SYNTHESIS OF NEURO-FUZZY CONTROLLER FOR DYNAMIC OBJECTS UNDER CONDITIONS OF UNCERTAINTY

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Abstract: Consider the problem of synthesis of fuzzy controller having adaptive properties of dynamical systems operating in conditions of uncertainty performance of facility management and environmental parameters. Provide a given quality of regulation in the control loop is enabled the function generator, and to bring those adaptive traits – being assessed the rate of change of the loop error. For learning fuzzy controller with a function generator algorithm is proposed to use the interactive adaptation. Calculation formulas for determining the weights of synapses so that when you spent training a neural network to reduce the time of regulation and deregulation in the system. After selecting the membership function and carrying out mathematical modeling of the process control system, there is the emergence of insensitivity to change the duration of the transition process and improving the quality of the transition process.

Keywords: adaptation, synthesis, neuro-fuzzy control, quality, uncertainty, function generator, membership function, correcting communication, intellectualization, algorithm.

Recently, process control systems have been increasingly finding use the so-called fuzzy control algorithms. Regulators, built on the basis of this innovative concept, in some cases, are able to provide higher levels of quality of transients in comparison with conventional controllers. Also, using the technology of synthesis of fuzzy control algorithms may carry out the optimization of complex control circuits without in-depth mathematical research (Brandt, 1999; Medvedev et al., 2002; Egupova, 2001).

Elaboration of control multidimensional process that can support the basic operating parameters in the set limits is a complex multicriterial problem of optimization under uncertainty performance of facility management and environmental parameters. For solving such a complex problem is the introduction of promising technologies of development of intelligent control systems based on fuzzy controller having adaptive properties (Medvedev et al., 2004, pp. 27-33; Siddikov et al., 2008, p. 72-75).

Consider the system of control of dynamic objects with fuzzy controller, the input values which introduced an additional correction connection on the dynamics of the transition process, the nature and parameters of which are given by a function generator (Figure 1).

The aim of the study is to determine the parameters of fuzzy controller providing specified quality control process. For this aim, the control circuit included functional converter (FC).

![Fig. 1. Structural scheme the control system with fuzzy controller](image-url)
Changing the functional converter allows you to adjust both dynamic and static characteristics of the control system. This structure of the torus regulator in combination with the optimal choice of the parameters of fuzzy controller, allows for adjustments to the minimum to implement adaptive control systems vague and non-stationary mechanisms regardless of their structure.

For giving adaptive properties of the fuzzy controller, in order to ensure the stability of the dynamical system to perturbations (changes in the parameters of the object and control of external influences), conducted an appraisal of the rate of change of the loop error $\Delta \varepsilon$.

From this structural scheme the control system shows that the control object is not a neural network, so there is some difficulty in learning fuzzy controller with a functional converter.

Order to overcome this difficulty, we propose an algorithm based on the theory of the interactive adaptation (Brandt, 1999, p. 201-215).

The essence of this algorithm is that the error, which is required for training, computed implicitly.

When using the interactive adaptation algorithm system is divided into several subsystems, each of which has an integrable input $x_n$ signal and integrable output $y_n$ signal, the relationship between them is represented as a functional dependence.

$$ F_n : X_n \rightarrow Y_n, n = 1,2, ..., N $$

The ratio of the i-th element of the system is as follows:

$$ y_i(t) = F_i[x_i(t)], i = 1,2, ..., N $$

Let interaction between the elements and the external signal $u_i(t)$ is linear and is described by the equation:

$$ x_i(t) = u_i(t) + \sum_{k \in J_i} \alpha_k \cdot y_i(t), i \in N $$

where $J_i = \{ K : y_K = i \}$ – the set of connected inputs i-th element;

$\alpha_k$ – weight relationships.

The ratio of the input and output of i-th element by the following equation:

$$ y_i(t) = F_i[u_i(t) + \sum_{k \in J_i} \alpha_k \cdot y_i(t)], i \in N $$

The purpose of the learning algorithm is to set up weights of connections in such a way that would minimize the loss function $E(y_1, ..., y_n, u_1, ..., u_n)$, which is a function of the system error.

Teaching of neural networks is to minimize the error control system. This is done by adjusting the weights of neural network.

If the system is described by equation (1), the weight of the connections configured by the following rule:

$$ \dot{\alpha}_k = F'_\text{inputK} [x_{\text{inputK}}] \cdot \frac{y_{\text{outputK}}}{y_{\text{inputK}}} \cdot \sum_{s \in \text{outputK}} \alpha_s \cdot \alpha_k - \gamma \cdot F'_\text{inputK} [x_{\text{inputK}}] \cdot y_{\text{outputK}} \cdot \frac{\partial E}{\partial y_{\text{inputK}}}, $$

(2)

where: $\gamma > 0$ – coefficient that determines the speed of learning;

$F'_\text{inputK} [x_{\text{outputK}}]$ – the Frechet derivative [2];

$E$ – the loss function (error) $k \in K$

Provided that (1) has a unique solution $\alpha_k$, where the loss function $E(y_1, ..., y_n, u_1, ..., u_n)$ will decrease monotonically in time and will satisfy the following equation:

$$ \dot{\alpha}_k = -\gamma \frac{\partial E}{\partial \alpha_k}, k \in K $$

(3)

With this approach, the neural network can be decomposed into its constituent elements, represented conceived as an elementary neural network (fig. 2).
Mathematically, the neural network learning algorithm can be represented as:

\[ P_n = \sum_{s \in D_n} \omega_s \cdot r_{pres} \]

\[ r_n = \sigma(P_n) \]

where \( n \) – the index of the neuron; \( s \) – the index of the synapse; \( D_n \) – a set of input neuron synapses \( n \); \( pres \) and \( post \) – the presynaptic and postsynaptic neuron corresponding synapse \( s \); \( \omega_s \) – weight synapse \( s \); \( P_n \) – the membrane potential of a neuron \( n \); \( r_n \) – excitation frequency of the neuron \( n \); \( \sigma \) – type of sigmoid activation function, is represented as:

\[ \sigma(x) = \frac{1}{1 + e^{-x}} \]

The weight of the synapse is determined by the formula:

\[ \dot{\omega}_s = r_{pres} \left( \varphi_{posts} \sigma(-P_{posts}) + \gamma \cdot f_{posts} \right) \]

where \( \varphi_n = \sum_{S \in D_n} \omega_s \cdot \omega_s \)

here: \( \gamma \) – coefficient immediate feedback for all neurons, \( \varphi_n \) – signal directly to feedback error.

It should be noted that the training algorithm is equivalent to the error back propagation algorithm, but for transmission errors from the output network to its entry does not require the use of a back propagation neural network.

Consider the features of this algorithm for the design of adaptive neuro-controller. Let neuro-controller has two inputs \( e_1 \) – error signal \( e_2 \) – \( e_1 \) delayed signal. Keeping the signal \( e_2 \) is a device that neuro-controller without memory. The output of the control object depends on the current control signal and the previous control signals (fig. 3).

Suppose that the controller output is generated in two ways:
1. On the way out – the tangential sigmoid function;
2. The output of the amplifying unit.
In this view, the neural network controller mathematical ratios are as follows:

\[ r_1 = x_1, \quad r_2 = x_2; \]
\[ P_3 = \omega_1 \cdot r_1 + \omega_2 r_2; \quad P_4 = \omega_3 \cdot r_1 + \omega_4 r_2 \]
\[ r_3 = \delta(P_3), \quad r_4 = \delta(P_4) \]
\[ P_5 = \omega_5 \cdot r_3 + \omega_6 r_4 \]

Then the loss function (error signal) is written as follows:

\[ E = x_i^2 = (r - y)^2 \]

Then the:

\[ \frac{dE}{dy} = -2r + 2y = -2(r - y) = -2x_1 \]

In this case, the adjustment of the scale neural network is as follows:

\[ \dot{\omega}_1 = x_1 \cdot \varphi_3 \delta(-p_1) \]
\[ \dot{\omega}_2 = x_2 \cdot \varphi_3 \delta(-p_1) \]
\[ \dot{\omega}_3 = x_1 \cdot \varphi_4 \delta(-p_2) \]
\[ \dot{\omega}_4 = x_2 \cdot \varphi_4 \delta(-p_2) \]

where \( \varphi_3 = \omega_5 \omega_5, \ \varphi_4 = \omega_6 \omega_6 \)

The function \( \varphi_n \) is determined from the output of the neuron synapses \( n \) as follows:

\[ \varphi_n = \frac{1}{2} \frac{d}{dt} \sum_{S \in An} \omega_S^2 = \sum_{S \in An} \omega_S \cdot \omega_S \]

where \( An \) – set output neuron \( n \). To calculate \( \omega_5 \) and \( \omega_6 \) using the Frechet derivative [1], we get:

\[ \dot{\omega}_5 = -\gamma \cdot \dot{F'_{postc}} [u] \cdot r_3 \cdot (-2x_i) \]

where \( \gamma \) – the speed of learning; \( F'_{postc} [u] \) – the Frechet derivative; \( u \) – external signal.
Provided that the Frechet derivative will be approximated by a constant, then including it in the speed of learning we get

$$\omega_5 = \gamma \cdot r_3 \cdot x_1$$

$$\omega_6 = \gamma \cdot r_4 \cdot x_2$$

To decrease the regulation and deregulation of the system is necessary to change the initial weight of the system by taking their values equal to install.

After teaching neural network based on the proposed approach is modeling of the dynamics of the control system.

The next critical step to perform various mathematical operations on the input and output of information is the selection of the membership function (MF). Currently, there are dozens of different types of MF. The most common are triangular trapezoidal and Gause forms of membership functions. The choice of the type of MF depends on the individual case.

We offer the trapezoidal membership function:

$$\mu\left(\frac{d\epsilon}{dt}\right) = \begin{cases} 
1 - \frac{b-x}{b-a}, & a \leq x \leq b \\
1, & b < x < c \\
1 - \frac{x-c}{d-c}, & c \leq x \leq d
\end{cases}$$

Choice is due to the fact that the membership function is described using 4-byte parameters (binary words), clearly defining it in the space considered changing the output variable.

In the mathematical modeling of control established that the use of fuzzy controller observed the occurrence of insensitivity to changes in the duration of the transition process, and in addition, its use can improve the quality parameters of the transition process.

The proposed approach to the fuzzy controller can significantly reduce the cycle time of development and implementation of control actions in conditions of uncertainty nature of the transition. This approach can be recommended when creating a control system functioning objects with incomplete or unreliable information about the parameters of the control object.

**Conclusion**

This paper proposes a new approach to the adaptation of control systems based on the theory of interactive adaptation. Designed on the basis of this theory, neural network learning algorithm does not require a neuro-emulator control object, and neuro-controller successfully trained to manage the various objects that are in the open form can be both stable and unstable. Tuning algorithm uses connections only local information. In applying the approximation in this algorithm does not require mathematical model of the data of the individual subsystems.

**References**


