THE ADVANCED VEHICLE CONTROL ALGORITHM USING NEURAL NETWORKS

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Abstract

In this paper, a new concept of the advanced integrated vehicle controller with a 4-wheel control system (ADIVEC-4WCS), to provide an automatic system guidance, is presented. The supplementary neuro-compensator is proposed to ensure a control system robustness and better controller adaptability upon the system uncertainties and model innaccuracies. This neural compensator is a part of integrated active control algorithm based on the centralized dynamic control strategy and full vehicle model. The validity and effectiveness of the proposed method based on adaptive capaibility of neural compensator for a four wheel steering system have been demonstrated by simulation experiments.

1 Introduction

The highest level of automation with road vehicles is the synthesis of their integrated active control systems. Full automatic control of motion and road vehicle performances is still in the experimental phase. Some satisfactory results have been achieved in the control of the vehicles operating with automated highway systems, i.e. with intelligent transportation systems [1],[2],[3]. The hybrid neuro-dynamic controller of the road vehicle described in this paper, takes simultaneously into account the complete system dynamics in all main directions of the vehicle body motion: longitudinal, lateral, vertical, as well as directions of roll, pitch and yaw angles. The centralized approach to control, by using the entire spatial model of the vehicle, makes the proposed controller advantageous over similar control schemes applied in motion control of autonomous vehicles with strongly expressed dynamics. Such case appears during the ride along a path at a rather high velocity, sudden variations of the vehicle course during motion, or with significant variations of the road geometry parameters.

The mathematical model of a road vehicle used in the synthesis of vehicle controller, describes only the most significant dynamic effects which exist in the system during motion. As a consequence, some dynamic effects such as the elastic modes in the vehicle mechanism, dynamics of vehicle actuators, time delays in drive units and control subsystems, real friction in joints of suspension system, fluid stiction in hydro-cylinders of the viscous absorbers, etc. were not explicitly modelled. These phenomena influence the whole dynamic behaviour of the road vehicle during motion. For the mentioned reasons, in order to control the vehicle while ensuring full controllability and stability on the road, it was necessary to add to the existing control structure of the dynamic controller a supplementary neuro-compensator of the corresponding system uncertainties.

The neural networks have brought considerable interest, recently in areas of identification and control of advance vehicle systems [4], [5]. The always present structural and parametric model inaccuracies we shall compensate posteriori by designing a supplementary neural compensator which takes into account the existing uncertainties in the system.

2 Model of the vehicle dynamics

The complex nonlinear model previously applied by Peng and Tomizuka in their simulation experiments [6] was used in the synthesis of the road vehicle dynamic controller. This model is rearranged and extended, taking into account the dynamics of the suspensions and tires. A nonlinear vehicle model having 22 DOFs, with the possibility of autonomous 4-wheel driving (4WD) and 4-wheel steering (4WS), was used for the stability analysis, control synthesis, parameters estimation, and simulation. The model describes motion of the vehicle mass centre (MC) in 3 coordinate directions (x, y, z) and 3 rotations (ϕ, θ, ε) of the vehicle about its main axes of inertia. The model also describes the dynamics of the 4-wheel suspension system in the vertical direction, as well as the tire dynamics in the same direction. Each wheel, in addition to the vertical tire deflection, possesses 2 extra DOFs: rotation about the horizontal axis at an angular velocity ω_i (for $i = 1, 4$) and, rotation about the vertical axis δ_i w.r.t. the road surface. The second rotation represents a change of the tire's ground steering angle.

The vehicle body model is determined by its rigid body dynamics, and it can be expressed via the vector equation:

$$H(q,d)\ddot{q} + h(q,\dot{q},d) = \tau + F(q,\dot{q},d) \tag{1}$$

where:

$$q = [x \ \ y \ \ \varepsilon \ \ z \ \ \phi \ \ \theta]^T, \quad \dot{q} = [\dot{x} \ \ \dot{y} \ \ \dot{\varepsilon} \ \ \dot{z} \ \ \dot{\phi} \ \ \dot{\theta}]^T \tag{2}$$

are (6×1) vectors of system state variables describing the position/orientation and velocity of the vehicle body MC with respect to the coordinate system fixed to the ground; x, y, z

are the longitudinal, lateral and vertical positions of the vehicle MC along the three coordinate directions, expressed in $[m]$; $\phi, \theta, \varepsilon$ are the corresponding angles of roll, pitch and yaw of the vehicle body in [rad]; $H(q, d)$ is a (6×6) inertia matrix, expressed in $[kg]$ and $[kgm^2]$, respectively; $h(q, \dot{q}, d)$ is a (6×1) vector of gravitational and centrifugal forces acting at the vehicle MC, expressed in $[N]$ and $[Nm]$, respectively; τ is a (6×1) vector of driving forces and torques referred to the vehicle MC, expressed in $[N]$ and $[Nm]$, respectively; $F(q, \dot{q}, d)$ is a (6×1) vector of the external forces and torques acting on the vehicle body during its motion along the road. Elements of this vector take into account forces and torques of tire rolling resistance, aerodynamic resistance forces during motion, as well as the damping torque of the yaw rate during cornering. The vector d represents an $l \times 1$ vector of the system parameters.

The "dynamic environment" of the road vehicle was approximated by a model of the vehicle suspension system in a broader sense. Thus it is assumed that the dynamics of tire-pneumatics in "vertical" direction can be reduced to the equivalent vehicle suspension system dynamics. The dynamic environment is usually represented in the linear impedance form: $M\ddot{q}(t) + B\dot{q}(t) + Kq(t) = -S\ F$, taking into account the inertial (M), damping (B) and elastic (K) characteristics of the environment. The environment dynamic model can be adopted in the nonlinear form, too:

$$M(q, \tilde{d})\ddot{q} + L(q, \dot{q}, \tilde{d}) = -S\ F \tag{3}$$

where $M(q, \tilde{d})$ is the (6×6) matrix describing the equivalent environment inertia in 6 coordinate directions, while $L(q, \dot{q}, \tilde{d})$ is the (6×1) nonlinear vector function which takes into account the equivalent elastic and damping characteristics of the environment interacting with the vehicle body. Parameters of the "dynamic environment" are in general variable. They are defined by the vector $\tilde{d}$ of dimension $(\tilde{l} \times 1)$. The transformation matrix S is (6×6) matrix. It takes into account the relative orientation of the vector of the external forces and moments F which act upon the environment w.r.t. the fixed coordinate system attached to the ground surface.

The model of dynamic environment in accordance to the decoupling of its dynamics in particular directions, can be described by the following relation:

$$\begin{bmatrix} M_{11} & M_{12} \\ M_{21} & M_{22} \end{bmatrix} \begin{bmatrix} \ddot{q}^{(1)} \\ \ddot{q}^{(2)} \end{bmatrix} + \begin{bmatrix} L^{(1)} \\ L^{(2)} \end{bmatrix} = -S \begin{bmatrix} F^{(1)} \\ F^{(2)} \end{bmatrix} \tag{4}$$

In order to simplify the modelling process , it is adopted that the roll and pitch axes of the vehicle body are passing through the vehicle body MC. In that case the matrix S is identical to a sixth-order square unit matrix $S \equiv I$.

3 Control strategy

The purpose of the integrated vehicle control is to ensure global motion stability of the road vehicle. The control strategy proposed in this paper is the strategy of the so-called *distributed hierarchy control* [7]. A solution which will be presented here is based on the knowledge of the entire vehicle dynamics. Thus, this control strategy can be named as the *strategy of centralized dynamic control*. The term "hierarchy" is used for the reason that the control of the object is realized at two levels: *tactical* and *executive*. They are separated w.r.t. the existing dynamic modules: the *vehicle body* and *vehicle active suspension*. The control is "distributed" because the global control signals that are generated on the higher level are distributed on the lower, executive control level, as reference signals.

The vehicle controller on the higher tactical control level, which is based on the information about errors of global state variables q and $\dot{q}$, calculates a vector of the control forces and torques which has to act at the vehicle MC to realize the desired motion. The control forces and torques calculated in this way are realized indirectly by the action of the vehicle end-effectors operating in the frame of the executive control level. For full automatic control of the vehicle motion and performances, various types of actuators can be applied. They operate in the scope of the particular vehicle active systems such as active suspension system, active 4WS (four wheel steering), and active 4WD(four wheel driven) system.

The vehicle autopilot demands exact and timely information about positions of the vehicle on the road, its relative velocity, distance from static and mobile obstacles along trajectory and, changes of road geometry parameters. Important prerequisites of the application of the autopilot system structure which will be described in the text to follow are: (I) Nominal vehicle trajectory has to be known in advance or it has to be generated in the real-time during the motion; (II) It is possible in every time instant to measure the current position of the vehicle body MC sufficiently exactly w.r.t. central line of road as a nominal path. It is also assumed that there are appropriate sensors on the vehicle that measure the relative attitude deflections and payload magnitudes in the vehicle MC; (III) It is possible to measure, or estimate in some way, the time-dependent magnitudes of the vehicle body velocities in all six coordinate directions of movement; (IV) Dynamic model expressed by the relation (1), by its structure and complexity, describes sufficiently well the main dynamic effects in the system; (V) Estimation of the vehicle dynamic parameters and parameters of interaction between the tire pneumatics and road surface is realizable in real time.

3.1 Synthesis of the vehicle dynamic controller

The dynamic controller of the road vehicle is synthesized on the tactical control level. Relating to the nature of the deviation error signal (position/velocity or force/moment) in the feedback loop of the control scheme, two different types of dynamic control algorithms can be synthesized: a *pure position control law* and a *combined position/force control law*. Which of these two control laws will be implemented in the scope of the vehicle dynamic controller depends on the concrete control requirements. Pure position control is relatively simple for the synthesis because it demands only information about the exact position and velocity of the vehicle body relative to the road surface. On the contrary, in the case of the implementation of the combined control law, it is not necessary to measure attitude deflections of the vehicle body directly. Instead, measurement of the corresponding forces and moments acting at the MC of the vehicle body w.r.t. its equilibrium state at rest is required.

On the basis of experience with road vehicles as large-scale dynamic systems it should be pointed out that dynamic interconnections inside the vehicle's mechanism are not of equal intensity in some particular directions. Thus, the longitudinal, lateral, and yaw motion of the vehicle body are mutually strongly coupled. Besides, the heave motion of the vehicle body during riding is directly dependent on the corresponding displacements in the rolling and pitching directions. That is the reason why the considered system can be dynamically decoupled in two dynamic modules: (I) the vehicle dynamics "*in plane of the road surface*" and, (II) the vehicle dynamics "*in the conditionally vertical plane*". Dynamic interconnections between the DOFs inside the mentioned dynamic modules are strongly expressed, while interactions between these modules are relatively weak. Having in mind the previous remarks and taking into account the fact that the system stabilization in longitudinal, lateral and yaw directions (x, y and ε direction) is the most important task of the vehicle control, this naturally imposes the necessity of applying the position/velocity control in these motion directions. In the remaining three directions (vertical, roll, and pitch) it is suitable to apply a force and moment control. In that case, a uniform tireload distribution upon the wheels is ensured, with the indirect positive influence on the entire system stability.

From the standpoint of previous considerations, partioning of the nominal position vector q_0 into two subvectors $q_0^{(1)}$ and $q_0^{(2)}$ is performed. The partition of the external forces vector F_0 is carried out in the same way. As mentioned above, the vehicle body possesses $n = 6$ motion DOFs in q-directions, so that the vector F of external forces and moments, acting upon the vehicle structure is also of order $m = 6$. In n_1 directions ($n_1 < n$), the vehicle nominal trajectory $q_0^{(1)}$ is prescribed directly. In these directions, position and velocity are directly controlled. Simultaneously, in m_2 directions ($m_2 < m$), the variation function of the programmed force/moment $F_0^{(2)}$ is prescribed. In these directions force/moment is controlled directly. The mentioned vectors $q_0^{(1)}$ and $F_0^{(2)}$ are of dimensions ($n_1 \times 1$) and ($m_2 \times 1$) respectively, and they are prescribed in advance as programmed (nominal) values. The remaining two subvectors $q_0^{(2)}$ and $F_0^{(1)}$ are of dimensions ($n_2 \times 1$) and ($m_1 \times 1$) and they are calculated indirectly by using the model (4). Having in mind all this, the vectors q_0 and F_0 can be defined in the following partioned form:

$$\begin{aligned} q_0 &= [q_0^{(1)T} \;\; q_0^{(2)T}]^T, \quad \text{where} \\ q_0^{(1)} &= [x_0 \;\; y_0 \;\; \varepsilon_0]^T \;\; \text{and} \;\; q_0^{(2)} = [z_0 \;\; \Phi_0 \;\; \theta_0 \;\;]^T \end{aligned} \tag{5}$$

$$\begin{aligned} F_0 &= [F_0^{(1)T} \;\; F_0^{(2)T}]^T, \quad \text{where} \\ F_0^{(1)} &= [F_X^0 \;\; F_Y^0 \;\; M_Z^0]^T \;\; \text{and} \;\; F_0^{(2)} = [F_Z^0 \;\; M_X^0 \;\; M_Y^0 \;\;]^T \end{aligned} \tag{6}$$

Elements of the described vectors belong to the set of real numbers: $q_0^{(1)} \in R^{n_1 \times 1}$, $q_0^{(2)} \in R^{n_2 \times 1}$, $F_0^{(1)} \in R^{m_1 \times 1}$, $F_0^{(2)} \in R^{m_2 \times 1}$. For the considered object of control, their dimensions are: $n_1 + n_2 = n$, $m_1 + m_2 = m$, $n = m = 6$, $n_1 = n_2 = 3$ and $m_1 = m_2 = 3$.

Dynamic Position Control Law: If in the relation (1) q denotes the (6×1) vector of global state coordinates (position and orientation of vehicle body), $q_0 = [x_0 \; y_0 \; \varepsilon_0 \; z_0 \; \phi_0 \; \theta_0]^T$ is the vector which denotes the desired, i.e. programmed, trajectory of the road vehicle. Hence, the position control law can be now expressed by:

$$\tau = \hat{H}(q,d)\,[\ddot{q}_0 + \Pi(\Delta q, \Delta\dot{q})] + \hat{h}(q,\dot{q},d) - F(q,\dot{q},d) \tag{7}$$

$$\begin{aligned} \Pi(\Delta q, \Delta\dot{q}) &= -K_V\;\Delta\dot{q} - K_P \Delta q \\ \Pi(\Delta q, \Delta\dot{q}) &= -K_V\;\Delta\dot{q} - K_P \Delta q - K_I \int_0^t \Delta q\; dt \end{aligned}$$

where $\hat{H}$, $\hat{h}$ and F are the corresponding estimated or measured values of matrices and vectors of the model (1); K_V, K_P and K_I are 6×6 matrices of velocity, position and integral control gains respectively, in PD or PID variant of the chosen controller. The matrix of control gains K_P, K_V and K_I can be defined as it was done in the paper, for the case when the system parameters are ideally known. In other case, i.e. when parameters uncertainty exist, the corresponding gains of the controller can be determined by applying the algorithm for the system practical stability test.

Dynamic Position/Force Control Law: The dynamic position/force control law demands the calculation of position and velocity errors of the vehicle body MC w.r.t. their desired (nominal) values, as well as deviations of external forces and moments which act at the MC. In the case of application of this control law it is not necessary to measure the state variables $q(t)$, $\dot{q}(t)$ in all coordinate directions but only in x, y and ε directions . Similarly, it is of importance with the components of force/moment vector $F(t)$ which have to be measured in the z, ϕ and θ directions. The basic idea of the combined position/force control law is the choice of position/velocity control in some chosen directions, while in the rest of directions the force/moment control is applied. Practical benefits of implementation of this control algorithm in the designed vehicle controller are viewed in the fact that in some directions it is easier to measure the force and moment than their positions and velocities. Separation of the directions is done under criteria of the *minimal dynamic coupling* between dynamic modules. Thus, the vectors q and F from the model (1) can be formally partitioned in two subvectors

$$\begin{aligned} q &= [q^{(1)T} \;\; q^{(2)T}]^T, \quad F = [F^{(1)T} \;\; F^{(2)T}]^T, \\ q^{(1)} &= [x \;\; y \;\; \varepsilon]^T, \quad\; q^{(2)} = [z \;\; \phi \;\; \theta]^T, \\ F^{(1)} &= [F_X \;\; F_Y \;\; M_Z]^T, \quad F^{(2)} = [F_Z \;\; M_X \;\; M_Y]^T \end{aligned} \tag{8}$$

in the way as it was done with their nominal forms in (6) and (7). One such partition of vectors q and F is done for the reason that the influence of forces/moments upon the corresponding displacements of the vehicle body ($F^{(1)}$ to the $q^{(2)}$ and $F^{(2)}$ to the $q^{(1)}$) are weak, and because the dynamic behaviour of the system in these directions can be mutually decoupled. In fact, it means that position will be controlled in the directions x, y and ε (longitudinal, lateral and yaw) while in the directions z, ϕ and θ (vertical, roll and pitch) force/moment control will be applied.

Hence, the dynamic position/force control law can be defined in the following form:

$$\begin{aligned}
\tau &= \hat{H}(q,d)\ddot{q}_c + \hat{h}(q,\dot{q},\tilde{d}) - F \qquad (9)\\
\ddot{q}_c &= \begin{bmatrix} \ddot{q}_c^{(1)} \\ \ddot{q}_c^{(2)} \end{bmatrix}\\
\ddot{q}_c^{(1)} &= \ddot{q}_0^{(1)} + \Pi(\Delta q^{(1)}, \Delta\dot{q}^{(1)})\\
\ddot{q}_c^{(2)} &= -\hat{M}_{22}^{-1}[(F_0^{(2)} + \int_0^t Q(\Delta F^{(2)})\ dt) +\\
&+ \hat{M}_{21}(\ddot{q}_0^{(1)} + \Pi(\Delta q^{(1)}, \Delta\dot{q}^{(1)})) + \hat{L}^{(2)}]\\
Q(\Delta F^{(2)}) &= -K_F^{(2)}(F^{(2)} - F_0^{(2)}) -\\
&- K_{FI}^{(2)}\int_0^t (F^{(2)} - F_0^{(2)})dt\\
Q(\Delta F^{(2)}) &= -K_F^{(2)}(F^{(2)} - F_0^{(2)})\\
\Pi(\Delta q^{(1)}, \Delta\dot{q}^{(1)}) &= -K_V^{(1)}(\dot{q}^{(1)} - \dot{q}_0^{(1)}) - K_P^{(1)}(q^{(1)} - q_0^{(1)})
\end{aligned}$$

where: F is the (6×1) vector of external forces and moments acting at the vehicle body MC; $\hat{M}_{22}$, $\hat{M}_{21}$ and $\hat{L}^{(2)}$ are the estimated matrices of the model (4); $Q(.)$ is one of the two disposable (3×1) vector functions which determine the character of the function describing the forces/moments in the transient process; $K_F^{(2)}$ and $K_{FI}^{(2)}$ are the (3×3) matrices of the force control gains of the PI or P-regulator; $F_0^{(2)}$ is the (3×1) vector of the nominal (programmed) values of forces/moments acting in the considered directions (vertical, roll and pitch); $K_P^{(1)}$ and $K_V^{(1)}$ are quadratic matrices of the position and velocity control gains of dimension (3×3). These control gains act in directions which are complementary to the directions in which force/moment control is applied. The feedback control gains included in the dynamic control algorithm are determined using automatic software procedure established by the practical stability test.

The control vector τ, partitioned in the two complementary vectors of control signals τ_I and τ_{II} which compensate for the inaccuracies of motion in the corresponding directions so that: τ_I acts in the z, ϕ and θ direction and, τ_{II} in the x, y and ε direction. The matrices S_1 and S_2 represent the diagonal (6×6) selectivity matrices which serve to separate the control directions. The control signals τ_I and τ_{II} are the reference signals at the lower control level. Control on the executive level depends on the choice of system's actuators and concrete solutions of the active systems design.

3.2 Synthesis of the supplementary neuro-compensator

A neuro-compensator which was added to the synthesized dynamic road vehicle controller. Under the notion of neuro-compensator we assume a compensator structure which is based on the artificial neural network (ANN) with four layers of perceptrons. The proposed model-based controller can ensure stable system motion and the desired quality of its dynamic behaviour if the mathematical model of the system sufficiently exactly describes the system dynamics as well as if the model parameters deviate relatively little from their real values. In the synthesis of the dynamic controller, we adopted the spatial model of the road vehicle (1) which describes relatively well the basic system dynamics in the considered six coordinate directions of motion. However, the mathematical model of the vehicle does not describe fully all dynamic effects involved in the system during motion, as for instance elastic modes of the vehicle mechanism, influence of the actuator dynamics, time delay in driving and control subsystems of road vehicle, Coulomb's friction at the joints of suspension system, some other nonlinearities existing in the system, etc. Measuring errors of the state variables and parameter estimation errors influence the control accuracy of the motion, too. All these phenomena influence the system stability. Thus, in order to meet the requirements of the vehicle controller capable to operate in real exploitation conditions, it is suitable to combine the model-based controller with the knowledge-based nonlinear compensator.

The structure of the hybrid neuro-dynamic controller consists of two functional blocks. The task of the first (model-based) block is to compensate for the main dynamic effects, while the second (knowledge based) block is based on the application of the artificial neural network for compensation of the system uncertainties. The automatic control system of the autonomous road vehicle is designed by integrating the dynamic control algorithm and the chosen ANN structure. On the other hand, a neural network can satisfactorily identify the above-mentioned phenomena which were not comprised by the mathematical model (1). The mentioned identification of the non-modelled dynamic effects by ANN is possible by training the procedure of the chosen net structure using some of the well known learning methods. In this paper we used the *standard back propagation learning method* which is frequently used for training multilayer nets in similar control tasks. The application of ANN in automatic control of the vehicle motion is performed in three phases: (I) the rough off-line training, (II) the fine on-line training and, (III) the implementation of the finally tuned net in the synthesized hybrid controller.

The structure of the learning process for the off-line identification of the unmodelled system dynamics is shown in Fig. 1. At the beginning, the appropriate input and output signals needed for the network training are selected. For that purpose, manual commands are set to the vehicle which produce variation of the input command signals such as tire angular velocities ω_i and variation of the ground steering angles δ_i, $i = 1, 4$. Besides, various external disturbances act upon the vehicle dur-

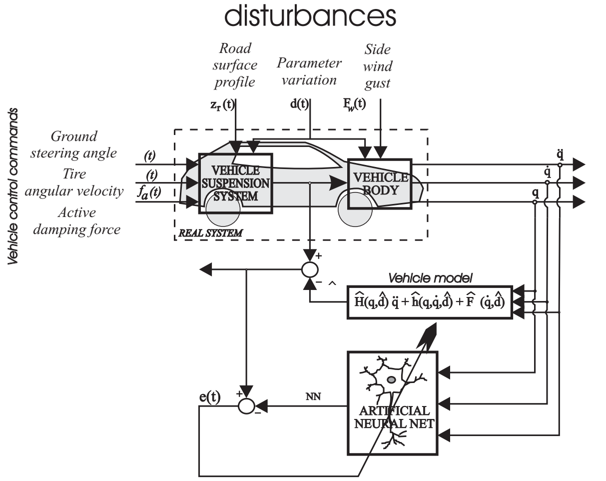

Figure 1: Structure of the learning process of the chosen ANN

ing motion. These are variation of the road surface profile, changes of the intensity and direction of the side wind gust, as well as variation of Coulomb's friction coefficients between tire pneumatics and road surface, etc. Using simulation experiments, the global state variables ($q(t)$, $\dot{q}(t)$, $\ddot{q}(t)$) are determined and saved. These state variables serve as input signals to the rough off-line training of the chosen ANN. These variables are used for computation of the vehicle mathematical model too. On the basis of the values of generalized forces $\hat{\tau}(t)$ calculated from the model and their real values $\tau(t)$ obtained by measuring at each time sample on the real system during the ride, the deviation vector $\Delta\tau(t) = \tau(t) - \hat{\tau}(t)$ can be defined. At the same time, the so-called compensation vector of forces/moments $\Delta\tau_{NN}$ is generated at the output layer of the neural network. Values of the (6×1) vector $\Delta\tau_{NN}$ correspond to the values of the identified magnitudes of the forces and torques which are not taken into account by the vehicle dynamics modelling. The obtained vectors $\Delta\tau(t)$ and $\Delta\tau_{NN}(t)$ are compared at the discriminator ($e(t) = \Delta\tau(t) - \Delta\tau_{NN}(t)$) (Fig. 1). The existing error $e(t)$ is used for further tuning of the ANN weighting matrices (Fig. 1). When the amplitude of the learning error $e(t)$ is below some predetermined, desired value ($e(t) \leq E$), the rough "off-line" learning process is terminated. The next step in the synthesis of the neuro-compensator is the so-called "fine net tuning". The weighting factors in the corresponding matrices of the suitably chosen net architecture, defined by the off-line learning process, serve as initial values for further "fine tuning" of the neural network. This procedure should be carried out in the real time on the real system, in the closed loop. When the desired quality of learning process is attained, "fine tuning" is ended.

In this work, a suitable multilayer neural net topology for control purposes is proposed. For its training, a standard back propagation algorithm was used. The topology of the proposed net structure intended for control purposes was defined by the four-layer neural network with one input layer, two hidden layers, and one output layer. A sigmoid function, as an activation function in two hidden layers of neurons, was chosen. Only in the input and output layers a linear function of identity was used as a function of activation. The output layer permits the net to generate signals out of the range $[-1, +1]$. For this reason, at the output of the net, but formally at its input too, the so-called matching gains G_u^i and G_y^i should exist. This is necessary because of realization of a better and faster net convergence, i.e. in order to accelerate the net learning rate.

The proposed neural network has an input layer with $n = 15$ neurons and an output layer with $m = 6$ neurons. Since the relative position of the vehicle MC in the fixed coordinate system connected to a point located on the road surface does not influence the behaviour of the vehicle dynamics, then the coordinates $q_1 = x$, $q_2 = y$ and $q_4 = z$ are omitted from the input vector U. The (6×1) output vector Y consists of the compensation forces and torques which should act at the MC of the vehicle body.

Based on simulation experiments, the optimal network topology was defined: the input layer with $n = 15$ neurons inside, the first hidden layer with $p = 81$ neurons, the second hidden layer with $q = 67$ neurons and, the output layer of the connectionist structure with $m = 6$ neurons in it. Finally, experimentally identified values of the matching gains G_u and G_y are defined, too.

4 Simulation experiments

A characteristic example of the vehicle motion along an arbitrary curvilinear trajectory was assumed. The nominal imposed trajectory, consisting of two circular (with $R_1 = 550$ and $R_2 = 450$ $[m]$ curve radii) and three linear path segments. In the considered simulation experiment the influence of the following external disturbances on the system stability were imposed: (I) variation of the road surface profile, (II) side wind gust, (III) slippery road, and (IV) time delays in the vehicle actuators. The vehicle motion was simulated against wind so that it had a permanent direction of blowing. Force impact intensity was introduced to be varied as function $F_w(t) = 500\ exp^{-\lambda\Delta t}$ $[N]$. The "weakness" parameter λ was defined from the condition that the wind force magnitude $F_w(t)$ diminished from 500 to 0.1 $[N]$ for the time period of $\Delta t = 2$ seconds. Side wind gust tends to destabilize the system motion and to change its forward velocity. Appearance of slippery (wet, icy) road causes a variation of the tire rolling resistance coefficients f_r on the road. They change as well as they are equal on the same-side tires ($f_r^1 = f_r^3$ and $f_r^2 = f_r^4$). For dry road it was assumed that the tire rolling resistance has the value of $f_r = 0.018$. Variation of the road surface profile was introduced as a "step" function of 8 $[mm]$ magnitude which appears on the right pair of tires . In the considered simulation experiment the effect of actuator dynamics of the robotized vehicle is taken into account as its time delay $\tau_d = 0.032$ $[s]$ which acts on the system as an internal disturbance.

Geometry and dynamic vehicle parameters in the considered simulation experiment were taken from [6]. The vehicle behaviour was tested for the synthesized hybrid neuro-dynamic controller with the position/force control algorithm implemented on the tactical control level. Control gains were defined so that the system is stable for the parameter variation in the range of predetermined limits and for moderate external disturbances. In this simulation experiment, various control commands were simulated in the open loop regime (Fig. 1) for the purpose of training the chosen neural net structure. For the purpose of excitation of the so-called "vertical" vehicle dynamics, variation of the road surface profile z_r (within the limits of $z_r^{max} = \pm 5\ [mm]$) upon all wheels was introduced. Time-varying values of the system dynamic parameters such as vehicle integral mass (in the range $\pm 10\%$), inertial moments around the main axis ($\pm 10\%$) as well as coefficients of friction between the tire pneumatics and the road surface (variation up to 70%) were simulated, too. For the net training, changes of the ground steering angles in the form of "step" functions (3.5 and $5.5\ [°]$) were imposed on the front pair of wheels. On the same pair of wheels, periodical input signals of the same amplitudes and different frequencies of 1 and $1.5\ [Hz]$ were introduced. On the rear wheels, random signals with maximal amplitudes of $\pm 1.5\ [°]$ were imposed. It was assumed that the vehicle moves with $V = 80\ [km/h]$ forward velocity and with periodical variation of its tire angular velocities in the range of $\pm 5\%$.

For training the neural network the back propagation method was applied. The network training parameters were preset: the target error $E = 180$, the maximal number of learning epochs $e_{max} = 10^5$ and the initial learning rate of the applied neural network $l_r = 0.01$.

It is obvious to see convergence of learning process (Fig. 2) and improvement of tracking errors by using neuro-compensator in comparison with the case without neuro-compensator. Also, a satisfactory dynamic vehicle body behaviour in the directions considered was achieved.

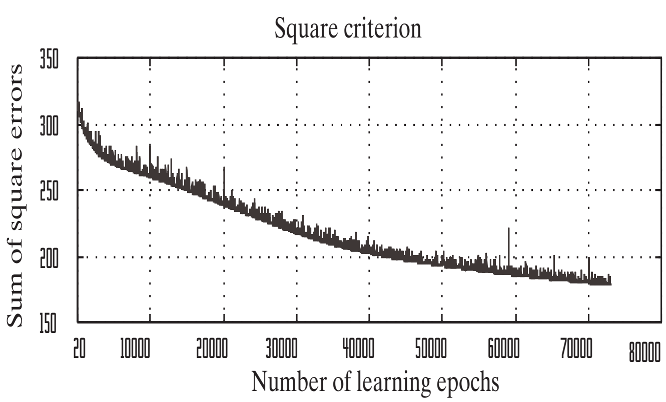

Figure 2: Error in learning process

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6 Conclusions

The proposed controller was synthesized in three stages: (I) First, non-adaptive integrated dynamic controller of road vehicle based on the application of the pure position or of the combined position/force control algorithm at the tactical control level was designed. (II) In the second stage, control gains were calculated on the basis of the practical stability test. (III) Finally, to the existing controller architecture, a supplementary neuro-compensator, based on the application of the multilayer neural network structure, was added. It gave an additional quality to the automatic control system - a higher robustness to the system modelling inaccuracies.

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