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ADAPTIVE IDENTIFICATION OF A NEURAL SYSTEM FOR CONTROL OF NONLINEAR DYNAMIC OBJECTS

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Abstract

An adaptive identifier is proposed for a neuro-fuzzy control system for a nonlinear dynamic object, operating under conditions of uncertainty of internal properties and external environment. Algorithms for structural and parametric identification in real time have been developed, which is a combination of an algorithm for identifying linear control coefficients and a method of interactive adaptation theory. An adaptive neuro-fuzzy system for controlling a nonlinear dynamic object, contains an identifier and a controller built on the basis of the Sugeno fuzzy model. This structure of the controller, combined with the optimal choice of parameters of the fuzzy controller, allows, with a minimum of settings, to implement adaptive control systems for uncertain and non -stationary mechanisms, regardless of their structure. To impart adaptive properties to the fuzzy identifier it is proposed to estimate the rate of change of error regulation The developed hybrid model, built on the basis of neural networks and fuzzy models, makes it possible to increase the efficiency of solving the problem of managing complex dynamic objects under conditions of uncertainty.

Keywords: nonlinear dynamic object, neuro-fuzzy identification, interactive adaptation, training, fuzzy logic, neural network, model.

Introduction

Most dynamic objects operating under conditions of uncertainty are characterized by complex and poorly understood relationships between technological variables and the presence of disturbing and random noise , _ _ _ _ We measure x with a large error. In addition , the presence of nonlinear elements complicates the use of linear algorithms for adaptive control of dynamic objects under conditions of uncertainty [1] .

Currently, neural and fuzzy controllers based on the theory of fuzzy logic and neural networks are widely used to control such objects . The hybrid application of a neural network and fuzzy logic in neuro - fuzzy systems that implement their positive properties gives high efficiency _ _ _ _ _ control process [3.4].

The development of control systems for many technological processes capable of maintaining the main operating parameters within specified limits is a complex multi-criteria optimization problem under conditions of uncertainty in the operating characteristics of the control object and environmental parameters . To solve such a complex problem, it is promising to introduce technology for the development of intelligent control systems based on a fuzzy controller with adaptive properties .

In this regard, the most relevant in the field of building control systems is the development of universal methods and algorithms for the automated synthesis of system parameters , based on neural networks and fuzzy logic.

In such systems, the control object and the regulator are described by fuzzy adaptive models , the structure of which is formed based on the analysis of technological variables and the nature of the connections between them with the ability to adjust to changing operating conditions of the object .

The work offers a highly effective way to build and train a neuro-fuzzy control system with a high ability to adapt .

Solution method . Let the dynamics of the control object be presented in the form of nonlinear difference control:

$$y(i+1) = f(y(i),...,y(i-r),\vec{x}(i),...,\vec{x}(i-s),u(i),...,u(i-q)), \quad (1)$$

where $i=\overline{1,N}$ is the current discrete time; y (i) - output signal :

$f(y(i),...,y(i-r),\vec{x}(i),...,\vec{x}(i-s),u(i),...,u(i-q))$ - some nonlinear function with known orders r , s , q .

The input coordinates of the object are limited at any time , i.e.

$$u^{\min} \le u(i) \le u^{\max} \quad (2)$$

$$\overline{x}^{\min} \le \overline{x}(i) \le \overline{x}^{\max}, i=\overline{1,N}$$

It is required to build a system for controlling a dynamic object (1) , which ensures a minimum of mean square errors when conditions (2) are met .

To solve this problem, we will use the combined principle of control with adaptation.

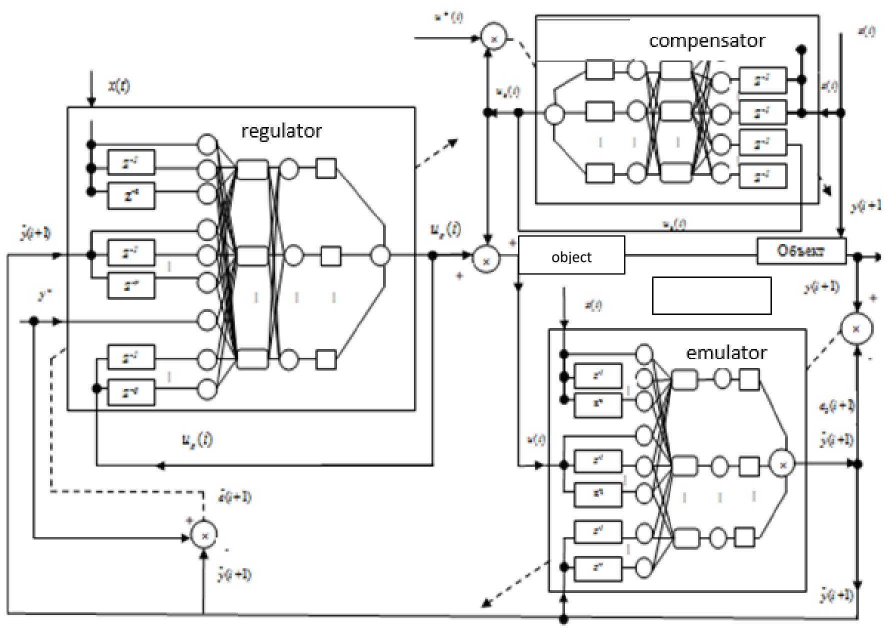

Fig.1. Simplified structure of a neuro-fuzzy adaptive control system

In this system, it is proposed to use an identifier to configure the controller parameters . In this case, the identifier is built on the basis of the Sugeno fuzzy model [5]. To form the value of input and output variables with a delay , elements with a $z^{-\tau}$ delay are added .
We present the dynamic model of the identifier as :

$$\hat{y}(i+1) = f_Э(u(i),...,u(i-q), \vec{x}(i),..., \vec{x}(i-s), y(i),..., y(i-r), \vec{c}_Э).(3)$$

having _ n orders q , s , r , which after formalizing the variables

$$\vec{x}_э(i) = (x_{э1}(i),..., x_{эм}(i)) = (u(i),..., x(i),..., y(i - r))\ (4)$$

it in the form of a fuzzy Sugeno model

$$R_э^{\theta} : \text{если } x_{э1}(i) \text{ есть } x_{э1}^{\theta}, x_{э2}^{\theta}(i) \text{ есть } x_{э2}^{\theta},..., x_{эм}(i) \text{ есть } x_{эм}^{\theta},$$
$$mo\ y^{\theta}(i+1) = b_{э0}^{\theta} + b_{э1}^{\theta} x_{э1}(i) + ... + b_{эм}^{\theta} x_{эм}(i), \theta = 1, n' \quad (5)$$

Here _ *With* - vector of identifier settings . The analytical expression of fuzzy identification has the form:

$$\hat{y}(i+1) = \sum_{\theta=1}^{n'} \beta_э^{\theta} \cdot y^{\theta}(i+1) \quad , \quad (6)$$

Where $\beta_э^{\theta} = \omega_э^{\theta}(i) / \sum_{\theta=1}^{n'} \omega_э^{\theta}(i);$ $\quad \omega_э^{\theta}(i) \prod_{i-1}^{m'} x_{э1}^{\theta}(x_{э1}(i)),$

its vector representation

$$\hat{y}(i+1) = \vec{b}_э^{T} \cdot \bar{\bar{x}}_э(i), (7)$$

as well as an algorithm for identifying coefficients $\vec{b}_э(i)$

$$H_э(i)=H_э(i-1)-\frac{H_э(i-1)\cdot \overline{\overline{x}}(i)\cdot \overline{\overline{x}}_э^T(i)\cdot H_э(i-1)}{H\cdot \overline{\overline{x}}_э^T(i)\cdot H_э(i-1)\cdot \overline{\overline{x}}_э(i)}$$

$$\vec{b}_э(i)=\vec{b}_э(i-1)+H_э(i)\cdot \overline{\overline{x}}_э(i)\cdot (y(i)-\overline{b}_э^T(i-1)\cdot \overline{\overline{x}}_э(i)),\qquad i=\overline{1,N},(8)$$

g de $\overline{\overline{x}}_э(i)=(\beta_э'(i),\ldots,\beta_э^n(i),\beta_э'(i)\cdot x_{э1}(i),\ldots,\beta_{эm'}^{n'}(i))^T$ - extended modified input vector; $(\beta_{э0}^1(i),\ldots,\beta_{э0}^{n'}(i),\beta_{э1}'(i),\ldots,\beta_{эm'}'(i),\ldots,\beta_{эm'}^{n'}(i))^T$ - vector customizable x identifier parameters. T - transposition sign . *main* characteristic defining the fuzzy set x is the *membership* function XE ,(xE), which has the form sigmoid

$$X_Э(x_Э)=(1+\exp(d_{э1}(x_э+d_{э2})))^{-1}$$

Parameters of identifier membership functions _

$$d_э=(d_{э1,l}{}^{\theta},d_{э2,l}{}^{\theta}),l=\overline{1,m'},\qquad \theta=\overline{1,n'},$$

are determined by the error backpropagation method by minimizing the quadratic discrepancy

$$E_э(i+1)=0{,}5e_э{}^2(i+1)=0{,}5(y(i+1)-y(\vec{d}_э,\vec{x}_э(i)))^2$$

gradient descent _

$$d_э(\lambda+1)=d(\lambda)-h_э\left(\frac{\partial E_э}{\partial d_э}\right),$$

where $h_э$ is the working step parameter. Using the least squares method, we determine the required values of the membership function parameters and create a system of equations:

$$\frac{\partial E_э}{\partial d_{э11}}=(y-\hat{y})\frac{(y^{\theta}-\omega_э{}^{\theta}\hat{y})}{\left(\sum_{j=1}^{n'}\omega_э{}^1\right)^2}\cdot\left(\prod_{\substack{j=1\\ j\neq 1}}^{m'}x_{э1}{}^{\theta}(x_{э1})\right)\left(1-X_{э1}{}^{\theta}(x_{э1})\right)\left(x_{э1}+d_{э2,l}{}^{\theta}\right),$$

$$\frac{\partial E_э}{\partial d_{э11}}=(y-\hat{y})\frac{(y^{\theta}-\omega_э{}^{\theta}\hat{y})}{\left(\sum_{j=1}^{n'}\omega_э{}^1\right)^2}\cdot\left(\prod_{\substack{j=1\\ j\neq 1}}^{m'}x_{э1}{}^{\theta}(x_{э1})\right)\left(1-X_{э1}{}^{\theta}(x_{э1})\right)\cdot d_{э2,l}{}^{\theta},l=\overline{1,m'},\theta=\overline{1,n'}.$$

For structural identification, a criterion is used that characterizes the average relative errors :

$$J_э = \frac{1}{N+1}\sum_{i=0}^{N}\left(\left|y(i+1) - \hat{y}(i+1)\right| / y(i+1)\right) \le J_э{}^H$$

Where $J_э$ - average relative error of an identifier with an acceptable value $J_э{}^H$.

Structural and parametric identification is completed when the condition is

$$J_э = \frac{1}{N}\sum_{i=0}^{N}\left(\left|y(i+1) - \hat{y}(i+1)\right| / y(i+1)\right) \le J_э^н, \text{met}$$

g de $J_p{}^H$ is the nominal value of the learning error.

Parameters of identifier $d_{p1,l}{}^{\theta}, d_{p2,l}{}^{\theta}, \theta = 1, n'', l = 1, m''$ membership functions are determined by learning to control it with a minimum square error

$$E = 0{,}5e^2(i+1) = 0{,}5(y^H - \hat{y}(i+1))^2$$

Using the gradient method

$$d_p(\lambda+1) = d_p(\lambda) + \Delta d_p(\lambda),$$

Where $\Delta d_p = (h_p \cdot \partial E \cdot \partial d_p)$ - working step , h $_p$ – parameter working step.

This structure of the controller , combined with the optimal choice of parameters of the fuzzy controller, allows, with a minimum of settings, to implement adaptive control systems for uncertain and non-stationary mechanisms, regardless of their structure .

To impart adaptive properties to the fuzzy identifier , in order to ensure the stability of the dynamic system to disturbances (changes in the parameters of the control object and external influences), the rate of error change was assessed regulation *E*. _

Such a control object is not a neural network, so a certain difficulty arises when training a fuzzy identifier with a functional transformer .

An important method of using a fuzzy identifier is its training.

To train the identifier, an algorithm based on the theory of interactive adaptation is proposed [1].

The essence of this algorithm is that the error required for training is calculated implicitly.

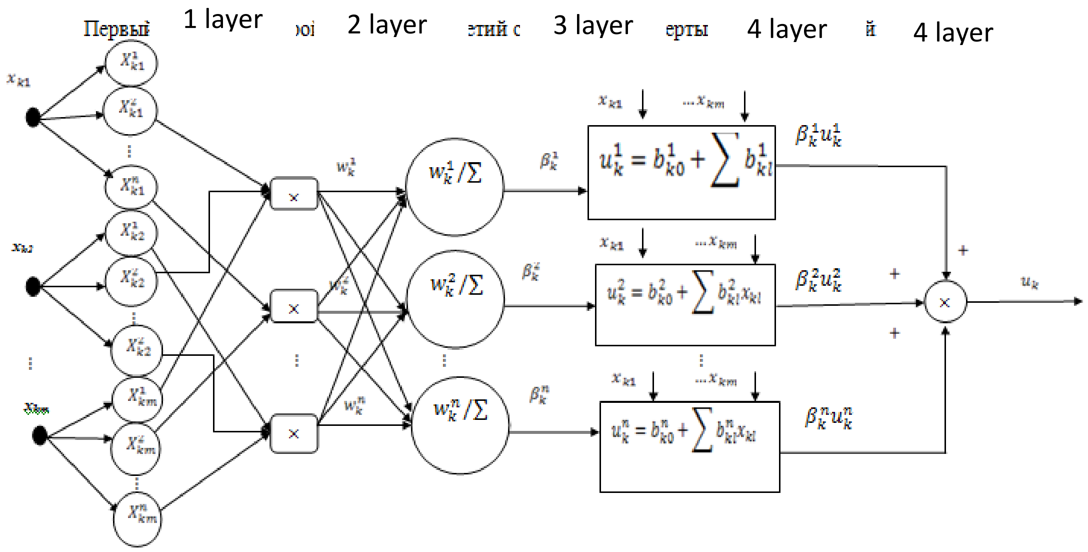

Fig.2. Structure of a fuzzy five-layer neural network

When using the interactive adaptation algorithm, the system is divided into N subsystems , each of which has an integrated output signal n and integrate the sth input signal x_n , the relationship between them is represented as a functional relationship

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

Attitude *The i* -th element of the system s has the form:

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

Let the interaction between the elements and the external signal $u_i(t)$ linear but also described _ equation:

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

where $J_i = \{K : y_K = i\}$ are the sets of connected inputs of *the i* -th element; α_K - weights of connections . In this case Relationship between input and output The *ith* element is described by the following equation:

$$y_i(t) = F_i[u_i(t) + \sum_{K \in J_i} \alpha_K \cdot y_i(t), i \in N .$$

Training neural networks is to minimize the error of the control system . This is accomplished by adjusting the weights of the neural network connections .
If the system is described by equation (1), then the weights of connections α_K are adjusted according to the following rule:

$$\alpha_K = F'_{\text{вх}K}\left[x_{\text{вх}K}\right]\cdot\left(\frac{y_{\text{вых}K}}{y_{\text{вх}K}}\right)\cdot\sum_{S\in Q_{\text{вых}J1}}\alpha_S\cdot\alpha_S-\gamma\cdot F'_{\text{вх}K}\left[x_{\text{вх}K}\right]\cdot y_{\text{вых}K}\cdot\frac{\delta E}{\delta y_{\text{вх}K}},\quad(2)$$

where $\gamma > 0$ is the coefficient that determines the learning rate; $F'_{\text{вх}K}\left[x_{\text{вх}K}\right]$- derivative Frechet [1]; E - loss function (error) ; to $\in$ K.
Provided that equation (1) has a unique solution for α_k, where the loss function $E(y_1, ..., y_k; u_1, ..., and_n)$ will decrease monotonically in time and the following equality will be satisfied:

$$\alpha_K = -\gamma\frac{\delta E}{\delta\alpha_K}, k\in K$$

Mathematically, we represent the neural network learning algorithm as:

$$Pn = \sum_{S\in Dn}\omega_S\cdot r_{pres}$$

$$r_n = \tau(Pn),$$

where n is the neuron index; S - synapse index; $P\,p$ - set of input synapses of neuron p; *pres* and *post* - presynaptic and postsynaptic neuron corresponding to synapse S ; ω_S - weight synapse S ; Pn - membrane potential of neuron n; r_n - neuron excitation frequency n; τ - activation function of the sigmoid type, which appears as :

$$\tau(x) = \frac{1}{1+e^{-x}}$$

In this case, the weight of synapses is determined by the formula:

$$\dot{\omega}_s = r_{pres}\left(\varphi_{posts}\tau\left(-P_{posts}\right)+\gamma\cdot f_{posts}\right),$$

Where $\varphi_n = \sum_{S\in A_n}\omega_s\cdot\dot{\omega}_s$

To reduce the time of regulation and over-regulation of the system, it is necessary to change the initial weights of the system , taking their values equal to the steady ones.
The next most important step to perform various mathematical operations on input and output information is the choice of membership function (MF). Currently, there are dozens of different types of AF. The most common are triangular, trapezoidal and Gaussian forms of membership functions. The choice of one or another type of FP depends on the specific case.
We propose a trapezoidal membership function:

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

The choice is due to the fact that this membership function is described using 4 byte parameters (binary words), which uniquely define it in the considered space of change in the output variable.

In the course of mathematical modeling of the control process, it was established that when using a fuzzy controller, insensitivity to changes in the duration of the transient process is observed, and in addition, its use allows improving the quality indicators of the transient process .

The proposed approach to creating a fuzzy controller makes it possible to significantly reduce the duration of the cycle of development and implementation of control actions under conditions of uncertainty in the nature of transient processes . This approach can be recommended when creating a control system for technological objects that operate in conditions of incomplete or unreliable information about the parameters of the controlled object .

Conclusion

An adaptive neuro-fuzzy control system for a nonlinear dynamic object, containing an identifier and a controller built on the basis of the Sugeno fuzzy model. Algorithms for structural and parametric identification have been developed , based on the method of interactive adaptation of models. A combination of the positive properties of neural networks and fuzzy models is proposed , which allows one to effectively solve problems of controlling complex and dynamic objects under conditions of uncertainty.

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