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APPLICATION OF A NEURAL NETWORK TO CONTROL INDUSTRIAL ROBOTS

Summary: Six main neural net models have been described. On the base of that description has been shown why the perceptron is the best. The paper presents an application of neural network to control industrial robots. Using the backpropagation algorithm it is possible to train the net how to adapt the connection weights and improve the robot accuracy.

1.Introduction

Modern industrial robots control systems are far from the perfection in spite of the robotics success. They can work only in a well known environment. Any change of the work conditions determines their faulty work. They have no possibility to adapt to changing work conditions. To solve this problem we can use neural nets [1].

Artificial neural nets are to be a copy of biological neural nets in human brain (like a robot arm is a copy of a human one). The progress of microelectronics and computer science in last years made it possible to apply it. In this paper the neural correction attachment used to improve the positioning accuracy of the industrial robot will be described.

2.The Research Area

The idea of neural correction attachment was presented by G.Josin, D.Charney and M.White in paper [2]. The attachment works as a part of the control system and this is the main advantage of that device. In that way the exchange of the control system can be avoided. The results of the simulation research were very promising, too. The accuracy was improved on average by a factor of 2 when the net wes trained on one point training set. The improvement in accuracy at approximately 6 times the accuracy of the naked controller after 8 points has been observed.

Two years later a similar idea was presented by B.Macukow in [3]. The idea of the correction attachment remained, however the mathematical apparatus has been changed. The results presented in that work are very interesting too. When the net was trained on one point training set the accuracy was improved by a factor of 2. When the 8 points training set was used the improvement at approximately 10 times has been observed. In the end the authors ascertain that 8 point training set should be sufficient.

Authors of that paper have decided to do research work of the attachment for an industrial robot with four control angles. The lower number of the control angles in an industrial robot is four. So our aim was to check how that device would work as a part of a control system of a more realistic robot. We decided that four control angles would be a proper number. A flat manipulator has only two control axis. (And the industrial robot has at least four). It is simple to describe the position of the gripper using simple equations. These equations link the control angles and a gripper position. It is easy to transform these equations to get the inverse kinematic equations. So it is possible to compute the values of two control angles. On the other hand it is impossible to get the inverse kinematic equations for the industrial robots. It means that it is impossible to find the relation between control angles and the position of the gripper. Hence it is necessary to find additional equations describing special work conditions.

3.The Review of Neural Net Algorithms

During research work the most essential task was the selection of the sufficient neural net model. Each net has been elaborated to meet with determined requirements. So each net is prepared to perform one task and it is not appropriate for the other one. And this involves the need of analyzing which of them is the most appropriate for the correction attachment.

The first discussed net is the Hopfield one [4]. It is used with binary inputs. This net has been worked out mainly as a content addressable memory. So it works very well when the input pattern is corrupted and the right pattern is needed. The result of computing is the stored pattern (representative of the class) and it is not the name of the class of the input pattern. One of the faults of that net is a small number of exemplar pattern which can be stored in the net. When a lot of exemplar patterns have been stored the net would work unstably.

The next net - Hamming net works differently [5]. The task of that net is to choose the proper class for the input pattern. This task is realized in two stages. Firstly the net computes the Hamming distance. In the second one the upper subnet called "Maxnet" chooses the node with the highest value of the Hamming distance. The number of the node corresponds to the number of the right class. The Hamming net has a lot of advantages. It needs 10 times fewer connections than the Hopfield net. Secondly this net doesn't produce an unstable answer when a lot of exemplar patterns have been stored.

The third analyzed net is the Carpenter Grossberg classifier [6,7]. The automatic recording of the exemplar patterns is the main advantage of that net. So this net can work without supervision. The first node in the output layer corresponds to the first presenting pattern. (This pattern is a representative of a class of patterns similar to that first one.) The second node corresponds to the second class etc. During the work the output signal from the node which corresponds to the proper class is enhanced. The number of that node is an answer of the net. When the input pattern does not correspond to any exemplar pattern then the first available output node is attributed to the class of the input pattern. It becomes the next exemplar pattern. Apart from these advantages this net has some faults. First of all when the vigilance threshold is too high the number of stored patterns can grow rapidly till all available nodes are accessible. Secondly the specific way of the modification of the stored patterns can cause the work of the net to be faulty. The modification rule uses a logic AND operation so the new stored pattern for the certain class can differ from the proper pattern for that class.

The fourth net - single layer perceptron is the first net in that review, which can be used with both continuous valued and binary inputs [8]. It can attribute an input pattern to one from two classes. The output signal has the value +1 when the input pattern belongs to class A and 0 (or -1) when it belongs to class B. But the perceptron works correctly only when it is possible to divide classes by a single line (called a decision boundary). When the classes are meshed perceptron works incorrectly.

It is possible to go round the limitations of the single layer perceptron using multi - layer perceptron [9]. It can distinguish meshed classes because it can create any decision regions. The hard - limited node function has been changed with the sigmoidal function.

The last presented net is the Kohonen net [10]. This one is a copy of the maps which are created by biological neural nets (a human brain). Each output node is attributed to classes represented by input patterns. The topographic distance can define the similarity of classes. So it is possible to classify the input patterns according to their location on the map.

Analyzing presented above six neural net models it is necessary to state that perceptron will work most effectively as a correction attachment. This net can create complex decision regions corresponding to complex problems which should be solved. Apart from that the perceptron can be taught to distinguish which node corresponds to particular control angles and can produce output signals from the partition < 0,1 >. The other nets do not have such possibilities.

4.Work and Advantages of the Correction Attachment

It is necessary to state clearly that control systems used in factories have a lot of limitations. At first the base of the robot can be shifted by a small amount. It involves the displacing of the robot coordination system. So the gripper is displaced by the same amount too. It is the "Constant Error" case [2]. Secondly the robot works in a variable environment. Every temperature change involves the change of the link length. Because the link length is a constant value in kinematic equations so every change of that value involves the displacing of the gripper. This is a "Quasiconstant Error" case. Thirdly it is necessary to take into account the fact that robot manipulates objects which sometimes are very heavy. So the distal link of the robot arm can bend and the position of the gripper can be changed. The bending depends on the weight of the manipulated object. And because of that it is a "Variable Error" case [2].

Application of a correction attachment makes it possible to avoid all these errors. In standard control systems values of control angles are described as follow:

$$\Theta_1 = arctg\left(\frac{z(R_1 - R_2C_2) + xR_2S_2}{x(R_1 - R_2C_2) - zR_2S_2}\right) \tag{1}$$

$$\Theta_2 = arctg\left(\frac{S_2}{C_2}\right) \tag{2}$$

$$\Theta_3 = 270 - \Theta_1 - \Theta_2 \tag{3}$$

$$\Theta_4 = arctg\left(\frac{y}{x}\right) \tag{4}$$

$$S_2 = \sin\Theta_2 = \sqrt{1 - C_2^2} \tag{5}$$

$$C_2=\cos\theta_2=\frac{\left(R_1^2+R_2^2-x^2-z^2\right)}{2R_1R_2} \tag{6}$$

Symbols θ_1, θ_2, θ_3 and θ_4 mean control angles. Coordinates of the gripper denoted by x,y,z. R_2 and R_1 are lengths of robot arms. Fig.1 shows the scheme of an industrial robot and its control angles.

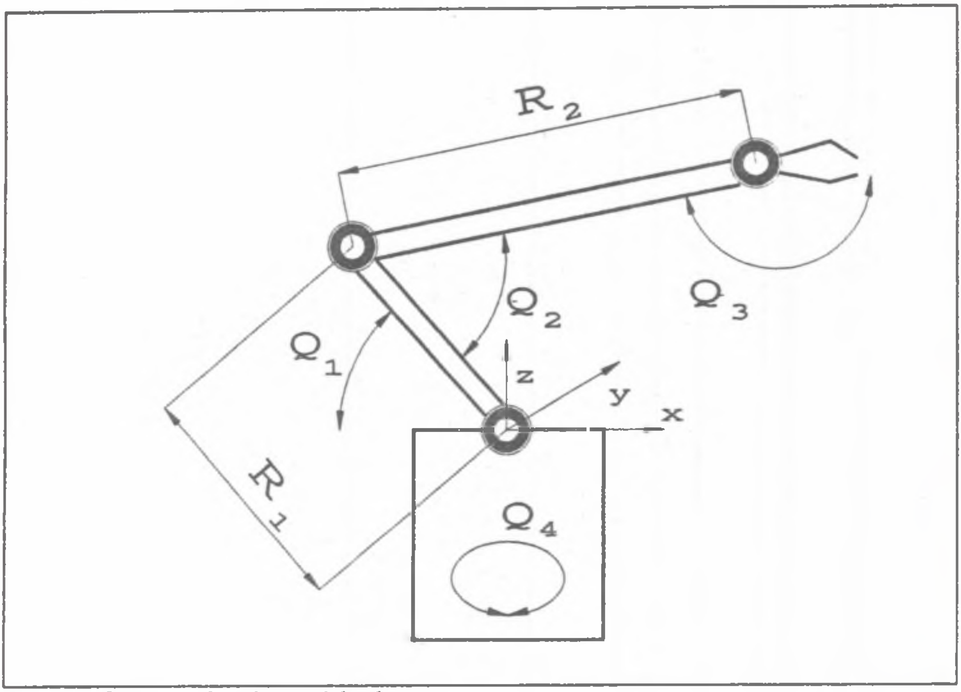

Figure 1. Scheme of an industrial robot.

During the training the net can be "trained" how to compute the corrections. The control system needs these corrections to compute the real values of the control angles. The value of the correction is a difference between the real value of the control angle and theoretical one. Theoretical and real values of control angles are denoted by indices th and r properly:

$$\Delta\theta_i=\theta_{i_r}-\theta_{i_{th}} \tag{7}$$

The perceptron works in two stages. At the beginning the net using the input data (the location of the gripper and the values of the control angles) learns how to compute the above mentioned values. The values computed by the net are compared with the real values of the deviation. Using that difference the net can modify the connection weights. The accuracy of the attachment depends on the number of iteration trials.

On the contrary in the second stage the net, using actual input data determines the values of corrections. The required location of the gripper and theoretically computed values of the control angles are the input data. Using these data the net can compute values of improvements and generate the control signals.

5.The Research Technique and the Method of Result Presentation

The computer simulation technique has been used to model the work of the perceptron attachment. On Fig.2 the control system with the attachment is shown. The perceptron attachment is included in the robot control system. So the application of that attachment do not require the change of the whole control system.

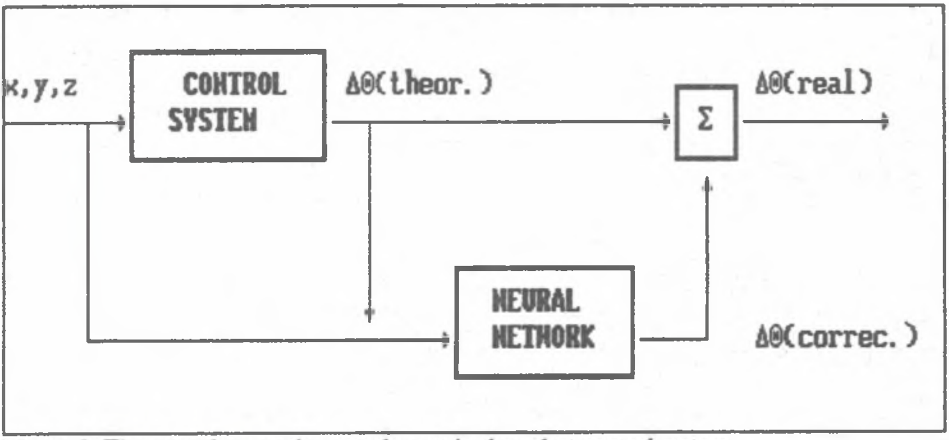

Figure 2. The neural correction attachment in the robot control system.

The configuration of the three layer perceptron is shown on Fig.3. The number of nodes on the first layer corresponds to the number of input data. The input data are coordinates of the target point (x,y,z) and theoretical computed values of control angles. The number of output nodes correspond to the number of control angles. In the medium layer there are 30 nodes. Input signals to each node are summed up and transformated according to the formulae:

$$I_{n,i}=\sum_{j=1}^{M} C_{i,j}^{n} O_{n-1,j} \tag{8}$$

$$O_{n,i}=\frac{1}{2}+\frac{1}{\pi} tgh(I_{n,i}) \tag{9}$$

$$n=2,3,4 \tag{10}$$

where:

$I_{n,i}$ - input signal to node number "i" in the layer "n"

$C_{i,j}^{n}$ - connection weight between the node "j" on the layer n-1 and the node "i" on the layer n

$O_{n,i}$ - output signal from the node "i" on the layer n

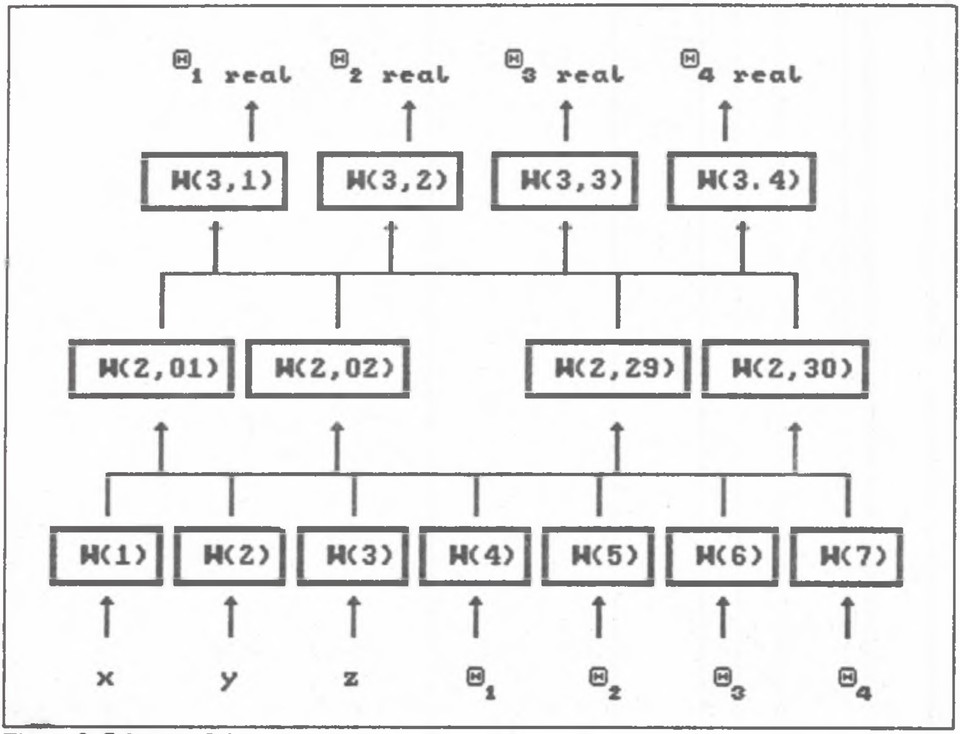

Figure 3. Scheme of the perceptron net.

Output signals from output nodes are compared with the real values of deviations. Using the results of that comparison and the backpropagation algorithm it is possible to compute new connection weights. The next formulae show how to modify weights:

a) for the output layer nodes

$$C_{i,j}^{3}(t)=C_{i,j}^{3}(t-1)+\nu\Delta C_{i,j}^{3}(t) \tag{11}$$

$$\Delta C_{i,j}^{3}(t)=\alpha\Delta C_{i,j}^{3}(t-1)+(1-\alpha)P_{3,i}f(I_{2,j}) \tag{12}$$

$$P_{3,i}=\left(O_{3,i}^{r}-O_{3,i}\right)f'(I_{3,i}) \tag{13}$$

b) for other layers

$$C_{i,j}^{n}(t)=C_{i,j}^{n}(t-1)+\nu\Delta C_{i,j}^{n}(t) \tag{14}$$

$$\Delta C_{i,j}^{n}(t)=\alpha\Delta C_{i,j}^{n}(t-1)+(1-\alpha)P_{n,i}*f(I_{i,j}) \tag{15}$$

$$P_{n,i}=f'(I_{n,i})\sum_{j=1}^{n}P_{n+1,j}C_{j,i}^{n+1} \tag{16}$$

where:

t - iteration step
n - learning rate
a - modification rate
$P_{3,i}$ - correction of the output signal
$O_{3,i}$ - required output signal
$P_{n,i}$ - correction of other signals

The computer program has been prepared basing on the describing net model. This program has been used to answer the following questions. Firstly - how the net modifies connection weights and secondly how the net will work as a correction attachment in an industrial robot control system.

Results are presented as diagrams showing changes of corrections during the training process. The relative value of corrections is computed using the following model:

$$B_r=\frac{\Theta_{i_r}-\Theta_{i_a}}{\Theta_{i_r}}*100\% \tag{18}$$

6.Discussion and Conclusions

Analyzing research results it is necessary to state that generally the perceptron attachment works correctly. The training process was effective and the matching of scores was made in about 3 to 7 trials. The average improvement of accuracy was about 300%. These are very promising results. On diagrams the relative values of corrections for particular control angles are denoted by ⊕, ⊗, ⊖ and ⊙ respectively.

But on the other hand some essential errors have been found. At first when one deviation is small and others are large the influence appearance is detected. As a result of that the value of the correction generated by the net increases instead of to decrease. It causes the increase of the positioning error. Fig.4 illustrates this case.

The narrow work range is the next error in work of the net. The perceptron cannot modify weights when angles difference doesn't belong to the work range. When the value of the difference is greater than the top value of the range then this value is the answer of the net. In the opposite case the bottom value of the work range is the answere of the net. This is the cause that the net can work only in a narrow range. Figure 5 shows that case.

Moreover the inertion appearance act certain role in the work of the net. This means that weights are matched in a cyclic way. The net frequently finds the optimal value. It causes the time of the work to be longer. It is shown on Fig.6.

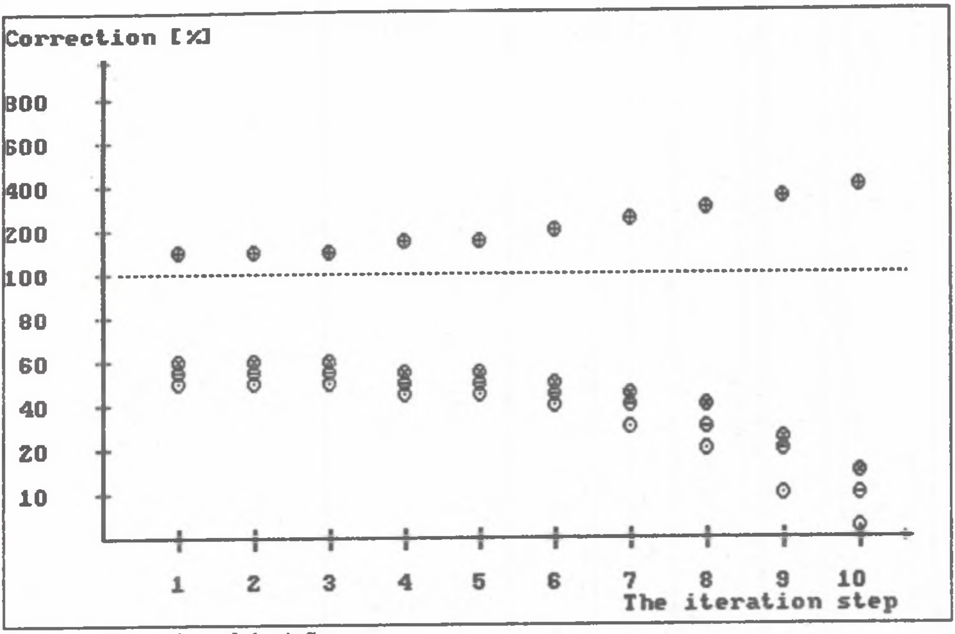

Figure 4. Ilustration of the influence case.

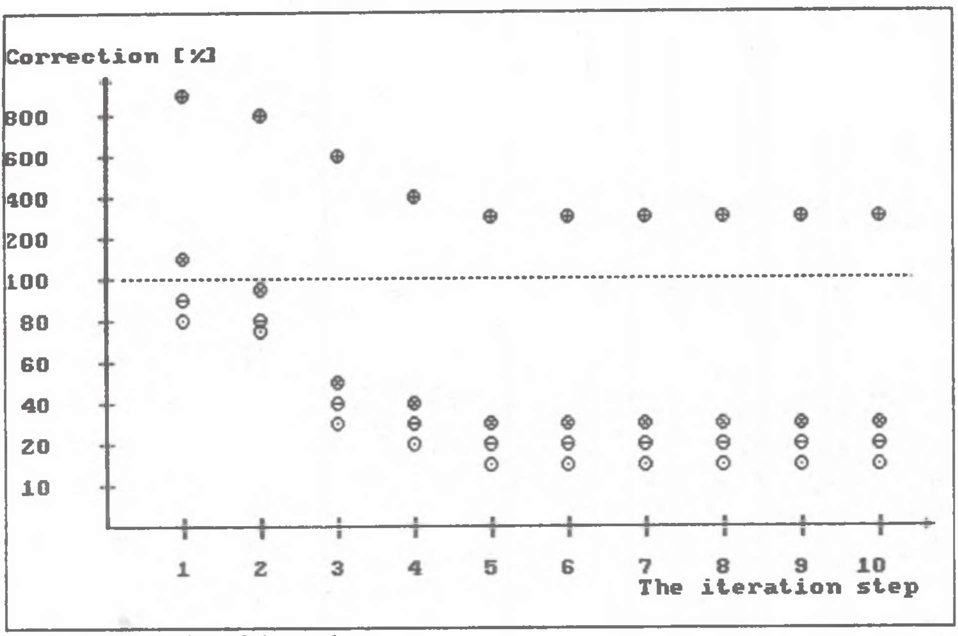

Figure 5. Restriction of the work range.

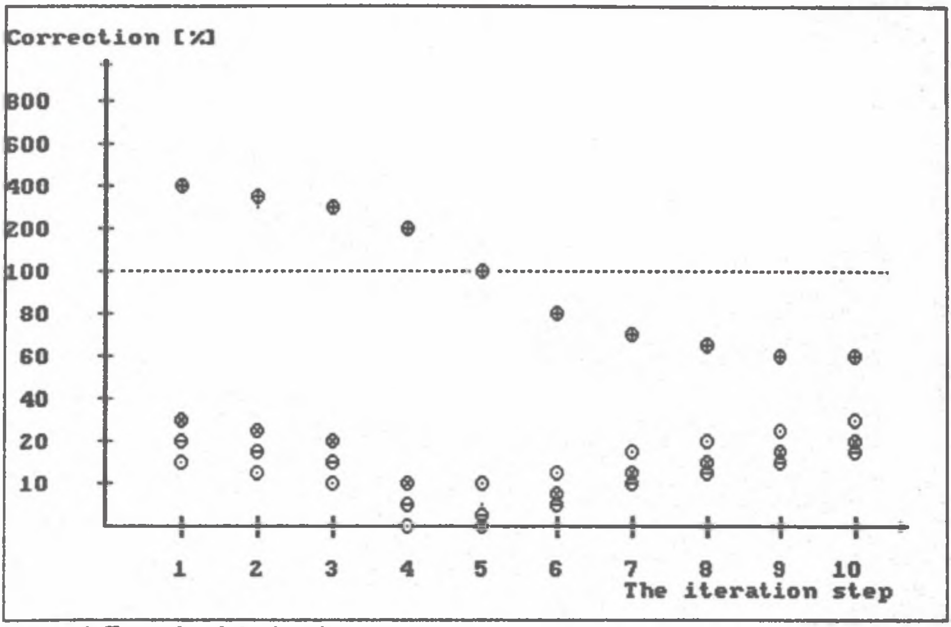

Figure 6. Example of the inertion appearance.

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ANWENDUNG NEURONALER NETZE ZUR STEUERUNG DES ROBOTERS

Zusammenfassung

In der vorliegenden Arbeit wird die Anwendung neuronaler Netze zur Position - Korrektur des Roboters dargestellt. Zunächst werden die sechs am häufigsten verwendeten Netztypen näher beschrieben. Aufgrund einer Analyse wird ein geeignetes zur Realisierung der Steuerbewegung neuronales Netz, d.h. Perceptron-Netz ausgewählt. Im folgenden wird die Struktur des Bewegungskorrekturmoduls sowie die Simulationsergebnisse beschrieben.

ZASTOSOWANIE SIECI NEURONOWEJ DO STEROWANIA ROBOTEM PRZEMYSŁOWYM

Streszczenie

W pracy przedstawiono zastosowanie sieci neuronowych do poprawienia dokładności pozycjonowania robota przemysłowego. Część pierwsza artykułu obejmuje opis sześciu głównych modeli sieci neuronowych, na bazie którego dokonano wyboru odpowiedniej, ze względu na zastosowanie, sieci. W drugiej części opisano budowę i zasadę pracy neuronowej przystawki korekcyjnej.

Wpłyneło do druku w marcu 1992r. Recenzent: Bohdan Macukow