Implementation of neural networks for optimal control in biotechnical exoskeleton systems

R A Tomakova1, M V Tomakov1, A I Pykhtin1 and A V Brezhnev2

1Southwest State University, 94, 50 let Oktyabrya Ave., Kursk, 305040, Russia
2Plekhanov Russian University of Economics, 36, Stremyanniy per., Moscow, 117997, Russia

E-mail: rtomakova@mail.ru

Abstract. Exoskeleton's dynamic properties are studied on the basis of a mathematical model of an exoskeleton's verticalisation. Received scalar quantities allow estimating quality of control system work of exoskeleton's verticalisation. Structural solutions for neural network control of an exoskeleton are made. Genetic algorithms of neural controllers for an exoskeleton's verticalisation control system are described: variation genetic algorithm and its input parameters; a hybrid genetic algorithm with an iterative process of increase in delays of a recurrent neural network; a hybrid genetic algorithm with the iterative process of the second criterion optimization. Implementation of the genetic algorithm synthesizes multilayered neural networks. Exoskeleton's verticalisation control with one optimized criterion is carried out on the basis of the hybrid genetic algorithm. It is possible during control of the first criterion in allowed values. Implementation of the hybrid genetic algorithm with the iterative process of the second criterion optimization synthesizes the exoskeleton's verticalisation control system with two optimized criteria. Experimental studies of quality indicators of exoskeleton's verticalisation control using neural controllers are conducted. Neural controllers have their own structure and are configured according to developed hybrid genetic algorithms.

1. Introduction

Currently, automated control systems are widely used in biotechnical rehabilitation systems [1, 2]. For the successful restoration of the functions of the damaged limbs, one of the possible ways of rehabilitation of patients is verticalisation with the help of an exoskeleton. Verticalisation is one of the effective rehabilitation procedures, which is prescribed to patients with diseases of the musculoskeletal system. It also contributes to the development of motor actions and functions of the upper limbs and can be used for young children - from 9-12 months. Verticalisation refers to the process of moving from a sitting position to a standing position. The effectiveness of such rehabilitation therapy in various neurological disorders is confirmed by clinical trials [3].

Known analytical methods of control synthesis are developed for simple control models. At the same time, computational methods of synthesis were developed to search for the values of optimal parameters in a narrow range of values [4-6]. For the implementation of methods for synthesis of structures of control systems requires large computational costs [5, 7].

However, effective algorithms to ensure optimal control in the process of verticalisation have not been developed at present. Therefore, the development and study of models and algorithms for the synthesis of motion control systems, taking into account the interaction of man and exoskeleton is an
urgent task of research.

To solve this problem, it is proposed to use artificial neural networks. The main component of imitating neurofeedback is a neural network (NS) [8-11] trained using a PID-controller. In this case, the training sample is examples of the dynamics of the reference controller (or recording of the behavior of the human operator). The training sample is composed of the values of inputs and outputs of the controller in the process of regular control of the object. Using the values of the obtained sample, the NS is trained by the method of back propagation of the error. After that, the NS completely reproduces the dynamics of the regulator, on the basis of which the training sample was based, and can be included in the control loop instead of the previous regulator.

2. Materials and methods
Implementation of multilayered direct neural networks is used for exoskeleton's verticalisation management. A block diagram of the offered neural controller is shown in figure 1.

The scheme of neural network control has five neural networks (NET, NET 1-1, NET 1-2, NET 2-1, NET 2-2). These networks are configured independently. Quality indicators of exoskeleton's verticalisation control are used for their configuration [4, 5]. According to the scheme (figure 1) configuration of neural network NET is done at first. Neural network NET is a proportional (P) analog. The neural network of counter error contamination is applied. This network is set up on the control model that allowed receiving a management emulator.

The sixth neural network (NET 3) represents the multilayered neural network of direct distribution. It is applied as a decision aggregator which is received from five neural networks outputs. The use of such architecture allows constructing the neural network controller for exoskeleton's verticalisation with accuracy and speed optimization.

![Figure 1. Structural scheme of neural controller with aggregation of optimized functionality.](image_url)

An algorithm of neural networks configuration for exoskeleton management in dynamics works with one or two optimized functionals. The consecutive configuration of the recurrent network is done in the process of delays optimization. The offered algorithm allows aggregating optimized quality functional
in a consecutive scheme of neural network management.

Input of verticalisation time $T_v$ is required in the algorithm. This time is the period when the patient moves to an upright position. During this time exoskeleton's gravity center traces out some optimum trajectory. At the same time quality functional is minimized. If this trajectory is function $\varphi(t)$, then time of verticalisation depends on sampling frequency of the $\varphi(t)$ vector component.

Functional quality $J_1$ represents trajectory deviation error of exoskeleton's gravity center movement:

$$J_1 = \sum_{i=1}^{3} \sum_{j=0}^{K-1} \| \varphi_i(t_j) - \tilde{\varphi}_i(t_j) \|$$

where $K = T_v / \Delta$, $\Delta$ is a discretisation step of control signals on neural controller's inputs.

The following procedure of an algorithm sets maximum delays values on an input signal (p) for control integrating (E) regulator of NET1 and an output signal (q) for differentiating NET2 regulator setup. It is stated that at the initial stage of control system configuration, one P-regulator is enough.

P detained operating signals and q detained output signals are used for an exoskeleton control in dynamic algorithm mode. Emulator of exoskeleton's control system in dynamic mode is formed as a result of autonomous control of neural networks with inputs of detained input and output signals.

The choice of integrator values starts with NET1 structure optimization. Increase of p stops at maximum value. After that transition to the similar procedure for differentiating regulator is done. So there are two neural networks for each optimized functional. Neural networks NET 1-1 and NET 1-2 are for $J_1$ functional.

The third functional is used for aggregation of two functionals. The third functional - $\min( J_1 + J_2 )$. In this case it is reasonable to use the multilayer neural network of NET3 direct distribution. It is configured according to the back error distribution algorithm.

Offered schemes of neural networks need to be trained. The database is formed for their training. This database is a set of lines with input vectors and related functions. The scientifically proven method is used for this database formation. This method is used to define movement parameters like “stand up and sit down”. It is also used to define dependences of link angles on time [1, 2]. Received dependences form databases for neural networks' training of neural controllers. These neural controllers control exoskeleton's verticalisation by means of experimental data approximation.

The hybrid genetic algorithm (GA) is developed for synthesis of the control system with one optimized criterion. This GA implements an iterative process of delays increase of input and output signal used in the recurrent neural network. GA provides a combination of genetic algorithms and a variation algorithm of neural networks' control [5, 6, 7]. Received p and q maximum of NET1 and NET2 neural networks is a result of GA work. The other result is $w_1, w_2, w_3$ weight coefficients on an input of NET3 neural network (figure 1).

In this case the neural network (neural controller) simulates the PID-regulator. So the PID-regulator model is implemented by recurrent neural network with an input and output delays. Dynamics of this neural network model is described by the following equation:

$$y(n+1) = F(y(n),...,y(n-q+1),x(n),...,x(n-p+1))$$

where F is some nonlinear function of arguments; $y(n), y(n-1),...,y(n-q+1)$ is input signal in time points on which the $y(n+1)$ model output depends; $x(n),...,x(n-p+1)$ are input signals.

It is necessary to define weight coefficients for the model (2) realization by means of the neural network like single-layer perceptron. That is why it is necessary to set up the following algorithm:

$$\{ w_0, w_1, w_2,...,w_p, w_{p+1},...,w_q \}.$$  \hspace{1cm} (3)

Minimum of mean-square error of operating trajectory deviation of an exoskeleton's verticalisation
is used as an optimized criterion:

\[ J = \frac{1}{N} \left( \sum_{n=0}^{N-1} (x(n) - y(n))^2 \right)^{1/2} \rightarrow \min \]  

(4)

where \( N \) is a number of discrete count on exoskeleton's verticalisation trajectory.

It is necessary to choose \( p \) and \( q \) parameters in the solution of this task. They should be chosen so that the adjusted multilayered neural networks can optimize \( J_1 \) and \( J_2 \) criteria.

HybridGA of two-criterion optimization has the following steps.

Step 1: choose \( p \) and \( q \) in a random way.

Step 2: variation GA configuration process of multilayered neural network (weight coefficient (3)) where \( p \) is variable, \( q \) is constant.

Step 3: variation GA configuration process of multilayered neural network (weight coefficient (3)) where \( p = p_{opt}, q \) is variable. Output: \( J_1 = J_1 - l_{opt}, q = q_{opt} \).

Step 4: if \( J_1 = J_1 - 2_{opt} \) is inadequate, then move to step 2 or to step 5.

Step 5: variation GA configuration process of the multilayer neural network (weight coefficients (3)) where \( p \) is variable, \( q = q_{opt} \). Output: \( J_2 = J_2 - 1_{opt}, p = p_{opt} \).

Step 6: variation GA configuration process of the multilayer neural network (weight coefficients (3)) where \( p = p_{opt}, q \) is variable. Output: \( J_2 = J_2 - 2_{opt}, q = q_{opt} \).

Step 7: if \( J_2 = J_2 - 2_{opt} \) is inadequate, move to step 5 or to step 8.

Step 8: definition of the optimal decision set according to Pareto. If there are two options with which an optimized criterion is in the admissible area so the second optimized criterion which is minimum (maximum if it is maximized) has preference.

Step 9: if optimal solution is not found, then move to step 2 where \( p = p_{opt} \) or stop.

3. Results and discussion

The one-criterion optimization algorithm is implemented as a basic algorithm of two-criterion optimization. There is input and output delay in such algorithm. Increase in values is until criterion values are changing. If this condition stops then move to another delay (from an output to input or vice versa). It is necessary to check conditions of non deterioration of the first criterion when implementing two-criterion optimization. It is also necessary to check the second criterion in admissible area. At the same time the current parameter is not optimal and is in the area of permissible values. An algorithm moves to optimization of the following criterion as soon as it is done. An optimization purpose is to achieve its maximum reduction or increase while keeping the second criterion in an admissible area.

One-criterion and two-criterion optimization of neural controller's parameters for control of exoskeleton's verticalisation is carried out on the basis of hybrid GA. Comparative analysis of the mass center movement trajectory of an exoskeleton by means of neural controllers is carried out. Comparative analysis shows improvement in quality of regulating indicators when using neural controllers which are configured according to an algorithm of two-criterion optimization.

It is possible to say that use of one-criterion optimization in neural networks control allows lowering amplitude of oscillations and control system errors. However at the same time it is not possible to remove oscillations completely. This is unacceptable for certain tasks (for example, mechanism's tremor is unacceptable when lifting the patient). HybridGA of two-criterion optimization is used for further improvement of control system quality.

Figure 2 shows the system movement change when using the neural controller which is configured according to the two-criterion optimization algorithm.
Figure 2. Mass centre movement trajectory of mechanism 1  
- set by mathematical model; 2 - received for neural  
controller with one-criterion optimization; 3 - received for  
nearal controller with two-criterion optimization

Comparative analysis of control quality of an exoskeleton's verticalisation with the PI-regulator and  
nearal controllers configured according to hybrid GA of one-criterion and two-criterion optimization  
shows smaller mass center deviation of an exoskeleton from a model trajectory during verticalisation  
control by means of the neural controller based on the two-criteria optimization algorithm.

Thus, regularities are defined and dynamic properties of an exoskeleton's verticalisation are studied  
on the bases of underlying mathematical model of an exoskeleton's verticalisation. Scalar quantities  
allowing to evaluate quality of control system work of an exoskeleton's verticalisation and to use them  
as optimize functional. Structural solutions for neural network control of an exoskeleton are developed.  
One of such solutions is development of counter-propagation error neural network which is set for  
control objects. This neural network allows receiving emulator of the control object with subsequent  
inversion in neural controller of consecutive neural control scheme. The solution is implemented by the  
nearal network emulator of exoskeleton's control system in dynamic mode using p of delayed managing  
signals and q of detained output signals. The configuration algorithm of neural networks' dynamic  
control of an exoskeleton allowing an aggregate to optimize quality functional in the consecutive scheme  
of neural control system is developed. The block diagram of neural network control which has five  
nearal networks of autonomous control and the sixth neural network as an aggregator allowing forming  
the neural network controller for exoskeleton's verticalisation with accuracy and speed optimization is  
formed.

4. Conclusion

Genetic algorithms of neural controllers' setup for the exoskeleton's verticalisation control system are  
developed. The following items are studied and developed: variation genetic algorithm and its input  
parameters. It is possible to synthesize the multilayered neural network for a nonlinear control system  
implementing this algorithm; hybrid genetic algorithm with the iterative process of delays increase of  
the recurrent neural network. Genetic algorithm allows synthesizing the neural controller for  
exoskeleton's verticalisation control with one optimize criterion; hybrid genetic algorithm with the  
iterative process of the second criterion optimization at the first criterion control in valid values. At the  
same time optimization according to Pareto's method is carried out. This optimization is done between
switching processes of configurable criteria. Implementation of this algorithm allows synthesizing the exoskeleton’s verticalisation control system with two optimized criteria.

Experimental study of control quality indicators of an exoskeleton’s verticalisation is carried out. It is done using neural controllers with developed structures and configured on the bases of hybrid genetic algorithms.

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