Neuromorphous structures of the adaptive control for technological modules

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Abstract. The article develops a scientific direction, which is based on the organization of the functioning of a complex technological process according to the rules of a simple, well-studied TP based on the methods of the theory of investment. The main thesis of embedding theory: comparison of complexly organized multiply connected physical systems with relatively simple, well-studied systems. TP in this case is a multi-agent system consisting of a set of parallel TMs - single-layer neural networks with a given topology of connections between agents.

1. Introduction
To control complex mechatronic systems and technological processes, various architectures of neural networks (NN) are used [1]. At the same time, most of the literature on neural control is devoted to multilayer neural networks [2]. This type of neural networks is of particular interest to control specialists due to the fact that such networks can be represented as blocks with inputs and outputs, suitable for both training and nonlinear mapping between two spaces of finite dimension with any given accuracy. In addition, the main algorithm for learning neural networks - the signal error backpropagation algorithm - belongs to the class of gradient methods of steepest descent in the parameter space and has an adaptive analogue - the velocity gradient method (VGM) [3, 4], the first attempts to apply which were made in [1, 5].

Therefore, further prospects of neural control [1, 2] are associated with the indication of parallels between the classical theory of adaptive control and approaches to the construction of neuroregulators (NR) based on NN and the study of neuromorphic structures. NS are nonlinear systems suitable for solving practical control problems, in principle associated with the presence of nonlinear characteristics. Neural networks make it possible to eliminate the quantitative uncertainty of information, since after training they can, due to interpolation (emulation) and extrapolation (adaptation and forecasting) of the input - output characteristics of a physical object, give the correct solution for obtaining new information that is not included in the training set.

2. Statement of the problem of neural control
The technological module characterizes the state of transitions from a specific input to a specific output of a physical system and takes into account a set of simple technological operations in the system. The number of such operations (transitions) is \( n(n + 2) \). The mathematical description of TM corresponds
to the equations of dynamics of a multidimensional simply connected technical system (SISO - systems): $m = 1, l = 1$. TM in this case will be called an agent [6].

Consider a technological process (TP), consisting of $l$ interacting technological modules (TM). TM have a common structure known in advance and differ only in transitions from the $j$-th input to the $i$-th output of the TP. We believe that each TM performs a certain function of a complex TP, and is described by a sequential connection of a linear differential system (linearized on the sampling interval (observation) of a nonlinear system of ordinary differential equations) of an object and a nonlinear inertialess converter (NIC) - a single-layer perceptron (artificial neuron). Such TMs form a class of absolutely stable nonlinear systems [4].

The equations of the $j$-th TM ($j = 1, l$) have the form

$$
\dot{x} = Ax + B\sigma(t, z, u) + \xi, \quad (1)
$$

$$
z = c^T x, \quad (2)
$$

$$
u = L z. \quad (3)
$$

For brevity of notation of variables and parameters of the system of equations (1) - (3), we omit the index $j$. In what follows, we assume that system (1) must satisfy the requirements for the existence and uniqueness of the solution; $\nu$ - vector of uncontrollable disturbances $\xi \equiv 0$.

In formulas (1) - (3) it is indicated: $x = (x_1, x_2, \ldots, x_n)$ - $n$-dimensional vector of the state of the $j$-th TM, $x \in R^n$;

$u$ - control of the $j$-th TM (measured scalar input of system (1)), $u \in U \subset C^1$;

$z$ - observation of the $j$-th TM (measured scalar output of system (1)), $z \in R^1$;

$A$ - constant parametrically indefinite Jacobi matrix of dimension $n \times n$;

$B = (B_1, B_2, \ldots, B_n)$ - constant vector of adjustable parameters of the NIC dimension $n \times 1$;

$c = (c_1, c_2, \ldots, c_n)$ - a column vector of the specified observation (regression) parameters of the dimension $1 \times n$;

$L$ - scalar parametric controller;

$\sigma(t, x, z)$ - scalar activation function (FA) of a single-layer perceptron, obtained by nonlinear transformation of the $j$-th control $u$ and the $j$-th observation $z$.

The structure of a single-layer neural network, parametrically adapted for the $j$-th TM, is shown in figure 1.

In figure 1, solid lines indicate the structure of a single-layer NN with non-linearity in a "straight circuit" (prototype is the structure of an adaptive controller (figure 1) in [3, p. 351]). The proposed structure differs from the traditional scheme of an adaptive controller (AR) by the presence of an NIC and positive rigid feedback on the scalar output.
Figure 1. The structure of a single-layer neural network, parametrically adapted for $j$-th TM.

This NN structure is added by a dotted line and an adder - an "internal feedback circuit" on a scalar input (prototype - the structure of an adaptive controller (figure 1) in [3, p. 351]), which corresponds to modified equations (1) $j$-th TM

$$\dot{x} = Ax + B(u + \sigma(t, z, u)) + \zeta.$$ (4)

Differential equations (4) describe a wide class of objects with uncertainty and allow to isolate discontinuous control systems into a new class of intelligent associative adaptation systems - associative automata [5].

FA defines the architecture of the neural network. There are currently no unequivocal recommendations on the choice of FA. In the off-line training mode, the most effective is the backpropagation algorithm of the signal error and the following FAs: hyperbolic tangential, linear and logical sigmoidal activation functions [2].

In the on-line mode (operational learning and control), when the NN works in real time and performs the functions of an adaptive controller, we will assume that the FA satisfies the conditions [5]

$$0 \leq zu \sigma \leq \tilde{q}_1 \alpha_1 z^2 + \tilde{q}_2 \beta u^2,$$ (5)

where $z \in (-\infty; \infty)$, $\tilde{q}_2 \in [0, 1]$, $\tilde{q}_1 = 1 - \tilde{q}_2$, $\alpha \in [0, \alpha]$, $\beta \in [0, \beta]$; $\tilde{q}_1, \tilde{q}_2$ are fuzzy coefficients corrected at observation intervals that determine the redistribution of signals from input to output and from output to input (NN operation mode); $\alpha, \beta$ are the weight coefficients of the corresponding physical dimension (units) for the variables on the right side of the constraints on $\sigma$.

NIC $\sigma(t)$ is determined by the right-hand side of expression (5)

$$\sigma(t, z, u) = \tilde{q}_1 \alpha \frac{z}{u} + \tilde{q}_2 \beta \frac{u}{z}.$$ (6)

Function (6) has two singular points $z = 0$; $u = 0$. We will preliminarily consider them isolated [4]. Since the observation $z$ and the equation $u$ are scalar functions, taking into account (3) NIC (6) can be represented as
\[ \sigma(t, z, u) = \sigma(L) = \frac{\alpha}{L} \bar{q}_1 + \bar{q}_2 \beta L. \]  

(7)

The dependence \( \sigma(L) = \sigma(L) \) at \( \bar{q}_1, \bar{q}_2 \), fixed is shown in figure 2.

\[ \text{Figure 2. Dependence of the activation function on the values of the controlled parameter for different } \bar{q}_1, \bar{q}_2 \text{ and } \alpha = 1, \beta = 1. \]

In the presence of singular points \( z = 0, u = 0 \), the sufficient condition for asymptotic stability is approximately satisfied in a certain region bounded by the vertical \( L^\pm \) and horizontal \( \sigma^\pm \) asymptotes of the function \( \sigma(L) \) (figure 2). This area is called the area of sliding modes [7]. At \( L > L^+ \) and \( L < L^- \), the function \( \sigma(L) \) is close to linear dependence, and, therefore, the parametric controller \( L \) in these ranges of variation of the argument is quasilinear.

The NIC \( B \sigma \) for the \( j \)-th TM in the theory of NN and fuzzy sets is called a single-layer perceptron with zero bias or fuzzifier, a row vector \( c^1 \) is called a regressor or defuzzifier [5]. NIC \( B(u + \sigma) \) (formula (1')) defines a single layer perceptron with non-zero offset.

With the adaptive approach, it is considered that there is a stable internal structure of a physical object [3, 4], but its parameters (matrix coefficients \( A \)) are unknown. In the description of the \( j \)-th TM, the linear part with the transfer function \( W(p) \) (object) and the nonlinearity with the characteristic \( \sigma(\cdot) \) are present and separable. Therefore, the coefficients of the transfer function \( B \) are unknown, and with respect to nonlinearity, the partial properties of the characteristic are indicated. In addition, the vector of tunable single-layer perceptron weights is unknown.

It is required to carry out operational control of the \( j \)-th TM using an adaptive parametric neuroregulator \( L \).
The proposed approach is based on a parallel with the self-tuning adaptive control scheme: the NN adjusts the control parameters that set the operation of a conventional controller, so that the output signal of the $j$-th TM is maintained as close as possible to the desired one: $\lim_{t \to \infty} x(t) = x_* = 0$. Such control of the $j$-th TM is called stabilizing [3, 4].

The task of synthesizing an adaptive parametric neuroregulator is solved in three stages:

- the selected class of nonlinear systems is investigated for stability;
- a stabilizing control is synthesized, which provides the goal of adaptation: $\lim_{t \to \infty} x(t) = \tilde{0}$;
- according to the stability conditions, the NN parameters are initialized.

3. Conclusion

Thus, the article shows that for the practical implementation of the adaptation algorithm based on a single-layer neural network, there is enough knowledge about the order of differential equations describing a physical object with a stable structure of relationships between its elements.

References

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