An Application of "Neocognitron" Neural Network for Integral Chip Images Processing

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Abstract. *The architecture of "neocognitron" neural network in the task of search of structural units on a gray scale image of an integrated circuit is considered. The updated rule for activation of the network neurons invariant to distortions of brightness is represented. The comparative outcomes of recognition have shown an advantage of neural network approach.*

Keywords: Neural Network, Image Recognition

1. INTRODUCTION

At present time different kinds of neural networks are applied in the tasks of recognition and image analysis [1-4]. In the report the search technology on a gray-scale photosnapshot of a chip of an integrated circuit (IC) and its structural units on the basis of the multilayer "neocognitron" neural network has been represented. The search algorithm of a separate unit on the image IC is realized by a scanning method of this image by the sliding window, where for each position of the window the fitness measure of the image in the window with the image of a required unit IC is defined. The multilayer neural network of the simplified "neocognitron" architecture with the modified algorithm of training has been applied for calculation of fitness measure.

2. NEURAL NETWORK ARCHITECTURE

The common scheme of the neural network architecture is represented in a fig.1.

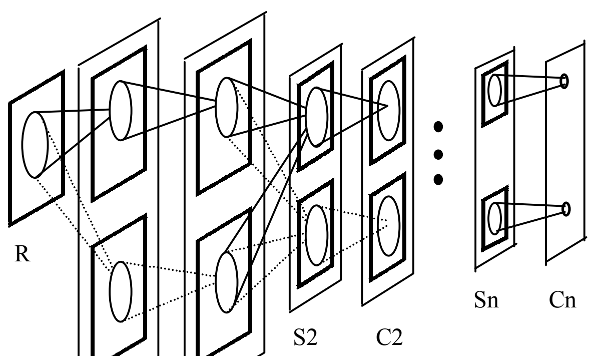


Fig.1 - The common network architecture

In structure "neocognitron" let us select the following units: *R*-layers, *S*-layers, *C*-layers, $\overline{S}$ -sublayers, $\overline{C}$ -sublayers, $\widetilde{S}$ -neurons, $\widetilde{C}$ -neurons, $\breve{S}$ -links, $\breve{C}$ -links. The *R*-layer is receptor layer, its neurons do not carry any functional load and answer only for transmission of the entry image to the neural network. *S* and *C*-layer are outlined in a figure by a thin line, they consist of $\widetilde{S}$ and $\widetilde{C}$ -neurons accordingly, which fulfil the function of feature detection on the image, such as lines, corners, intersections and etc. Everyone *S* and the *C*-layer is divided on $\overline{S}$ and $\overline{C}$ -sublayer, which are outlined by a thick line. $\overline{S}$ -sublayer consists of $\widetilde{S}$ -neurons, which detect the same feature of the image, for example, a line. Thus, $\overline{S}$ -sublayer forms some kind of a map of this feature in the previous layer.

$\widetilde{S}$ -neurons have $\breve{S}$ -links with modified weight coefficients, which accept the values during sublayer training. $\breve{S}$ -links to be directed from one $\widetilde{S}$ -neuron form in the previous layer a field receptors, which can be divided on *P* subgroups according to an amount $\overline{C}$ -sublayers in the previous layer. Each receptor field subgroup is characterized by size and position in previous sublayer. The size of a receptor field subgroup corresponds to a size of detected feature. The position of a receptor field is defined by a position of a $\widetilde{S}$ -neuron in $\overline{S}$ -sublayer, i.e. the position of receptor fields for neurons from one $\overline{S}$ -sublayer differs only by parallel shift rather each other. As the neurons from one $\overline{S}$ -sublayer detect the same feature, then it is possible to train only one neuron from this sublayer and use its weight coefficients for all remaining neurons.

$\widetilde{S}$ -neuron is trained on the base of function of weight coefficients change

$$w(t+1) = w(t) + \frac{1}{t+1} \cdot \left[u(t+1) - w(t)\right] \qquad (1)$$

where t is number of training iteration, w is value of weight coefficient, u is value of activity for the neuron on an input of link to be trained.

The activation function of $\widetilde{S}$ -neuron corresponds to the radial basic function.

$$U_{Sl}(n,k) = \exp\left(\sqrt{\frac{\sum_{p=1}^{P_{Cl-1}} \sum_{v \in Al} (\widetilde{U}_{Cl}\ (n+v,p) - w(v,k))^2}{N}} \right) \qquad (2)$$

where l is the serial number of a layer; k is the number of a trained plane; n - two-dimensional index of a neuron in k-th plane; w - weight coefficient of link; v - two-dimensional shift of entry link in a subgroup of links Al; Al - two-dimensional value describing a size of a receptor subgroup in previous $\overline{C}$-sublayer, N, p, - total amount of entry links and serial number of sublayer to be joined with a trained neuron correspondingly. The argument $\widetilde{U}_{Cl}(n+v,p) = U_{Cl}(n+v,p) - \min\limits_{\forall v}(U_{Cl}(n+v,p))$ is entered into a relation with the purpose of exception in receptor a subgroup of a constant component influence. This is necessary because the neural network mast be invariant to change of brightness for the recognized image.

$\overline{C}$-sublayer consists from $\widetilde{C}$-neurons, that generalize one feature from previous sublayer. The generalization means, that if in receptor field of $\widetilde{C}$-neuron is found out even one active neuron, then $\widetilde{C}$-neuron too passes in active state, i.e. the fuzzy logic function "or" on all neuron receptor field is fulfilled and its value is assigned to an output signal of a neuron.

$$U_{Cl}(n,k) = \max(U_{Sl-1}(n+v,p)), \forall v \in Dl, \forall p \in P \qquad (3)$$

where l is serial number of a layer; p, P - serial number of a plane and set of planes from the previous S-layer accordingly; Dl - two-dimensional value describing sizes of $\widetilde{C}$-neuron for a receptor subgroups; v - two-dimensional index of link inside these subgroups.

Usually $\widetilde{C}$-neurons form receptor field in one sublayer from the previous layer, or in several, when it is necessary to combine features to be detected by these sublayers. For example, when in $\overline{C}$-sublayer the feature of brightness overfall is detected, then the links from it $\overline{C}$-sublayer are necessary for installing with two $\overline{S}$-sublayers from the previous layers, first of which detects feature of brightness overfall on dark, and second - with dark on bright.

The position of receptor fields subgroups for $\widetilde{C}$-neuron is defined similarly as for $\widetilde{S}$-neuron.

3. TRAINING

The applied architecture of the neural network is outlined in fig.2,

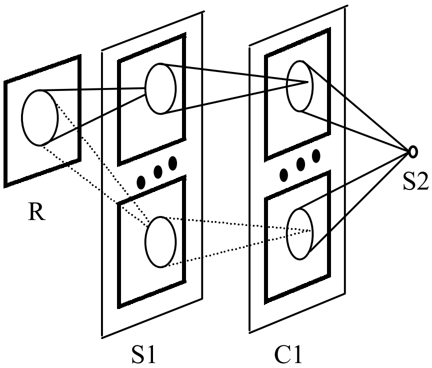


Fig.2 - The used network architecture

where a *R*-layer is receptor layer. The size of a receptor layer is equal to a size of an image of the unit of IC.

The *S1*-layer is intended for detection of common features for all units of IC, such as linear boundaries of different orientation brightnesses overfalls. All sublayers of this layer consist of neurons with identical sizes of subgroups for receptor field including 4x4 neurons. The learning images for these sublayers are shown in a fig. 3.

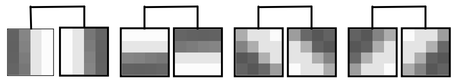


Fig.3 - *S1*-layer training images

The *C1*-layer is intended for generalization of features to be detected in a *S1*-layer, and receptor subgroups of its neurons are organized to combine such pair features, as vertical brightness overfalls with dark on light and with light on dark. Such features are joined in fig.3 by rectangular bracket. As result 4 sublayers in a *C1*-layer are obtained. The size of receptor field subgroups is such, that the activity of neurons from this layer was invarianted in relation to small shifts of features to be detected in the previous layer and makes a 2x2 field.

The *S2*-layer is intended for detection of feature amount to be belonged one concrete unit of IC. As the *S2*-layer forms output value of the network, it consists of one $\widetilde{S}$-neuron, and sizes of receptor field subgroups of this neuron coincides with a size $\overline{C}$-sublayer from the previous layer. As the weight coefficients of this neuron keep the unique information on the required image, the creation of the database of IC units is possible.

The structure of the program system is represented on fig.4

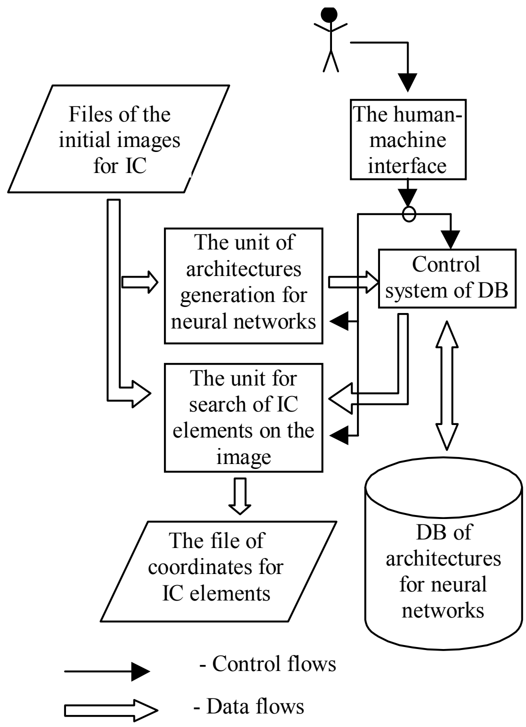


Fig.4 - The program system structure

Taking into account the circumscribed above approach to creation of the architecture of the neural network the program system is realized that fulfils the following operations:

1. Requests of the images samples for required units or loads the indicated architecture from a data base (DB) are fulfilled.
2. The architecture for search of these units on the IC image is formed
3. The information about this architecture of the neural network in a DB, including: a sizes for receptor of a layer and matrix of weight coefficients for output $\widetilde{S}$-neuron is saved.
4. The search of units on the IC image, with forming of the file containing coordinates of the locations of an indicated unit is made.

4. TESTING

As input data for testing the gray-scale fragments of the photo-image of IC polysilicon layer (fig.5) were used.

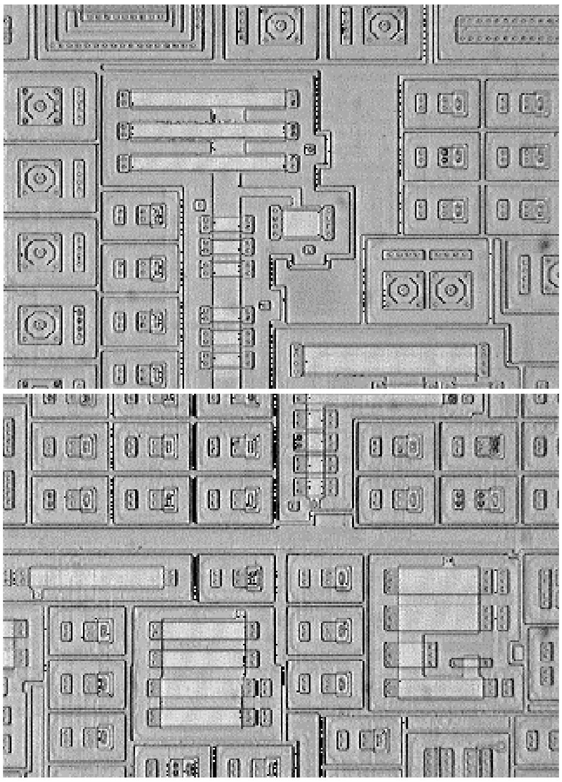
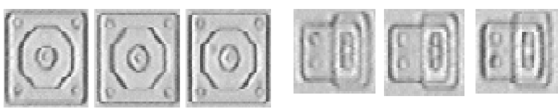


Fig.5 - The IC polysilicon layer images

Two variants of the neural network training have been produced. The learning samplings for these variants are represented in a fig.6



Variant 1 Variant 2

Fig.6 - *S2*-layer training images

To determine the efficiency neural network method for creation of fitness measure the matching with a correlation method was produced. The correlation method consists in an average of the image of IC unit on all learning sampling and calculation of correlation coefficient between the averaged image and image obtained in the moving window. The coefficient of correlation is evaluated in accordance with the relation:

$$\mu = \frac{\sum_{x,y} a_{x,y} \cdot b_{x,y}}{\sqrt{\sum_{x,y} a_{x,y}^2 \cdot \sum_{x,y} b_{x,y}^2}} \qquad (3)$$

where x, y are the point coordinates for the images to be compared, a, b - color value of a point for the averaged image and image in the moving window accordingly

The results of testing can be observed in the table 1. The testing has shown, that the method of criterion creation of similarity for two images on the base of circumscribed neural network is best in comparison with a correlation method these two images. This outcome was obtained because the neural network is invariant to distortions of the form and brightness of the recognized object image, and also requires a smaller amount of learning samples to reach necessary accuracy.

Table 1. Testing results

Size of training set	Accuracy (percent of recognition)			
	Correlation method		Neural network	
	Variant 1	Variant 2	Variant 1	Variant 2
1	63,1	67,4	87,0	89,0
3	72,3	73,6	96,3	97,0
6	81,4	84,2	98,5	99,0

5. CONCLUSION

The algorithm for processing of gray scale IC images on the basis of the “neocognitron” neural network is represented. The designed neuron activation algorithm of the network has property of invariance to the image brightness oscillations for the recognized object. The advantage of neural network approach to classification of the images in matching with a correlation method within the framework of learning sampling size decrease and increase of recognition accuracy is shown. The average recognition accuracy is equal to 98,7 %.

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