



Synthesis Of An Adaptive Identifier For A Neural Fuzzy Control System Under Uncertainty

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ABSTRACT

In the article an adaptive identifier is proposed for a neuro-fuzzy control system of a nonlinear dynamic object operating under conditions of uncertainty of internal properties and the external environment. Algorithms of real-time structural and parametric identification have been developed, which is a combination of an algorithm for identifying linear control coefficients and a method of interactive adaptation theory. 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 in conditions of uncertainty.

Keywords:

dynamic object, uncertainty, disturbing, linear algorithms, neural, adaptive controls, fuzzy regulators, neuro-fuzzy system, optimization, intelligent control system.

Most dynamic objects operate under conditions of uncertainty, which are characterized by complex and poorly understood relationships between process variables, the presence of disturbing and random noise, measured 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, 2].

Currently, neural and fuzzy regulators based on the theory of fuzzy logic and neural networks are widely used to control such objects. The hybrid application of neural systems and fuzzy logic in neuro-fuzzy systems, realizing their positive properties, provides high efficiency of the control process [3,4].

The development of control systems for many technological processes capable of maintaining basic 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.

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

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

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

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

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

orders r, s, q .

The input object coordinates are limited at any given time, that is.

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

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

It is required to build a control system for a dynamic object (1) that provides a minimum of mean square errors, subject to the fulfillment of conditions (2).

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

In this system, it is proposed to use an identifier to configure the controller

$$\hat{y}(i + 1) = f_{\theta}(u(i), \dots, u(i - q), \bar{x}(i), \dots, \bar{x}(i - s), y(i), \dots, y(i - r), \vec{c}_{\theta}). \quad (3)$$

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

$$\bar{x}_{\theta}(i) = (x_{\theta 1}(i), \dots, x_{\theta m}(i)) = (u(i), \dots, x(i), \dots, y(i - r)) \quad (4)$$

represent it in the form of a fuzzy Sugeno model

$$R_{\theta}^{\theta} : \text{если } x_{\theta 1}(i) \text{ есть } x_{\theta 1}^{\theta}, x_{\theta 2}(i) \text{ есть } x_{\theta 2}^{\theta}, \dots, x_{\theta m}(i) \text{ есть } x_{\theta m}^{\theta}, \quad (5)$$

$$\text{то } y^{\theta}(i + 1) = b_{\theta 0}^{\theta} + b_{\theta 1}^{\theta} x_{\theta 1}(i) + \dots + b_{\theta m}^{\theta} x_{\theta m}(i), \theta = 1, n'$$

Here c is a vector of identifier settings. The analytical expression of fuzzy identification has the form:

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

where

$$\beta_{\theta}^{\theta} = \omega_{\theta}^{\theta}(i) / \sum_{\theta=1}^{n'} \omega_{\theta}^{\theta}(i); \quad \omega_{\theta}^{\theta}(i) = \prod_{i=1}^{m'} x_{\theta 1}^{\theta}(x_{\theta 1}(i)),$$

its vector representation

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

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

$$H_{\theta}(i) = H_{\theta}(i - 1) - \frac{H_{\theta}(i - 1) \cdot \bar{x}(i) \cdot \bar{x}_{\theta}^T(i) \cdot H_{\theta}(i - 1)}{H \cdot \bar{x}_{\theta}^T(i) \cdot H_{\theta}(i - 1) \cdot \bar{x}_{\theta}(i)}$$

$$\vec{b}_3(i) = \vec{b}_3(i-1) + H_3(i) \cdot \bar{x}_3(i) \cdot (y(i) - \vec{b}_3^T(i-1) \cdot \bar{x}_3(i)), \quad i = \overline{1, N}, \quad (8)$$

where $\bar{x}_3(i) = (\beta_{30}^1(i), \dots, \beta_{30}^{n'}(i), \beta_{31}^1(i) \cdot x_{31}(i), \dots, \beta_{3m'}^{n'}(i))^T$ - extended modified input vector;
 $(\beta_{30}^1(i), \dots, \beta_{30}^{n'}(i), \beta_{31}^1(i), \dots, \beta_{3m'}^1(i), \dots, \beta_{3m'}^{n'}(i))^T$ - vector of customizable identifier parameters; T - transposition sign.

The main characteristic defining the fuzzy set x is the membership function of X_3 , (x_3), which has the form of a sigmoid

$$X_3(x_3) = (1 + \exp(d_{31}(x_3 + d_{32})))^{-1}$$

Identifier membership function parameters

$$d_3 = (d_{31,l}^\theta, d_{32,l}^\theta), l = \overline{1, m'}, \quad \theta = \overline{1, n'}$$

determined by the backpropagation method by minimizing the quadratic discrepancy

$$E_3(i+1) = 0,5e_3^2(i+1) = 0,5(y(i+1) - y(\vec{d}_3, \bar{x}_3(i)))^2$$

gradient descent

$$d_3(\lambda + 1) = d_3(\lambda) - h_3 \left(\frac{\partial E_3}{\partial d_3} \right),$$

where h_3 - working step parameter.

$$\frac{\partial E_3}{\partial d_{31l}} = (y - \hat{y}) \frac{(y^\theta - \omega_3^\theta \hat{y})}{\left(\sum_{j=1}^{n'} \omega_3^j \right)^2} \cdot \left(\prod_{\substack{j=1 \\ j \neq l}}^{m'} x_{3j}^\theta(x_{3j}) \right) \left(1 - X_{3l}^\theta(x_{3l}) \right) (x_{3l} + d_{32,l}^\theta)$$

$$\frac{\partial E_3}{\partial d_{32l}} = (y - \hat{y}) \frac{(y^\theta - \omega_3^\theta \hat{y})}{\left(\sum_{j=1}^{n'} \omega_3^j \right)^2} \cdot \left(\prod_{\substack{j=1 \\ j \neq l}}^{m'} x_{3j}^\theta(x_{3j}) \right) \left(1 - X_{3l}^\theta(x_{3l}) \right) \cdot d_{32,l}^\theta, l = \overline{1, m'}, \theta = \overline{1, n'}$$

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

$$J_3 = \frac{1}{N+1} \sum_{i=0}^N (|y(i+1) - \hat{y}(i+1)| / y(i+1)) \leq J_3^H$$

where J_3 - average relative identifier error with acceptable J_3^H value.

$$u_p(i) = \bar{b}_p^T \cdot \tilde{x}_p(i),$$

where

$$\tilde{x}_p^T(i) = [\beta_p^1(i), \dots, \beta_p^{n''}(i), x_{p1}(i) \cdot \beta_p^1(i), \dots, x_p(i) \cdot \beta_p^{n''}(i), x_{pm''}(i) \cdot \beta_p^1(i), \dots, x_{pm''}(i) \cdot \beta_p^{n''}(i)] \text{ exten}$$

ded input vector; $\beta_p^\theta(i) = \omega_p^\theta(i) / \sum_{\theta=1}^{n''} \omega_p^\theta(i)$ - fuzzy function.

Structural and parametric identification is completed when the condition is met where J_p^H is the nominal value of the learning error.

The parameters of the membership functions identifiers $d_{p1,l}^\theta, d_{p2,l}^\theta, \theta = 1, n'', l = 1, m''$ are determined by learning to control it with a minimum squared 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 - parameters of the 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 a 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 change of the control error was assessed.

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 makes it possible to improve 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 operating in conditions of incomplete or unreliable information about the parameters of the controlled object.

Conclusion

The work proposes an adaptive neuro-fuzzy control system for a nonlinear dynamic

object containing an identifier n controller built on the basis of the Sugeno fuzzy model. Structural and parametric identification algorithms have been developed, which, along with the interactive method, were used to adapt models. A combination of the positive properties of neural networks and fuzzy models is proposed, which allows one to effectively solve problems of managing complex dynamic objects under conditions of uncertainty.

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