Research Article

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Verification hybrid control of a wheeled mobile robot and manipulator

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Abstract: In this article, innovative approaches to realization of the wheeled mobile robots and manipulator tracking are presented. Conceptions include application of the neural-fuzzy systems to compensation of the controlled system’s nonlinearities in the tracking control task. Proposed control algorithms work on-line, contain structure, that adapt to the changeable work conditions of the controlled systems, and do not require the preliminary learning. The algorithm was verification on the real object which was a Scorbot - ER 4pc robotic manipulator and a Pioneer - 2DX mobile robot.

Keywords: mobile robot; manipulator; neuro fuzzy system; position-force control

1 Introduction

The current development of science and technology poses challenges to the research community to develop innovative engineering solutions and is an inspiration to undertake research on the optimal solutions for mechatronic systems, which among others include wheeled mobile robots and manipulators. Robotics issues are interdisciplinary tasks, requiring knowledge of multiple disciplines. In particular, robots are nonlinear, non-holonomic mechatronic systems consisting of cooperating sets of mechanical, electrical, electronic and software components. Motion planning and its implementation in a changing work environment is one of the most important issues in robotics. The complexity of the problem means that, as of yet, no universal methods have been developed as a premise to take on the proposed topic. Artificial neural networks, because of the possibility of approximation of nonlinear mappings and the ability to learn, have become an attractive tool for solving various inaccurately described decision-making processes. The combination of the characteristics of neural networks and fuzzy systems resulted in an increased search for methods to convert fuzzy systems into neuro-fuzzy systems, which are characterized by their ability to learn from the data and periodic representation of knowledge [1–3]. In this paper, an intelligent servo motion controller was developed based on neural networks and fuzzy logic systems whose task is to compensate the nonlinearity and uncertain modelling of the mobile wheeled robot and manipulator. The resulting hybrid system is called the neuro-fuzzy system [2]. It combines the advantages of both neural networks and fuzzy logic systems. This system has been designed in such a way as to permit modification of properties due to the changing working conditions. Verifications were performed when the selected point of the mobile robot moves along a trajectory in the shape of a loop [2–5]. The end of the manipulator moves in a straight line [6–8]. The conducted groundbreaking research is an attempt to apply the mechanics of modern information technology, understood as real-time control, taking into account the parametric and nonparametric inaccuracies of modelling a nonlinear object.

2 Description of the mobile robot motion and neuro fuzzy nonlinearity compensator

The controlled object is a mobile robot [9]. The basic elements of this robot are the frame work, drive wheels, and self-supporting caster wheel. Wheels 1 and 2 are driven by separate electric motors, which together with a transmission form a drive train, and the encoders measure the angle of rotation of the wheels. The dynamic equations of motion of the two-wheeled mobile robot can be represented in the form of Equation (1) [9]
where $a_i$ are the parameters resulting from the configuring geometry, weight distribution and motion resistance of the system. General adopted coordinates in the form of the rotation angle of wheels $M_1$ and $M_2$ are instances of wheels being driven, which are control signals. The vector-matrix notation, Equation (1) can be represented in the form of Equation (2)

$$ M\ddot{a} + C(\dot{a})\dot{a} + F(\dot{a}) = u, $$

where $a_d = [a_1, a_1]^T$, $a_d = [\dot{a}_1, \dot{a}_1]^T$, $a_d = [\ddot{a}_1, \ddot{a}_1]^T$.

In nonlinear motion control of objects, especially in robotics, the accepted control signals are in the form of the Equation (3) [6, 9]

$$ u = f + K_D s - \zeta, $$

where $K_D s$ is the structure of the PD, $\zeta$ is an additional control whose task is to compensate for inaccuracies, and $f$ is the estimation of nonlinear functions of the controlled object that results from the mathematical description represented in Equation (4). The nonlinear function $f(x)$ is a dependence given as

$$ f(x) = M\dot{\nu} + C(\dot{\nu})\nu + F(\dot{\nu}), $$

where $\nu = \dot{a}_d + \Lambda e$, $\dot{\nu} = \ddot{a}_d + \Lambda \dot{e}$. The control error in this equation is in the form of Equation (5)

$$ e = a_d - a $$

and the generalized error in the form of Equation (6)

$$ s = \dot{e} + \Lambda e. $$

In this solution, the properties of the sliding motion system with a variable structure are used by adopting a generalized error control in the form of Equation (6). This approach to the problems of the traffic control system allows for the replacement of a non-stationary system with a stationary system and it also reduces the rule of the system under analysis. This means that the original problem can be written in the form of Equation (7) as a function of generalized errors

$$ M\ddot{s} = -C(\dot{a})s + f(x) - u. $$

Non-linearity in the form of Equation (4) is approximated with the neuro-fuzzy system. Because of the explosion of solutions resulting from the large number of input variables, this function was broken up into 6 components of the function given in Equation (8) [2, 10]

$$ f_1(x) = g_1 + g_2 + g_3 $$

$$ f_2(x) = g_4 + g_5 + g_6. $$

Each of these functions has two input signals which allowed the use of this structure in real time. In this paper, the neuro-fuzzy system [2] was used for approximation of nonlinear functions. In this system the parameters of the conclusions and conditions of the base rules of the Sugeno model must be learned.

$$ R_j : \text{IF}(x_1 = A_{j1}) \text{AND}(x_2 = B_{j1}) \text{THEN}(g = w_j), \quad j = 1, 2, \ldots, N. \quad (9) $$

The degree to meet the conditions of the given rule was adopted in the form

$$ \phi_j = \mu_{A_{j1}}(x_1) \cdot \mu_{B_{j1}}(x_2). \quad (10) $$

Using a singleton blur, assuming the function pertaining to the form of the Gaussian function and the degree of compliance with the conditions in (Equation (10)), we can register the fuzzy model in the relative form (Equation (11)).

$$ g_k = \sum_{j=1}^{N} w_{kj} \phi_j, \quad k = 1 \ldots 6. \quad (11) $$

The process of learning to adapt depends on the scale and measures of the Gaussian function, interpreted as a fuzzy set and described as the relation (Equation (12))

$$ \mu_{A_{j1}}(x_1) = e^{-r_1^2(x_1-c_{j1})^2}. \quad (12) $$

Considering (Equation (12)), the degree which meets the conditions of the rule (Equation (10)) is written as

$$ \phi_1 = e^{-r_1^2(x_1-c_{j1})^2-R_2^2(x_1-c_{j1})^2}. \quad (13) $$

This type of assumption permits recording the non-linearity of the mobile robot in the form of (Equation (14)) interpreted as a neuro-fuzzy model. Each of these $g_i$ functions can be expressed as a weight with an index multiplied by the degree of the condition. The sizes of these figures will undergo learning in real time and then we can say that we will have a neuro-fuzzy system.
\[
\hat{f} = \begin{bmatrix}
\hat{f}_1 \\
\hat{f}_2
\end{bmatrix}
\]
\[
= \begin{bmatrix}
W^{(1)T} \cdot \phi_{(1)} + W^{(2)T} \cdot \phi_{(2)} + W^{(3)T} \cdot \phi_{(1)} \\
W^{(4)T} \cdot \phi_{(4)} + W^{(5)T} \cdot \phi_{(5)} + W^{(6)T} \cdot \phi_{(6)}
\end{bmatrix},
\]
where
\[
W^{(1)T} \cdot \phi_{(1)} = \begin{bmatrix}
w_{(1)1}^{(1)} & w_{(1)2}^{(1)} & \cdots & w_{(1)19}^{(1)}
\end{bmatrix}
\]
As a result of the adopted non-linear approximation of the structure of the robot and its approximation, of the function describing the fuzzy sets while taking into account the aspect of linearization, the description of the closed system was obtained as
\[
M \ddot{\mathbf{s}} = - [K_D + C(\dot{\mathbf{s}})] \dot{\mathbf{s}} + \hat{W}^T \left[ \ddot{\mathbf{\phi}} - A^T \ddot{\mathbf{r}}_ji - B^T \ddot{\mathbf{c}}_ji \right] + \ddot{d}_s + \zeta,
\]
where the adopted parameters of the neuro-fuzzy sets are based on the correlation of Equations (17)-(19) with a resistant control signal. All of these signals arise from the analysis of the stability of the closed control system.

\[
\hat{W} = F_w \ddot{\mathbf{\phi}}_s - F_w \left( A^T \ddot{\mathbf{r}}_ji + B^T \ddot{\mathbf{c}}_ji \right) \mathbf{s}^T - F_w ||\dot{\mathbf{W}}|| \ddot{\mathbf{W}}
\]
\[
\ddot{\mathbf{r}}_{ji} = F_r A \hat{W}s - F_r ||\mathbf{s}|| \dddot{\mathbf{r}}_{ji}
\]
\[
\ddot{\mathbf{c}}_{ji} = F_r B \hat{W}s - F_c ||\mathbf{s}|| \dddot{\mathbf{c}}_{ji},
\]
where \(\zeta\) is the robust control signal and its value is:
\[
\zeta = \frac{\hat{\mathbf{s}}}{||\dot{\mathbf{s}}||} K_D^T \mathbf{Y},
\]
whereas \(Y(d_s, \hat{W}, \ddot{\mathbf{r}}_{ji}, \dddot{\mathbf{c}}_{ji})\) is a measurable matrix (available) of signals. A schematic of the neuro-fuzzy control system is shown in Figure 1

3 The experimental study
In this paper the Matlab/Simulink package and dSPACE’s hardware platform were employed for the verification of the proposed solutions of the neuro-fuzzy control of a real object, which was the Pioneer 2DX wheeled mobile robot. The set trajectory for the neuro-fuzzy control of the mobile robot’s motion adopted the form of a loop, which was determined from the task of inverse kinematics. In the verification studies five stages of movement were considered, i.e., the start, maintaining a constant speed, moving in a circular path of radius \(R\), moving and braking in a straight line. The trajectory of a loop was chosen because it is a typical implementation for practical solutions. Verification involved learning the conclusions and evidence of the rule base. The distribution of fuzzy sets in the space considerations and conclusions of the parameters was adopted. Using the control algorithm (Equation (3)), the learning algorithm of network weights (Equation (17)), and the parameters of the conditions (Equation (18)) and (Equation (19)), the value of the control signal was obtained as well as the compensation which was received during the learning of conclusions and conditions of the rule base of the neuro-fuzzy model.

Analyzing the runs, it can be seen that both the rule base conclusions and the width or the means found in the premises of the rule base adapt to the changing working conditions of the robot. In order to better compare the research on the real object, the results of the research, i.e., errors in the form of a mean-square, were compared in the form of bar graphs. Thus, Figure 4 shows the errors of wheel rotation as a mean-square for wheel 1 and 2.

4 Description of the manipulator motion and neuro fuzzy nonlinearity compensator
Dynamic equations of motion of the manipulator with geometrical constraints take the form [11, 12]
\[
M(q) \ddot{q} + C(q, \dot{q}) \dot{q} + F(q) + G(q) + \tau_d(t) = u + J_b(q) \lambda,
\]
where \(q \in \mathbb{R}^n\) is - the vector of generalised coordinates, \(M(q) \in \mathbb{R}^{n \times n}\) is - the inertia matrix, \(C(q, \dot{q}) \dot{q} \in \mathbb{R}^n\) is - the vector of moments of centrifugal and Coriolis forces, \(F(q) \in \mathbb{R}^n\) is - the friction vector, \(G(q) \in \mathbb{R}^n\) is - the gravity vector, \(\tau_d(t) \in \mathbb{R}^n\) is - the vector of disturbances bounded by \(||\tau_d|| < b, b > 0, u \in \mathbb{R}^n\) is - the control input vector, \(J_b(q) \in \mathbb{R}^{m \times n}\) is - a Jacobian matrix associated with the contact surface geometry, \(\lambda \in \mathbb{R}^m\) is - a vector of the Lagrange multiplier interpreted as the constraining force exerted normally to the contact surface, \(n\) is - the number of degrees of freedom of the manipulator, and \(m\) is - the
Figure 1: Schematic of the neuro-fuzzy control system for a wheeled mobile robot

Figure 2: Total control and compensation signals received during the learning of conclusions and conditions of the neuro-fuzzy rule base.

Figure 3: The course of control signals with the aid of the PD regulator and the robust control signal.

Figure 4: The course of lag errors and errors of speed for wheel 1 and 2.

Figure 5: The course of the angular velocity of the driving wheels and value of the weight of conclusions of the rule base.
number of directions, in which movement is restricted due to the existence of the contact surface. The shape of this surface produces the geometrical constraints, which may be written as an equation of the holonomic constraints \( h(q) = 0 \). The Jacobian matrix \( J_q \) is associated with this equation and has the following form

\[
J_q(q) = \frac{\partial h(q)}{\partial q}.
\] (22)

The existence of holonomic constraints reduces the number of degrees of freedom to \( n1 = n - m1 \), therefore the dynamics of the manipulator can be written in terms of the reduced position variable \( \theta_1 \in \mathbb{R}^{n1} \). The vector \( q \) can be decomposed as follows \( q^T = [\theta_1^T \theta_2^T]^T \), where the vector \( \theta_2 \in \mathbb{R}^{m1} \) depends on \( \theta_1 \) in the following way \( \theta_2 = \gamma(\theta_1) \), where the relation \( \gamma \) arises from the holonomic constraint.

Let us define the extended Jacobian:

\[
L(\theta_1) = \begin{bmatrix} I_{n1} & \frac{\partial \gamma(\theta_1)}{\partial \theta_1} \end{bmatrix},
\] (23)

where \( L(\theta_1) \in \mathbb{R}^{n \times n1} \), and \( I_{n1} \in \mathbb{R}^{n1 \times n1} \) is an identity matrix. Relation between the velocity \( \dot{\theta}_1 \) and the full joint velocity \( \dot{q} \) is given by the formula

\[
\dot{q} = L(\theta_1) \dot{\theta}_1,
\] (24)

and by differentiating Equation (24) we obtain

\[
\ddot{q} = L(\theta_1) \ddot{\theta}_1 + \dot{L}(\theta_1) \dot{\theta}_1.
\] (25)

Taking into account Equations (23) - (25) and relation \( \gamma \) in Equation (21), the reduced-order dynamics can be written in terms of \( \theta_1 \) as

\[
M(\theta_1) \ddot{\theta}_1 + V_1(\theta_1, \dot{\theta}_1) \dot{\theta}_1 + F(\theta_1) + G(\theta_1) = \tau_d(t) + u + J_2^T(\theta_1) \Lambda
\] (26)

with the matrix \( V_1(\theta_1, \dot{\theta}_1) = M(\theta_1) \dot{\theta}_1 + C(\theta_1, \dot{\theta}_1) L(\theta_1) \).

Pre-multiplying Equation (26) by \( L^T(\theta_1) \) by and taking into account that \( J_0(\theta_1), L(\dot{\theta}_1) = 0 \), we obtain

\[
\dot{M} \ddot{\theta}_1 + \dot{V}_1 \dot{\theta}_1 + \dot{F} + \dot{G} + \dot{\tau}_d = L^T u,
\] (27)

where \( \dot{M} = L^T ML, \dot{V}_1 = L^T V_1, \dot{F} = L^T F, \dot{G} = L^T G, \dot{\tau}_d = L^T \tau_d \).

The purpose of the hybrid position-force control is the realisation of the desired trajectory of motion \( \theta_{id}(t) \in \mathbb{R}^{n1} \) and the desired force trajectory \( \lambda_d(t) \in \mathbb{R}^{m1} \). Let us define a motion error \( e_\theta \in \mathbb{R}^{n1} \), a filtered motion error \( s \in \mathbb{R}^{n1} \), a force error \( \tilde{\lambda} \in \mathbb{R}^{m1} \) and an auxiliary variable \( u_1 \in \mathbb{R}^{n1} \) as:

\[
e_\theta = \theta_{id} - \theta_1, \quad s = \dot{e}_\theta + \Lambda e_\theta,
\]

\[
\tilde{\lambda} = \lambda_d - \Lambda, \quad \upsilon_1 = \dot{u}_1 + \dot{\lambda}_d + \Lambda e_\theta,
\] (28)

where \( \Lambda \in \mathbb{R}^{n1 \times n1} \) - the positive definite diagonal design matrix. Description Equation (27), while taking into account Equation (28), takes the form

\[
\dot{M} \ddot{s} = -\dot{V}_1 s + L^T \left[ f(x) + \tau_d - u \right],
\] (29)

where the nonlinear function \( f(x) \in \mathbb{R}^n \) has the form

\[
f(x) = ML \dot{\upsilon}_1 + V_1 \upsilon_1 + F + G
\] (30)

and depends on the structure of the manipulator’s dynamics model and variables grouped in the vector \( x = [\dot{\theta}_1^T, \dot{\theta}_1^T, \upsilon_1^T, \upsilon_1^T]^T \). According to the theory of nonlinear systems control, the mathematical structure of the position-force control law was assumed in the form proposed by [11]

\[
u = \hat{f}(x) + K_d s - J_h^T \left[ \tilde{\lambda} + K_{fr} \tilde{\lambda} \right] - \zeta.
\] (31)

This control law includes successively: compensation of object nonlinearities \( \hat{f}(x) \), the form of the proportional-differential control \( K_d s \), an interaction force control \( J_h^T \left[ \tilde{\lambda} + K_{fr} \tilde{\lambda} \right] \) and a robust control \( \zeta \in \mathbb{R}^n \). In Equation (11), \( K_d \in \mathbb{R}^{n \times n} \) and \( K_{fr} \in \mathbb{R}^{m1 \times m1} \) are matrices of position and force gain. A nonlinear function in the form of Equation (30) is approximated with the neuro-fuzzy system [1, 3]. Because of the explosion of solutions resulting from the large number of input variables, this function was broken up into \( p \) ‘smaller’ components. In order to adjust the compensation to the nonlinear function, the Sugeno neuro-fuzzy model with adapted parameters of conclusion and the premise of the rule base is applied [2]. Rules have the form

![Figure 6: The course of learning the width and center of the Gaussian function located in the premises of the rule base.](image)
where $x_1$, $x_2$ are input signals, $A_{ij}$ and $B_{ij}$ are fuzzy sets in the form of the Gaussian functions, for which the width and the center are parameters, and $w_j$ is conclusion of the rule. Using a singleton defuzzification, assuming the Gaussian membership function, and the degree of compliance with the premise, we can write the fuzzy model as

$$g_k = \sum_{j=1}^{N} w_j \varphi_j, \quad k = 1, 2, \ldots, p.$$  \hspace{1cm} (33)

Omitting index $k$, we consider any nonlinear function and write:

$$g = \sum_{j=1}^{N} w_j \varphi_j = w^T \varphi, \quad w^T = [w_1, \ldots, w_N],$$  \hspace{1cm} (34)

where $w$ is the vector of conclusions of the rule base, and $\varphi$ is the vector of the premise of the rule base. The degree to meet the premise of the given rule is adopted in the form

$$\varphi_j = \mu_{A_j}(x_1) \cdot \mu_{B_j}(x_2),$$  \hspace{1cm} (35)

where $\mu_{A_j}(x_1)$ and $\mu_{B_j}(x_2)$ are fuzzy sets in the form of the Gaussian function.

$$\mu_{\varphi_j}(x_i) = \exp \left( -r_{ij}^2 (x_i - c_{ij})^2 \right),$$  \hspace{1cm} (36)

where $r_{ij}$, $c_{ij}$ are the width and the center of this function, respectively. Taking into account Equation (36), the degree to meet the premise of the rule $R_j$ is written as

$$\varphi_j = \exp \left( -r_{ij}^2 (x_1 - c_{ij})^2 - r_{ij}^2 (x_2 - c_{ij})^2 \right).$$  \hspace{1cm} (37)

Neuro-fuzzy approximation of a manipulator’s nonlinearities, taking into account Equations (32)-(37), can be written in the form

$$f = W^T \Phi + \varepsilon$$

$$= \begin{bmatrix} w_1 & \cdots & w_{p/2} & 0 & \cdots & 0 \\
0 & \cdots & 0 & w_{p/2+1} & \cdots & w_p \end{bmatrix} \begin{bmatrix} \varphi_1 \\
\vdots \\
\varphi_p \end{bmatrix} + \varepsilon,$$  \hspace{1cm} (38)

where $\varepsilon$ - an error of nonlinear function approximation, $\|\varepsilon\| \leq \varepsilon_N$, $\varepsilon_N > 0$. Equation (38) describes the ideal neuro-fuzzy system. Due to the unknown values of $W$ and $\Phi$, an approximation of the manipulator’s nonlinearity is introduced in the form

$$\hat{f} = \hat{W}^T \Phi(x) = \begin{bmatrix} f_{nf1} \\
\vdots \\
f_{nf2} \end{bmatrix}$$

$$= \begin{bmatrix} \hat{w}_{1}^T \varphi_1 + \cdots + \hat{w}_{p/2}^T \varphi_{p/2} \\
\hat{w}_{p/2+1}^T \varphi_{p/2+1} + \cdots + \hat{w}_{p}^T \varphi_{p} \end{bmatrix},$$  \hspace{1cm} (39)

where $\gamma$ denotes an estimate of $\gamma$. The function described by Equation (39) can approximate the nonlinear function Equation (30). For the adaptation of the width and the center of the Gaussian function as well as the conclusion of the rule base, adaptation laws derived from Lyapunov’s stability theory are used, namely:

$$\hat{W} = F_{w} \Phi(Ls)^T - F_{w} \left( A^T \hat{r}_{ji} + B^T \hat{c}_{ji} \right)$$

$$- k_{F} \|Ls\| \hat{W},$$  \hspace{1cm} (40)

$$\hat{r}_{ji} = F_{r} A \hat{W} Ls - k_{F} \|Ls\| \hat{r}_{ji},$$  \hspace{1cm} (41)

$$\hat{c}_{ji} = F_{c} B \hat{W} Ls - k_{F} \|Ls\| \hat{c}_{ji},$$  \hspace{1cm} (42)

where $F_w$, $F_r$, $F_c$ are matrices of adaptation gain coefficients. A schematic of the neuro-fuzzy control system is shown in Figure 7.

5 The experimental study

In our study we considered the robotic manipulator with two degrees-of-freedom, in which links can move in the $xy$ plane. The dynamics of the manipulator have the form given by Equation (21). In the control laws Equation (31) we assumed the design matrices and parameters as: $K_p = \text{diag}(0.5, 0.5)$, $A = 3$, $K_r = 5$, $K_I = [0.1, 0.01, 0.01, 0.01]^T$, $\eta = 0.02$. In the adaptation laws Equation (40) - Equation (42) we assumed matrices of adaptation gain as: $F_w = 0.25 \cdot I$, $F_r = 15 \cdot I$, $F_c = 15 \cdot I$, where $I$ is the identity matrix. In the initial state, the centres of the Gaussian function are arranged regularly on an input space from -1 to 1, and the widths of all functions are equal to 1. The weights estimate $\hat{W}$, and in the initial state, is zero. The laboratory stand for this research consists of the Scorbot-ER 4pc robotic manipulator, the dSpace DS1006 control and measurement system and a PC workstation with Matlab+Simulink and ControlDesk. The manipulator’s tip is equipped with the force/torque sensor...
Figure 7: Schematic of the neuro-fuzzy control system for a manipulator.

Figure 8: The parameter estimates of the neuro-fuzzy system: a), b) weights of the rule base conclusions, c) selected widths of the Gaussian functions, d) selected centers of the Gaussian functions.

Figure 9: The motion error and its derivative, b) the form of the filtered motion error, c) the realised downforce and the force error.
ATI FTD-Gamma SI-130-10. The force/torque sensor measures the contact force and provides the feedback necessary for the implementation of the force control.

The characteristic feature of the adaptive systems, such as neuro-fuzzy systems, is that in the initial phase of adaptation, parameters of the neuro-fuzzy model, i.e. the weights, widths and centres of functions, are mismatched, namely often selected arbitrarily or are equal zero, Figure 8.

The parameter estimates are adapted until the motion error is nonzero. In real mechanical systems, due to disturbances, control errors never reach a constant zero value, so the weights estimates never achieve fixed values. The motion error defined by Equation (28), and some forms of the filtered motion error $||Ls||$, shown in Figure 9, oscillate around zero and are bounded. The term $||Ls||$ is a combination of the manipulator links motion errors and their derivatives, and its limitation is associated with system stability. The realised downforce and the limited force error, are shown in Figure 9c.

In the Figure 10 all components of the control signal are presented.

In Figure 10a overall control signals for each link are presented. On the subsequent graphs, all components of the control signal $u$ are shown. The main part of control takes the compensatory control (Figure 10b) generated by the neuro-fuzzy controller. The controller requires the robust control (Figure 10c), to ensure the system stability. The PD control (Figure 10d) reduces the error of motion, which results from inaccuracies of the nonlinearities compensation and motion resistant on the contact surface. All the mentioned parts of control are associated with the position control. The control of interacting force was realized by the control terms $u_{F1}$ and $u_{F2}$ (Figure 10e). In the present case, terms $u_{F1}$ and $u_{F2}$ have similar values. According to the Lyapunov stability theory, all the signals in the closed-loop control system are bounded.

### 6 Summary

The effectiveness of the designed neuro-fuzzy control algorithm was confirmed by tests on a real object. They confirm the validity of the control method. The analysis of the results of verification shows that the error convergence is faster when you take into account the control signal of the neuro-fuzzy approximation of the non-linearity of the test object. The verification results show that when information of the neural and fuzzy control is entered into the control system of the object the accuracy of achieving the planned movement increases. The proposed control method of a nonlinear object, which is a wheeled mobile robot and manipulator, constitutes a tool which uses neuro-fuzzy information in a very efficient manner.

### References


