with the row images. The training process stops after fixed number of cycles or when the amount of errors in the training cycle will be lower than a predefined value.

Distortions. The training image set can be enlarged by adding new images obtained applying distortions to the

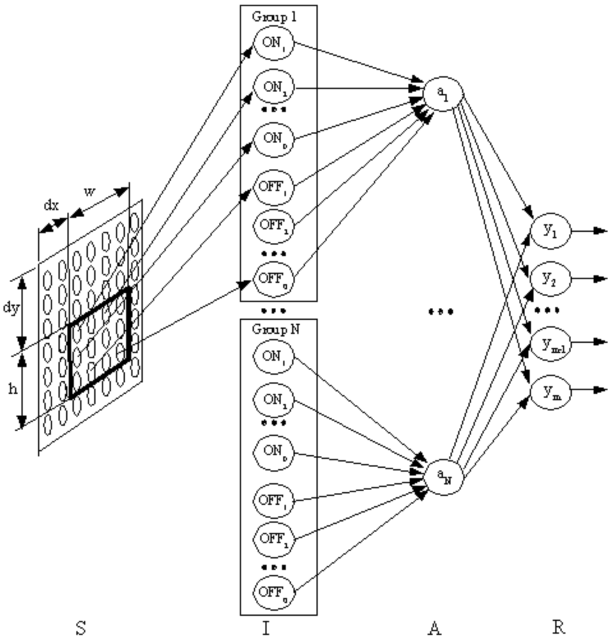

Figure 2: LIRA gray scale neuronal classifier structure.

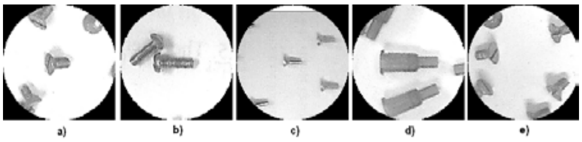

Figure 3: One example of each one of the 5 image classes from the used database. a) screw I, b) screw II, c) tube base, d) cone y e) no central piece.

original images. In our work, we applied rotational distortions. Each image was rotated in clockwise and counterclockwise directions forming the pairs of new images $\pm I°, 2 \cdot I°, ..., P \cdot I°$, where I is the rotation step for each pair and P is the number of pairs.

5. Used database

The database used for our experiments is formed by 4 types of work pieces. It was created in our lab using a low resolution CCD camera and a computer software specially designed. The database contains gray scale images with fixed dimensions (150 x 150 pixels). Work pieces are centered and have fixed orientation 0°. A circular-vindow algorithm is applied to the images for image rotation. The work pieces aren´t isolated, because the image contains another pieces in the work area. This database contains 30 images for each of 5 diferent classes of work pieces, 15 for the training set (which can be enlarged by distortions) and 15 for the test set. The 5 classes consist of 4 different types of work pieces (screw I, screw II, tube base, cone) and the fifth class which corresponds to the absence of workpiece in the center of the image. Fig. 3. Database images have low resolution, different illumination and some of them have the shadows.

6. Experiments and results

The described neural classifier was applied to the images database to find the parameters for achieve the best recognition. Several experiments was made for this purpose. Another type of experiments was made for work piece position recognition.

6.1. Work pieces recognition

We tested several parameter combinations for the classifier. In the first group of experiments (serie A) we didn´t use distortions of the training set. We show some significant experiments from this group in the Table 1. The best results was achieved in experiment VIII, with a LIRA windows ($w \cdot h$) of 15x15 pixels, 175 000 in A layer, 4 ON neurons and 3 OFF-neurons in each group, eta (η) iqual to 1.0 and T_E iqual to 0.15. For these parameters the percentage of active neurons in A layer was 0.164%. In these experiments percentage of correct recognitions was 94%. We verify than recognition rate for a given set of parameters converges with a certain number of training cycles. For experiments of serie A the best performance was reached with 40 training cycles.

Distortions experiments. The parameters used in the second group of experiments (serie B) was obtained as the best parameters of the previous group of experiments. We tested several parameter sets achieving always less performance. These experiments was made adding distortions to the training set, the purpose was to improve classifier capacity for recognize several orientations work pieces. The results of this experiments are presented in the Table 2. The best result was obtained in experiment I, where 3 distortion pairs (+/- 5°, 10°, 15°) were added.

The training time for 75 images in the experiments of serie A was inferior than 1.5 minutes, the training time for 16 distortions of the training set was approximate 16 minutes; the recognition time of any image from the whole database was less than 0.4 seconds. All the experiments was realized with an Intel^{TM} P4 computer at 2.66 GHz.

6.2. Position recognition

Once the LIRA gray scale classifier was trained with distortions it is prepared to recognize work pieces in the image with dimension $W \cdot H$ pixels. Then we applied the position algorithm to find needed work piece in the image. First, the image is converted to gray scale. The algorithm contains the procedure which moves the windows with dimension $W \cdot H$ across the whole image. This movement is made in the form of counterclockwise snail and serves to find a specific work piece. In each windows position, a subimage was extracted and assigned to the classifier for recognition, the subimage was rotated until the work piece was recognized or a complete revolution was made. When a given work piece is recognized the system draws on the image a rectangle representing the windows and puts the mark in the center, which corresponds to the work piece center. In Figure 4 two recognized cones are shown. Piece centers are founded not exactly. Sometimes work pieces is recognized not correctly. To improve this algorithms new efforts must be done and new experiments must be made.

7. Conclusions

LIRA gray scale neural classifier was tested for five classes recognition. The recognition rate was 94% without distortions of training set and 92% with distortions. The classifier training process with distortions was applied to find work pieces in the images. The results are acceptable, nevertheless it is necessary to improve the accuracy of work pieces position detection. The LIRA gray scale classifier has good performance in work pieces recognition in the images of low quality. It has also good perspectives for piece position finding. The training and

Experiment	I	III	VIII	XIII	XIV	XV	XVIIa	XVIIIa	XVIIIc
$w \cdot h$	$12 \cdot 12$	$15 \cdot 15$	$15 \cdot 15$	$10 \cdot 10$	$13 \cdot 13$	$17 \cdot 17$	$15 \cdot 15$	$15 \cdot 15$	$10 \cdot 10$
η	0.8	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
N	175000	175000	175000	175000	175000	175000	175000	200000	200000
p	3	3	4	4	4	5	4	4	4
q	4	4	3	3	3	3	3	3	3
active neurons(%)	0.060	0.090	0.164	0.123	0.129	0.084	0.166	0.167	0.146
successes (%)	68%	89%	94%	93%	85%	88%	93%	89%	89%

Table 1: Some experiments of the Serie A.

Experiment number	I	II	III	IVa
distortions angles	+/- 5, 10, 15	+/- 10, 20, 30, 40, 50	+/- 3, 6, 9, 12, 15	+/- 3, 6, 9, 12, 15, 18, 21, 24
training cycles	80	10	60	80
successes (%)	92%	68%	88%	90%

Table 2: Some experiments of the Serie B.

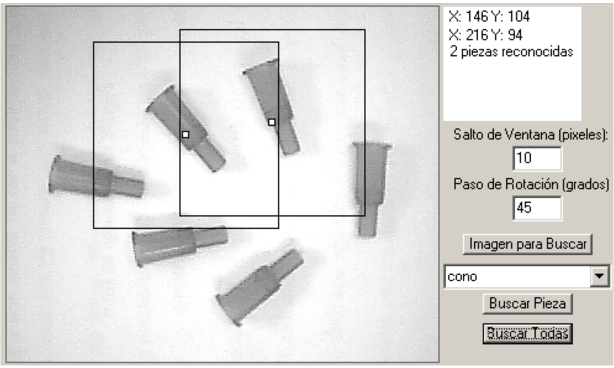

Figure 4: Work pieces position recognition. The system shows the coordinates of the center of two recognized pieces.

recognition computer time is rather small.

8. Acknomledgements

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9. References

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