Neural Network Identifier of a Four-wheeled Mobile Robot Subject to Wheel Slip

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Abstract:
The paper presents a sequential neural network (NN) identification scheme for the four-wheeled mobile robot subject to wheel slip. The sequential identification scheme, different from conventional methods of optimization of a cost function, attempts to ensure stability of the overall system while the neural network learns the nonlinearities of the mobile robot. An on-line weight learning algorithm is developed to adjust the weights so that the identified model can adapt to variations of the characteristics and operating points in the four-wheeled mobile robot. The proposed identification system that can guarantee stability is derived from the Lyapunov stability theory. Computer simulations have been conducted to illustrate the performance of the proposed solution by a series of experiments on the emulator of the wheeled mobile robot.

Keywords: *mobile robot, tracking control, wheels' slip, neural network, Lyapunov stability,*

1. Introduction

In the adaptive control, unknown systems are parameterized in terms of known basic structures or functions but with unknown parameters. Two broad classes of adaptive controllers include the direct adaptive controllers and indirect adaptive controllers. In the indirect adaptive tracking controller often two feedback networks are used. One network is a plant identifier that has the role of identifying (or learning) the plant dynamics model online in real time. The tuning law for the plant identifier depends on the identification error, which is desired to be small. After the plant has been identified, the controller network can be computed using a variety of methods depicted in [1].

The problem of identification consists in choosing an appropriate identification model and adjusting its parameters such that the response of the model to an input signal approximates the response of the plant under the same input [5, 9, 12, 13].

For identification process both on-line [3, 6, 11] and off-line [8] methods can be used.

In [3] an adaptive critic identifier for wheeled mobile robot was presented. The architecture of adaptive critic identifier contains a neural network (NN) based adaptive critic element (ACE) generating the reinforcement signal to tune the associative search element (ASE), which is applied to approximate nonlinear functions of the mobile robot.

In [11] the task of identifying the parameters of mobile robot was performed using tuning model method. The mathematical description for a robot model was derived on the basis of the Appell's equations.

An interesting approach to building multi-input and single-output fuzzy models was presented in [6]. A model is composed of fuzzy implications, and its output is inferred by simplified reasoning. The implications are automatically generated by the structure and parameter identification. In structure identification, the optimal or near optimal number of fuzzy implications is determined in view of valid partition of data set. The parameters defining the fuzzy implications are identified by genetic algorithm hybrid scheme to minimize mean square errors globally.

The synthesis of the wheeled mobile robot state identifier is a complex problem because objects like that are non-linear with respect to occurring slips and are also multidimensional systems. Application of neural network architectures to identification of non-linear systems has been demonstrated by several studies in discrete time [9, 10]. Lots of the studies in discrete-time systems are based on replacing the unknown function in the difference equation by static neural networks first, and then deriving update laws using optimization methods for the cost function. Although such schemes are adequate in many cases, in general some problems may arise, including the stability of the identification scheme and convergence of the output error [9]. To overcome the above limitations, in this paper a sequential identification scheme for a continuous model of wheeled mobile robot subject to wheel slip using neural networks is presented. The nonlinearities of the mobile robot are assumed to be unknown. The sequential identification scheme, different from the conventional methods of optimization of a cost function, attempts to ensure stability of the overall system while the neural network learns the nonlinearities of the mobile robot. An on-line weight learning algorithm is developed to adjust the weights so that the identified model can adapt to variations of the characteristics and operating points of the four wheeled mobile robot. To guarantee stability, the proposed identification system is derived from the Lyapunov stability theory.

The present article is the continuation of works [2, 3]. The paper is organized as follows. Chapter 2 describes a two-layer neural network. Dynamic equations of the four-wheeled mobile robot and identifier properties are included in Chapter 3. Chapter 4 presents results of the identification algorithm investigations, obtained using numerical simulations. Chapter 5 summarizes the results of the research.

2. Linear-in-the-parameter Neural Networks

There are two layers of neurons shown in Fig. 1 (a two-layer NN [7]), with one layer having *N* neurons feeding into the second layer having *r* neurons, with linear activation functions on the output layer.

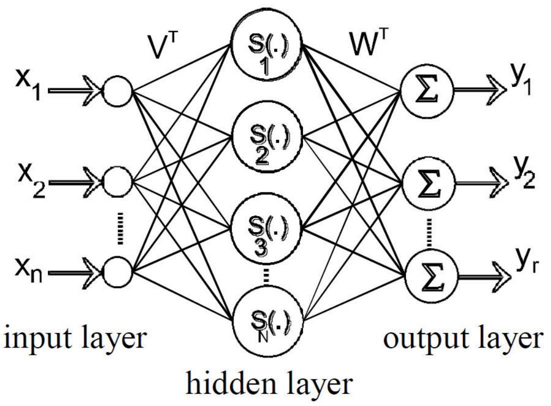

Fig.1. Schematic diagram of the neural network

After assuming the element of input vector $x_0 \equiv 1$ and the vector of threshold values as the first column of matrix $\mathbf{V}^T$, one obtains:

$$\mathbf{y} = \mathbf{W}^T \mathbf{S}(\mathbf{V}^T \mathbf{x}), \tag{1}$$

where $\mathbf{S} = [S_1(.), S_2(.), ..., S_N(.)]^T$ is the vector of functions describing neurons, $\mathbf{V}$ and $\mathbf{W}$ are weights of neural network (see Fig. 1), $\mathbf{V}^T \in \mathbf{R}^{N \times (n+1)}$ and $\mathbf{W}^T \in \mathbf{R}^{r \times N}$.

From the mathematical point of view, a two-layer network is able to approximate any continuous nonlinear function of several variables. An arbitrary continuous function $\mathbf{f}: \mathbf{D}_f \subset \mathbf{R}^n \to \mathbf{R}^r$, where $\mathbf{D}_f$ is a compact subset of $\mathbf{R}^n$, can be approximated with arbitrary accuracy by a two-layer neural network with appropriately chosen weights [7]. That is, for a given compact set $\mathbf{D}_f$ and a positive value of the approximation error $\boldsymbol{\varepsilon}$, there exists a two-layer neural network, such that the non-linear function $\mathbf{f}(\mathbf{x})$ can be written as:

$$\mathbf{f}(\mathbf{x}) = \mathbf{W}^T \mathbf{S}(\mathbf{V}^T \mathbf{x}) + \boldsymbol{\varepsilon} \tag{2}$$

for $||\boldsymbol{\varepsilon}|| < z_\varepsilon$.

If weights of the first layer of the network $\mathbf{V}^T$ are determined with certain method, then weights $\mathbf{W}^T$ of the second layer of the network define its properties, and it is in fact a single-layer network.

If one puts $\boldsymbol{\varphi}(\overline{\mathbf{x}}) = \mathbf{S}(\mathbf{V}^T \mathbf{x})$, then the relationship (1) can be written as:

$$\mathbf{y} = \mathbf{W}^T \boldsymbol{\varphi}(\overline{\mathbf{x}}), \tag{3}$$

where $\overline{\mathbf{x}} \in \mathbf{R}^N$, $\mathbf{y} \in \mathbf{R}^r$, $\boldsymbol{\varphi}(.) : \mathbf{R}^{n+1} ® \mathbf{R}^N$.

Network like that is linear with respect to its parameters ($\mathbf{W}^T$ weights). Therefore this kind of neural network is attractive from the point of view both control and identification tasks and is often use in practical applications [2, 4].

The form (3) will be adopted to approximate robot nonlinearities in the further analysis.

3. Modelling of the Robot and Identifier Properties

The object analyzed in the present article is a four-wheeled mobile robot. Diagram of its kinematic structure is shown in Fig. 2 [4, 14, 15, 16]. In the model, the following basic robot components can be distinguished: 0 – mobile platform (robot body with additional frame to accommodate control and measurement equipment), 1–4 – wheels, 5–6 – toothed belts (tracks).

In the analyzed robot, at either side the front wheel is connected with back wheel by means of the toothed belt.

The following symbols are adopted for *i*-th wheel: A_i – geometric centre, r_i – radius, θ_i – wheel rotation angle. Mobile platform angular velocity is denoted ${}^o\dot{\varphi}_{oz}$. It is assumed that motion of the mobile robot occurs in the ${}^o x {}^o y$ plane (as shown in Fig. 2).

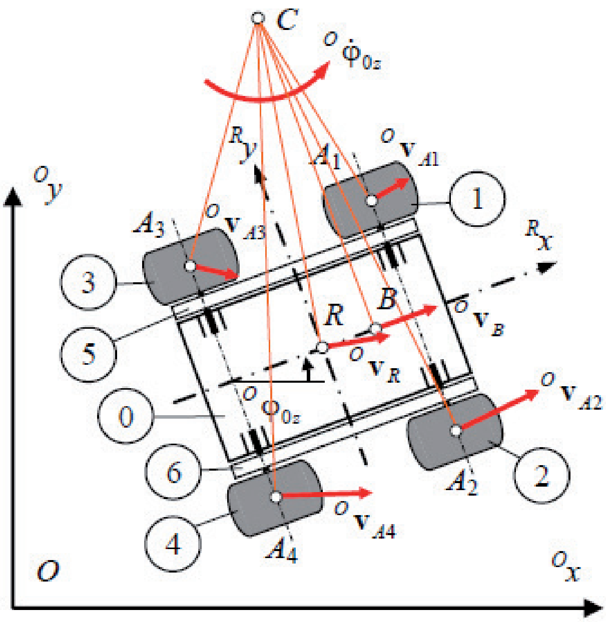

Fig. 2. Model of the analyzed robot

Position and orientation of the mobile platform are described by generalized coordinates vector:

$$\mathbf{q} = \left[{}^o x_R, {}^o y_R, {}^o \varphi_{0z}\right]^T, \tag{4}$$

where: $x_R = {}^o x_R$, $y_R = {}^o y_R$ – coordinates of the point *R* of the mobile platform, $\varphi_z = {}^o\varphi_{0z}$ – rotation of the mobile platform with respect to *z*-axis, both in the stationary coordinate system {*O*}.

Generalized velocities vector $\dot{\mathbf{q}}$ can be determined based on the value of velocity of motion of the point *R* of the robot along direction of *x*-axis of the {*R*} system connected with the robot that is v_R, and the angular velocity of the mobile platform that is $\dot{\varphi}$, based on the kinematic equations of motion in the form:

$$\dot{\mathbf{q}} = \begin{bmatrix} \dot{x}_R \\ \dot{y}_R \\ \dot{\varphi}_z \end{bmatrix} = \begin{bmatrix} \cos(\varphi_z) & 0 \\ \sin(\varphi_z) & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} v_R \\ \dot{\varphi} \end{bmatrix}. \qquad (5)$$

The above equation is valid if robot moves on a horizontal ground. In the control of position and heading of the robot, one assumes that motion of the robot is realized based on the desired vector of its position and heading, which has the form:

$$\boldsymbol{q_d} = \left[x_{Rd}, x_{Rd}, j_d\right]^T, \qquad (6)$$

where: x_{Rd}, y_{Rd} – desired coordinates of characteristic point R of the robot in (m), $\varphi_d = {}^o\varphi_{0zd}$ – desired rotation of the mobile platform with respect to z-axis in (rad), both in the $\{O\}$ coordinate system.

In order to define the problem of tracking control, based on the relationship (6) let us define desired parameters of motion of the point R in the form of equation:

$$\dot{\mathbf{q}}_d = \begin{bmatrix} \dot{x}_{Rd} \\ \dot{y}_{Rd} \\ \dot{\varphi}_d \end{bmatrix} = \begin{bmatrix} \cos(\varphi_d) & 0 \\ \sin(\varphi_d) & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} v_{Rd} \\ \omega_d \end{bmatrix}, \qquad (7)$$

where: v_{Rd}, $\omega_d = \dot{\varphi}_d$ – respectively desired linear velocity of the characteristic point R of the robot in (m/s) and desired angular velocity of its mobile platform in (rad/s), in the stationary coordinate system $\{O\}$.

In Fig. 3 schematic diagram of the analyzed robot with marked reaction forces acting on the robot in the wheel-ground contact plane is presented.

For description of motion of the four-wheeled, the model elaborated in [15] will be used. In this model the tire-ground contact conditions are characterized by coefficients of friction and rolling resistance. A simple form of a tire model, which considers only the most important effects of tire-ground interaction ,is applied. The robot dynamics model also includes

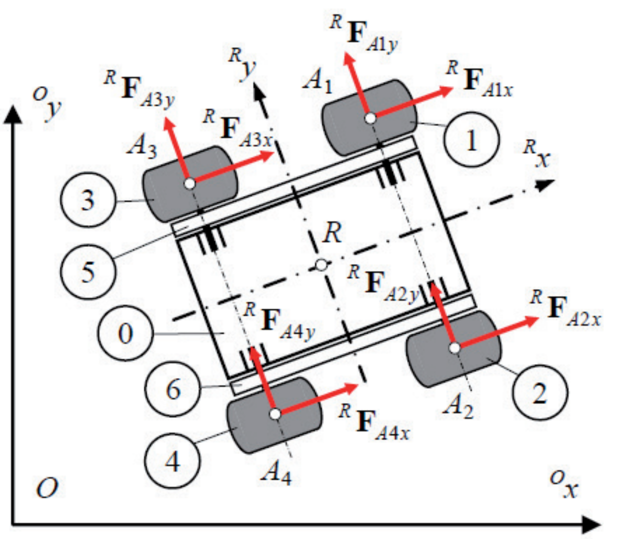

Fig. 3. Diagram of reaction forces acting on the robot in the wheel-ground contact plane

the presence of friction in kinematic pairs and the electromechanical model of servomotor drive unit.

According to proposed model, it is assumed that the tire-ground coefficient of adhesion changes according to the Kiencke model, and values of longitudinal slip ratios λ_3 and λ_4 depend respectively on angular velocities of driven wheels $\dot{\theta}_3$ and $\dot{\theta}_4$. Additionally, equality of driving torques for passive and active wheels is assumed, that is, $\tau_1 = \tau_3$ and $\tau_2 = \tau_4$.

After taking into account the above assumptions, dynamic equations of motion for the mobile platform version with the hybrid drive system, i.e. with wheels and toothed belts, are written as [15]:

$$\mathbf{M}\ddot{\boldsymbol{\theta}} + \mathbf{C} = \boldsymbol{\tau}, \qquad (8)$$

where

$$\mathbf{M} = \begin{bmatrix} 2a_1 & 0 \\ 0 & 2a_1 \end{bmatrix}, \; \ddot{\boldsymbol{\theta}} = \begin{bmatrix} \ddot{\theta}_3 \\ \ddot{\theta}_4 \end{bmatrix}, \; \boldsymbol{\tau} = \begin{bmatrix} \tau_3 \\ \tau_4 \end{bmatrix},$$

$$\mathbf{C} = \begin{bmatrix} 2a_2\,\mathrm{sgn}(\dot{\theta}_3) + 4\lambda_p\lambda_3/(\lambda_p^2 + \lambda_3^2)(a_3 + a_4 a_{Rx} - a_5 a_{Ry}) + \\ +2(a_6 + a_7 a_{Rx} - a_8 a_{Ry})\,\mathrm{sgn}(\dot{\theta}_3) \\ 2a_2\,\mathrm{sgn}(\dot{\theta}_4) + 4\lambda_p\lambda_4/(\lambda_p^2 + \lambda_4^2)(a_3 + a_4 a_{Rx} + a_5 a_{Ry}) + \\ +2(a_6 + a_7 a_{Rx} + a_8 a_{Ry})\,\mathrm{sgn}(\dot{\theta}_4) \end{bmatrix},$$

and λ_p, a_{Rx}, a_{Ry}, Δt are respectively: a constant associated with the model of wheel-ground adhesion, components of acceleration of the characteristic point R of the robot in the $\{R\}$ coordinate system associated with the robot.

In turn, constants a_i that occur in equation (8) result from analyzed robot geometric properties and mass distribution, and were determined in the work [15].

In the present work we use the idea of the identifier, introduced in [9], which allows estimation of parameters of the mobile robot mathematical model.

After putting $\mathbf{x} = [\theta_3, \theta_4, \dot{\theta}_3, \dot{\theta}_4]^T$, $\mathbf{u} = \boldsymbol{\tau}$, dynamic equations of motion (8) can be written in state space representation:

$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, \mathbf{u}), \qquad (9)$$

where $\mathbf{f}(.) \in \mathbf{R}^4$ is a non-linear function vector.

The identification model for the mobile robot (9) can by expressed by

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{G}(\mathbf{x}, \mathbf{u}), \qquad (10)$$

where $\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{G}(\mathbf{x}, \mathbf{u})$, and $\mathbf{A} \in \mathbf{R}^4$ is a Hurwitz matrix.

Suppose that a neural network is used to approximate the non-linear function $\mathbf{G}(\mathbf{x}, \mathbf{u})$ according to

$$\mathbf{G}(\mathbf{x}, \mathbf{u}) = \mathbf{W}^T \boldsymbol{\varphi}(\overline{\mathbf{x}}) + \boldsymbol{\varepsilon}, \qquad (11)$$

where: $\mathbf{W}^T$ – the ideal approximating weights, $\boldsymbol{\varphi}(\overline{\mathbf{x}})$ – function with a suitable basis, $\boldsymbol{\varepsilon}$ – the approximation error with $\|\boldsymbol{\varepsilon}\| \le z_\varepsilon$.

Then the estimate of $\mathbf{G}(\mathbf{x},\mathbf{u})$ is given by

$$\hat{\mathbf{G}}(\mathbf{x},\mathbf{u}) = \hat{\mathbf{W}}^T \varphi(\bar{\mathbf{x}},\bar{\mathbf{u}}). \tag{12}$$

This yields the following identification model

$$\dot{\hat{\mathbf{x}}} = \mathbf{A}\hat{\mathbf{x}} + \hat{\mathbf{W}}^T \varphi(\bar{\mathbf{x}},\bar{\mathbf{u}}), \tag{13}$$

where $\hat{\mathbf{x}}$ denotes the state vector of the network model.

Let us define the state error vector as

$$\tilde{\mathbf{x}} = \mathbf{x} - \hat{\mathbf{x}}, \tag{14}$$

so that the dynamic expression of the state error is given by

$$\dot{\tilde{\mathbf{x}}} = \mathbf{A}\tilde{\mathbf{x}} + \tilde{\mathbf{W}}\varphi(\bar{\mathbf{x}},\bar{\mathbf{u}}) + \boldsymbol{\varepsilon}. \tag{15}$$

Description of the closed structure of identification is shown in Fig. 4.

In Fig. 4, two neural network structure are shown. The first structure, i.e. tracking control structure, generates necessary signals $\mathbf{u},\mathbf{x}$ for identification. The second structure is neural network based identifier. In the proposed solution, the weights $\mathbf{W}$ of the network are learned without the preliminary process of learning. In order to prove stability of the proposed structure of identification of the mobile robot state, let us introduce the assumption that weights $\mathbf{W}$ are limited, i.e. the inequality $\|\mathbf{W}\| \le W_m$ is fulfilled.

Let us introduce the Lyapunov function in the form:

$$L = 0.5\tilde{\mathbf{x}}^T\tilde{\mathbf{x}} + 0.5\gamma^{-1}\,\mathrm{tr}\left(\tilde{\mathbf{W}}^T\tilde{\mathbf{W}}\right), \tag{16}$$

where $\mathrm{tr}(.)$ denotes the trace of a matrix.

The first derivative of the Lyapunov function L with respect to time t reads

$$\dot{L} = \tilde{\mathbf{x}}^T\mathbf{A}\tilde{\mathbf{x}} + \tilde{\mathbf{x}}^T\tilde{\mathbf{W}}^T\varphi(\bar{\mathbf{x}},\bar{\mathbf{u}}) + \gamma^{-1}\,\mathrm{tr}(\tilde{\mathbf{W}}^T\dot{\tilde{\mathbf{W}}}) + \tilde{\mathbf{x}}^T\boldsymbol{\varepsilon}. \tag{17}$$

Since

$$\tilde{\mathbf{x}}^T\tilde{\mathbf{W}}^T\varphi(\bar{\mathbf{x}},\bar{\mathbf{u}}) = \mathrm{tr}\left(\tilde{\mathbf{x}}^T\tilde{\mathbf{W}}^T\varphi(\bar{\mathbf{x}},\bar{\mathbf{u}})\right) = \mathrm{tr}\left(\tilde{\mathbf{W}}^T\varphi(\bar{\mathbf{x}},\bar{\mathbf{u}})\tilde{\mathbf{x}}^T\right), \tag{18}$$

equation (17) becomes

$$\dot{L} = \tilde{\mathbf{x}}^T\mathbf{A}\tilde{\mathbf{x}} + \mathrm{tr}\left(\tilde{\mathbf{W}}^T\varphi(\bar{\mathbf{x}},\bar{\mathbf{u}})\tilde{\mathbf{x}}^T\right) + \gamma^{-1}\,\mathrm{tr}(\tilde{\mathbf{W}}^T\dot{\tilde{\mathbf{W}}}) + \tilde{\mathbf{x}}^T\boldsymbol{\varepsilon}. \tag{19}$$

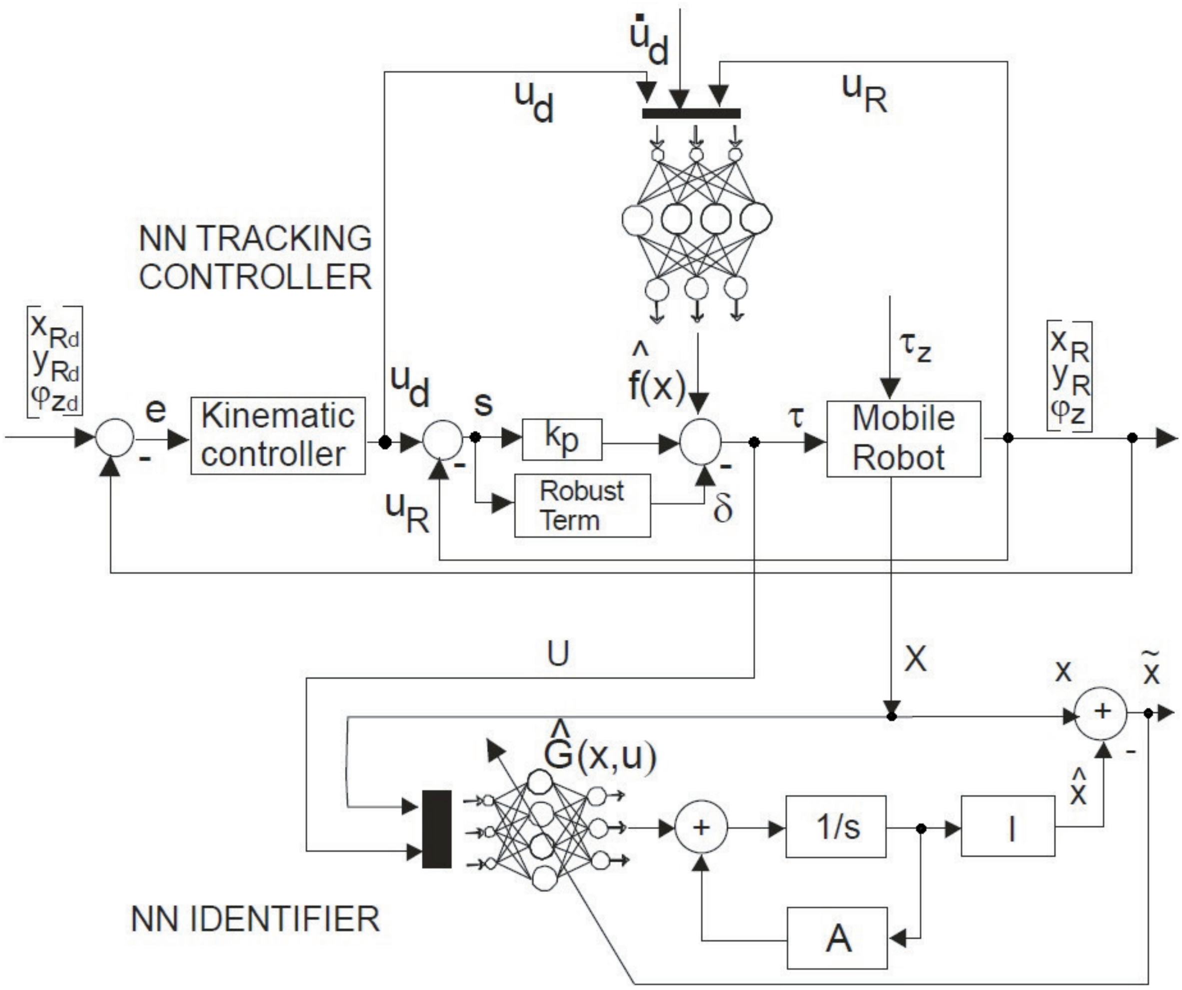

Fig. 4. Identification based on neural networks

If the estimation law for the weight matrix is given by

$$\dot{\hat{\mathbf{W}}} = \gamma\varphi(\bar{\mathbf{x}},\bar{\mathbf{u}})\tilde{\mathbf{x}}^T, \tag{20}$$

we will obtain

$$\begin{aligned}\dot{L} &= \tilde{\mathbf{x}}^T\mathbf{A}\tilde{\mathbf{x}} + \tilde{\mathbf{x}}^T\boldsymbol{\varepsilon} \le -|\lambda_{\max}(\mathbf{A})|\|\tilde{\mathbf{x}}\|^2 + \\ &+\|\tilde{\mathbf{x}}\|\;\|\boldsymbol{\varepsilon}\| \le -|\lambda_{\max}(\mathbf{A})|\|\tilde{\mathbf{x}}\|^2 + \|\tilde{\mathbf{x}}\| z_\varepsilon,\end{aligned} \tag{21}$$

where $\lambda_{\max}(\mathbf{A})$ is the maximum eigenvalue of the matrix $\mathbf{A}$.

Therefore, the Lyapunov derivative is negative semi-definite as long as

$$\|\tilde{\mathbf{x}}\| > z_\varepsilon / \lambda_{\max}(\mathbf{A}). \tag{22}$$

Therefore, the identification error $\tilde{\mathbf{x}}$ is bounded with a practical bound given by the right-hand side of equation (22). As long as the existing disturbances will be less than this value, the proposed system will work properly.

Since L is positive define and $\dot{L} \le 0$, this demonstrates stability in the sense of Lyapunov, so that $\tilde{\mathbf{x}}$ and $\tilde{\mathbf{W}}$ (and hence $\hat{\mathbf{W}}$) are bounded.

4. Simulation Results

In simulation investigations it was assumed that input $\mathbf{u} = [\tau_3, \tau_4]^T$ and desired signals $\mathbf{x} = [\theta_3, \theta_4, \dot{\theta}_3, \dot{\theta}_4]^T$ for the neural network identifier were generated from the neural network tracking control system [4], as shown in Fig. 4.

Simulation investigations were realized for movement of a chosen point R of a mobile robot on a desired path in the shape of a loop (Fig. 5a). Fig. 5c shows the actual angles of rotation θ_3 and θ_4 for wheels 3 and 4, and Fig. 5d actual angular velocities $\dot{\theta}_3, \dot{\theta}_4$. The obtained control signals τ_3, τ_4 (i.e. desired torques for driven wheels) that realize desired trajectory of motion of the point R of the mobile robot are shown in Fig. 5b. In the simulation of neural tracking control system, the parametric disturbance occurring for $t \ge 12$ s is assumed in the form of increase in rolling resistance coefficient by Δf_r=0.3 when the characteristic point R of the robot moves along the curvilinear path.

In order to use the procedure of identification of kinematic parameters of the mobile robot (section 3), let us rewrite the dynamic equations of motion (8) in the form (10)

$$\begin{bmatrix}\dot{x}_1\\ \dot{x}_2\\ \dot{x}_3\\ \dot{x}_4\end{bmatrix} = \begin{bmatrix}-a_1 & 0 & 0 & 0\\ 0 & -a_2 & 0 & 0\\ 0 & 0 & -a_3 & 0\\ 0 & 0 & 0 & -a_4\end{bmatrix}\begin{bmatrix}x_1\\ x_2\\ x_3\\ x_4\end{bmatrix} + \begin{bmatrix}x_3 + a_1\, x_1\\ x_4 + a_2\, x_2\\ g_3(x,u_1)\\ g_4(x,u_2)\end{bmatrix}, \tag{23}$$

where $[x_1, x_2, x_3, x_4]^T = [\theta_3, \theta_4, \dot{\theta}_3, \dot{\theta}_4]^T$, a_{ii}= 8, $[u_1, u_2]^T = [\tau_3, \tau_4]^T$

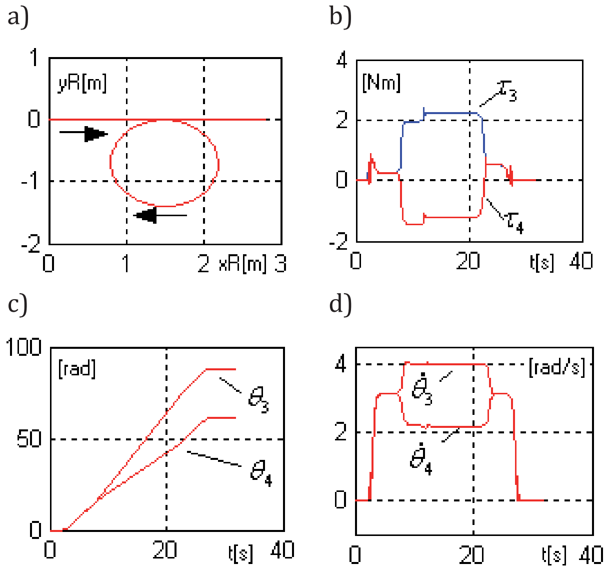

Fig. 5. Desired signals for identification

and:

$$\begin{bmatrix}g_3(x,u_1)\\ g_4(x,u_2)\end{bmatrix} = \begin{bmatrix}(u_1 - f_3)/2a_1 + a_{33}x_3\\ (u_2 - f_4)/2a_2 + a_{44}x_4\end{bmatrix}, \tag{24}$$

$$\begin{bmatrix}f_3\\ f_4\end{bmatrix} = \begin{bmatrix}\begin{pmatrix}2a_2\,\mathrm{sgn}(x_3) + 2(a_6 + a_7a_{Rx} - a_8a_{Ry})\mathrm{sgn}(x_3) + \\ +4\lambda_p\lambda_3/(\lambda_p^2 + \lambda_3^2)(a_3 + a_4a_{Rx} - a_5a_{Ry})\end{pmatrix}\\ \begin{pmatrix}2a_2\,\mathrm{sgn}(x_4) + 2(a_6 + a_7a_{Rx} + a_8a_{Ry})\mathrm{sgn}(x_4) + \\ +4\lambda_p\lambda_4/(\lambda_p^2 + \lambda_4^2)(a_3 + a_4a_{Rx} + a_5a_{Ry})\end{pmatrix}\end{bmatrix}. \tag{25}$$

For approximation of non-linear functions $\mathbf{G}(\mathbf{x},\mathbf{u}) = [g_3, g_4]^T$, equation (12) was applied where the neural network described in section 3 is used with sigmoid functions describing neurons, assuming that each element of the $\mathbf{G}(\mathbf{x},\mathbf{u})$ vector is approximated with 6 neurons. In the neural network of the identifier, initial weights were chosen equal to zero, and then adapted in a learning process for $\gamma = 500$.

The simulation results of the neural identifier for the desired motion parameters are shown in Figs. 6 and 7. The actual and estimated states of dynamic system against time t are shown in Figs. 6a and 6c. The errors of identification of rotation angles $\tilde{x}_1, \tilde{x}_2$ and angular velocities $\tilde{x}_3, \tilde{x}_4$ are shown in Figs. 6b and 6d.

In the presented simulations, during the mobile robot movement, five disturbances occurred, marked in Fig. 6d by ellipses (**1**, **2**, **3**, **4**, **5**), which cause the errors of identification. Disturbances **1** and **5** are associated with realization of two phases of robot motion: accelerating and braking. Disturbances **2** and **4** are connected with the entrance and the departure of the mobile robot from the loop. The disturbance **3** is the parametric disturbance occurring for $t \ge 12$ s assumed in the form of increase in rolling resistance coefficient.

Initial values of the identifier errors are the highest, and are reduced during neural networks adaptation process. During time periods when disturbances appear, the temporary increase of the identification errors occurs. The neural networks weights adaptation process enables reduction of the tracking errors when the signal produced by the identifier is adapted

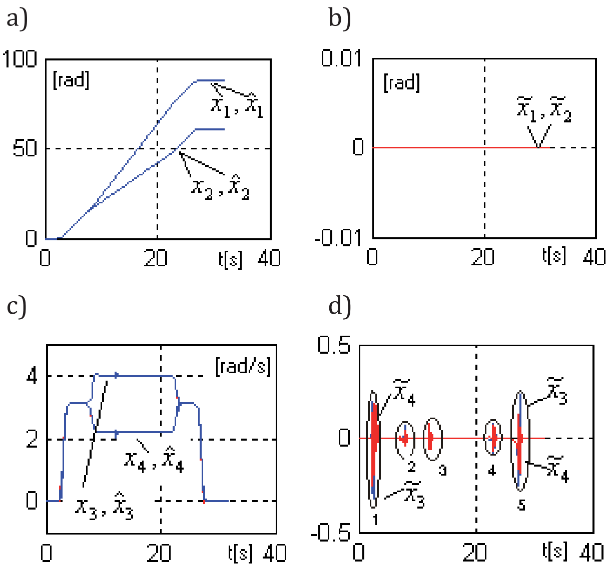

Fig. 6. Results obtained from simulation of the neural network identifier

to the changed dynamics of the mobile robot.

Weights of the non-linear function g_3 of the neural network, shown in Fig. 7a, are bounded and converge to fixed values after the learning process, similarly as weights of the non-linear function g_4, shown in Fig. 7b.

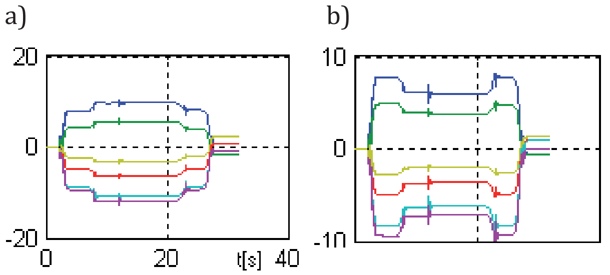

Fig. 7. Time histories of weights in non-linear neural network functions: a) g_3, b) g_4

For quantitative evaluation of the results obtained from simulation investigations of the neural network identifier, the following quality indices are introduced:

– maximum values of the errors $\tilde{x}_{3\max}$ and $\tilde{x}_{4\max}$ in (rad/s):

$$\tilde{x}_{(.)\max} = \max_k(\mathrm{abs}(\tilde{x}_{(.)}(k))),\ k=1,2,\ldots n,$$

– the square root of the mean squared error (RMSE) of the identifier in (rad/s):

$$\tilde{x}_{(.)R} = \sqrt{\frac{1}{n}\sum_{k=1}^{n}\left(x_{(.)R}(k)-\hat{x}_{(.)R}(k)\right)^2},$$

where k is the ordinal number of a discrete value and n = 32 000 is the total number of discrete values.

Values of all quality indices of realization of tracking motion are summarized in Table 1.

Table 1. Values of the introduced quality indices

$\tilde{x}_{3\max}$	$\tilde{x}_{4\max}$	$\tilde{x}_{3R}$	$\tilde{x}_{4R}$
0.3237	0.2517	0.01976	0.01917

5. Summary

A sequential identification scheme for a continuous non-linear model of four-wheeled mobile robot with unknown nonlinearities using neural networks has been developed. The algorithm works online and renders the time consuming trial-and-error preliminary learning unnecessary. The stability of the overall identification scheme and convergence of the model parameters are guaranteed by parameter adjustment laws developed using the Lyapunov synthesis approach. The operation of the sequential identification algorithm was presented based on the conducted simulation investigations and the results conformed to theoretical expectations.

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