Design features and research on the neuro-like learning control system of a vehicle

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Abstract—The application features of neuro-like learning control systems of vehicles are considered in this paper. The structure of a fuzzy control system, the description of a system operation are given, and the necessity of design of the control system integrating advantages both fuzzy and neuron systems are substantiated Here we analyzed the operation of well-known hybrid control systems of mobile robots and developed the fuzzy control system of the vehicle. The fuzzy control system of the vehicle has a modular structure. The modules of the fuzzy control system are neuro-fuzzy networks. We used genetic algorithms for training the modules. Research of training algorithms was conducted. Information about the duration of search for optimal parameters of the system modules and accuracy of obtained results is presented. We developed the special application for researches.

Keywords—Hybrid system, learning, motion control, neuro-fuzzy networks, vehicle.

I. Introduction

A vehicle control can be implemented both by convenient control theory methods and by artificial intelligence. The necessity to develop a neuro-like learning vehicle control system is stated here. The feature of membership function parameters optimization is that a fuzzy control system makes it learning.

The model of functions approximation on the basis of an intelligent identification technology is given. The selection of membership function parameters for fuzzy terms providing the minimum difference of the model (theoretical) and experimental (desired) results is carried out using genetic optimization algorithms.

The known neural and fuzzy systems have both advantages and disadvantages. Here we analyzed strengths and weaknesses of such systems on the basis of works, which consider the development of hybrid control systems for mobile robots and other vehicles based on adaptive cruise control systems.

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The neuro-fuzzy inference system (ANFIS), the system of Takagi-Sugeno-Kang (TSK), the adaptive neuro-fuzzy system in the form of a simple neural network (FSNN), and the adaptive fuzzy control system with a defuzzificating neural network are used for the vehicle control. Analysis of the above-listed systems operation results in the uncertainty conditions allows synthesis of the structure of the learning fuzzy vehicle control system.

The vehicle control system presented in this paper consists of three interrelated operating modules: the motion direction control module; the velocity control module; the module of obstacle parameters identification. The modules are three neuro-fuzzy networks (NFN_1, NFN_2, and NFN_3).

The training of the fuzzy control system modules is based on the developed genetic algorithms (GA). The research of the fuzzy control system training based on GA is performed experimentally using a special software application. For objective experiments, we considered the tasks of motion control of autonomous mobile robots along a predetermined path while avoiding obstacles [1], [2].

II. Neuro-like learning vehicle control systems

In a fuzzy set the membership function of an element to the set is not binary (yes / no), and can take any value between 0 and 1 This makes it possible to define the fuzzy concepts "far", "near", "fast", etc. Fuzzy logic allows performing logical operations on such variables and provides the opportunity to develop the knowledge bases and the fuzzy systems, which are capable to store and process inaccurate data [3], [4]. The structure of the fuzzy control system is shown in Fig. 1. The control system can be considered as a learning fuzzy control system. The system receives information from the environment and the control object, analyzes it, and takes into account in the control laws.

Fuzzy information is transmitted from the fuzzification block to the storage of fuzzy control history and to the estimation block of controlled object state, where the transformation of the set of controlled object properties into the system of parameters assessment takes place. The error assessment is carried out in the block of estimation of the controlled object state.

The decision, whether to further optimize system parameters, is made on the basis of the output value $e(t)$ of the block of estimation of the controlled object state. If the value $e(t)$ exceeds admissible values of the system error, the decision to optimize the membership function parameters is made. The feature of the membership function parameters optimization is that the fuzzy control system makes it learning. The model of function approximation on the basis of the intelligent identification technologies [5] is shown in Fig. 2.

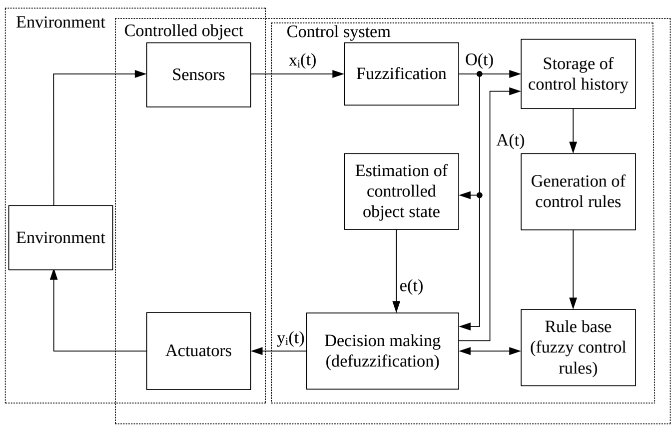


Fig.1 Fuzzy control system

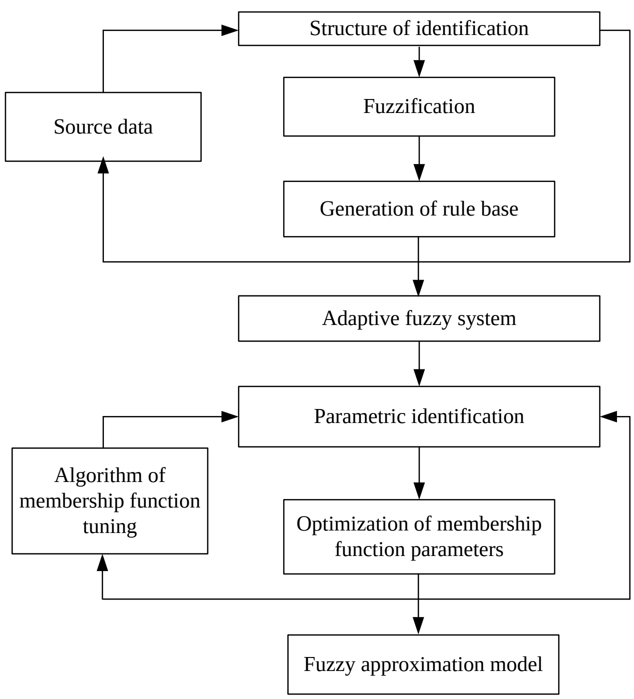


Fig. 2. Development of fuzzy approximation model

Initially, the development of the approximate object model and its rough tuning by development of a knowledge base on the source data are carried out. However, one can not guarantee conformity between the fuzzy inference results and experimental data. So, then fine-tuning, i.e. parametric identification, of the fuzzy model is carried out. Seeking for the membership function parameters of fuzzy terms, providing the minimum difference between the model (theoretical) and experimental (desired) results occurs.

The stage of fine-tuning is a nonlinear optimization problem which is solved using an optimization GA.

The blocks of controlled object history storage, generation of rules, and rule base have different functions, but the control rules in the form of IF ... THEN ... are generated after the storage of controlled object history. The control rules are stored in the rule base. Information from the decision making (defuzzification) block is transmitted to the control history storage block.

Decision about correspondence of the results to reference is made after defuzzification. If the results correspond to a reference (the control error does not exceed the value specified by an expert or it is missing), then the algorithm of the fuzzy learning system stops, and the processing of the next results starts. If the results does not correspond to the reference (the control error exceeds the value specified by the expert), then the decision is made to reconfigure the control system parameters until the desired result will be achieved at the output of the control system.

The opportunity to use the learning fuzzy vehicle control systems is stipulated due to the following [6] – [9]:

- a convenient reasoning regarded as a special case of fuzzy reasoning in fuzzy logic;
- knowledge is interpreted as a set of flexible or fuzzy constraints on the set of fuzzy variables in fuzzy logic;
- an output is considered as a continuation of fuzzy constraints;
- any logic can be fuzzificated.

The fuzzy learning control systems have the following disadvantages [10]:

- training or tuning of membership function parameters leads to the use of certain identification methods, that increases the time of tuning and decision making;
- the lack of a standard approach to fuzzy systems development;
- the use of the fuzzy approach in comparison with a probabilistic approach does not increase the accuracy of calculations.

Based on the advantages of neural and fuzzy systems, analyzing the shortcomings of such systems we made a conclusion about necessity to develop the vehicle control system combining advantages of both fuzzy and neural systems.

III. Design of Adaptive Control Systems

As a learning control system we mean a neuro-fuzzy control system. Neural networks are universal functional approximators. Modification of a neuron model during adaption to fuzzy systems is concerned with the choice of an activation function and the implementation of the sum and product operators. It’s caused by modeling of the sum by any triangular k-norm and by modeling of the product by a triangular norm in fuzzy logic.

Neuro-fuzzy systems (NFS) are implemented on the basis of fuzzy neurons. The fuzzy neural control system is a conventional feed forward neural network, which is based on the multi-layer architecture with the use of AND-, OR-neurons [11].

The use of NFS for the classification of fuzzy input vectors into fuzzy classes is convenient for solving the problem of a complex object control. In such NFS inputs and outputs operate as fuzzy control systems. Training or tuning of NFS parameters can be carried out with the help of learning algorithms of neural networks.

The development of hybrid control systems of mobile robots and vehicles on the basis of adaptive cruise control systems is considered in [12] – [14]. There are several control systems based on neuro-fuzzy logic:

- an adaptive neuro-fuzzy inference system (ANFIS) [15];
- an adaptive neuro-fuzzy system of Takagi-Sugeno-Kang (TSK) [16];
- a neuro-fuzzy system in the form of a simple neural network (NSNN) [16];
- an adaptive fuzzy control system with the neural network for defuzzification (NND) [16], [17].

The TSK and ANFIS systems have the same principle of design, they are developed by the same algorithm, and the ANFIS system is a modified model of TSK. The TSK and ANFIS systems are used in practice more than the control systems with a neural network for defuzzification and the fuzzy systems in the form of a simple neural network.

However, the process of decision-making in the TSK and ANFIS systems is performed using the traditional methods of defuzzification. It is a disadvantage for the vehicle motion direction control systems. To overcome this disadvantage, the fuzzy control systems in the form of a simple neural network were proposed in [16], [17]. Table I shows the main results of the before mentioned hybrid systems [18] and the adaptive fuzzy control systems operation under uncertainty [19].

Table I

Control system	TSK	ANFIS	NSNN	NND
Allowable deviation of vehicle direction (0.5%)	1^o	1^o	1^o	1^o
Average number of trials (iterations)	259	205	146	139
Maximum number of trials (iterations)	400	350	182	180
Minimum number of trials (iterations)	180	163	99	96
Number of trials	50	50	50	50

According to the results of the control system research, NND has the best results in the control of motion direction, and the TSK system has the worst results at the given allowable tolerance. To control the velocity and distance, it is better to use the NSNN systems because they do not require a complex structure like TSK and ANFIS. Tables II and III show the main results of the operation of the before mentioned velocity and distance hybrid control systems.

The NSNN fuzzy system in the form of a simple neural network has almost the same results as compared to ANFIS in controlling the motion direction and the best results in comparison with the TSK and NND systems.

Table II

Control system	TSK	ANFIS	NSNN	NND
Allowable deviation of vehicle direction (0.5%)	0.5 м/с	0.5 м/с	0.5 м/с	0.5 м/с
Average number of trials (iterations)	68	50	50	87
Maximum number of trials (iterations)	110	93	86	135
Minimum number of trials (iterations)	45	30	28	52
Number of trials	50	50	50	50

Table III

Control system	TSK	ANFIS	NSNN	NND
Allowable deviation of vehicle direction (0,5%)	5 м	5 м	5 м	5 м
Average number of trials (iterations)	59	52	51	83
Maximum number of trials (iterations)	103	90	90	126
Minimum number of trials (iterations)	42	34	31	48
Number of trials	50	50	50	50

Based on the analysis of the fuzzy vehicle control systems one could state that NND can be used as a direction control module NFN_1, NSNN can be used for the velocity control NFN_2 and for the control NFN_3 of the vehicle distance from an obstacle [20]. The structure of such system is shown in Fig. 3.

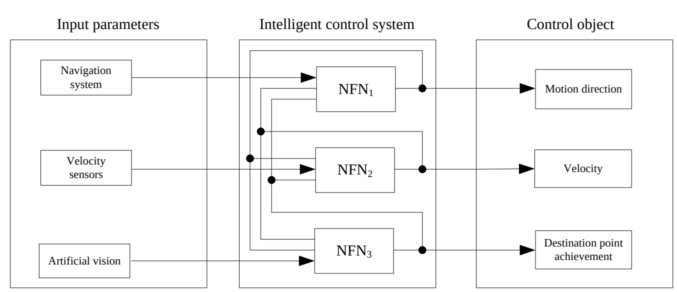


Fig. 3. Structure of fuzzy learning vehicle control system

The individual modules of the fuzzy control system are interconnected consequently and receive information simultaneously. They are connected by the feedback providing all information about the state of the controlled object for a decision making with taking into account all the parameters of the external and internal environment. The feature of the developed system is a choice of the training algorithm which determines the duration of decision making with minimal error and standard deviation.

IV. EXPERIMENTAL SOFTWARE APPLICATION

For research purposes NeuroAndFuzzy software system was created by means of the high-level language C# in the programming environment Microsoft Visual Studio. The structure of NeuroAndFuzzy system is presented in Fig. 4.

The software application is composed of four blocks: the block of NFN $_{1,2,3}$ parameters creation and correction; the block of training algorithms launching; the block of control system tuning; the block of results analyse and issue. The external block of parameters estimation is the interface that allows connecting the external procedures for estimation of the control system parameters and the parameters of training algorithms. The parameters are formed as a result of interaction between the external block and a user.

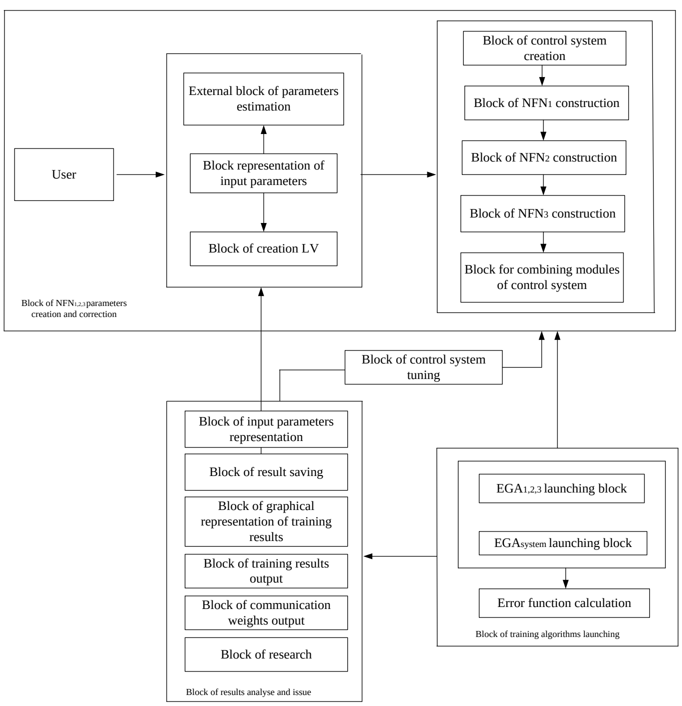


Fig. 4. Structure of NeuroAndFuzzy dataware

The block of NFN $_1$ construction is the control system module for the vehicle motion direction control. In this block the construction of fuzzy rules and the tuning of fuzzy inference defuzzification algorithm is carried out using a learning neural network. The block of NFN $_2$ construction is the module for the vehicle velocity control. In this block the construction of fuzzy rules and the tuning of inference defuzzification algorithm takes place on the basis of the centroid method. The block of NFN $_3$ construction is the module classifying obstacles on a vehicle path. In this block the construction of fuzzy rules and the tuning of inference defuzzification algorithm takes place also on the basis of the centroid method.

The block for training algorithms launching is assigned to implement the NFN training procedure with a learning sample formed by the user. I.e. the user inputs the parameters of motion paths x_1, x_2, x_3, …, x_n with information about obstacles. The user selects training method: whether to train the system by modules or in general. For the training by modules three individual training algorithms for each module were developed and described in $EGA_{1,2,3}$ launching block. $EGA_{1,2,3}$ block is the subsystem for individual launching of each module. EGA_{system} block is the subsystem of launching training algorithm for the control system in general.

The block for analyse and issue of results is assigned to gather information about the training process, the control system operation, and the system modules. Experiments with given parameters are carried out in the research block. The weights issue block allows visualisation the intermediary and final values of weight coefficients from each module and from the whole system.

The training results block visualizes information about the intermediary and final control values formed by the individual modules and the whole control system at each training step. The error output block visualizes the intermediary and final values of the objective function of the whole control system and each module.

The block of graphical representation of results shows the training results: the error, the number of iterations, the input and output signals of the modules and the control system.

The application is launched by the NeuroAndFuzzy.exe executable file. In Fig. 5 the main form of the modeling program is shown. The number of fuzzy variables can be increased, decreased or edited in the dialogue window.

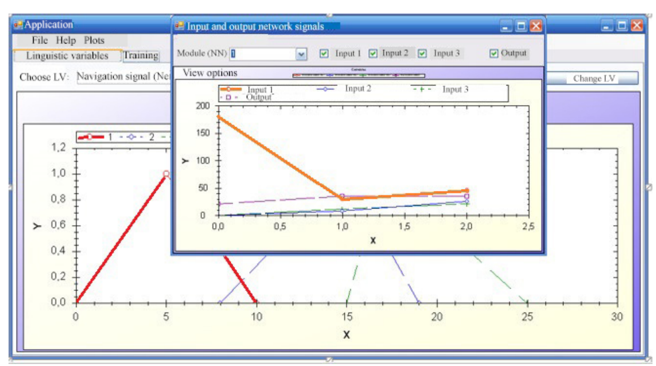


Fig. 5. Main form of NeuroAndFuzzy software application

We show the window where the user can input motion path description in Fig. 6. The windows displaying the NFN training results in a numerical and graphical form are also shown in Fig. 6.

V. EXPERIMENTAL DESIGN

The schedule of experiments was developed for the research purposes. The set of experiments includes three experiments. For the first experiment the input parameters and the desired values (control actions) of the vehicle control system outputs are shown in the table IV, where φ is the direction, V is the velocity and L is the distance to an obstacle. The schedule of the second experiment is shown in table V. The schedule of the third experiment is shown in table VI.

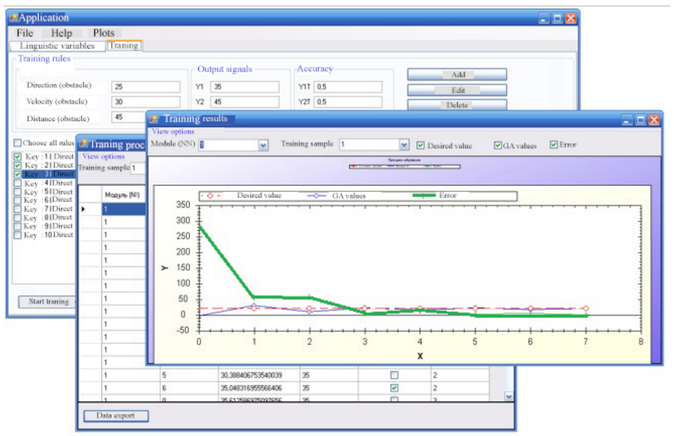


Fig. 6. Input of motion path description and training results

Table IV

Input and desired output values of vehicle control system in the first experiment

Input parameters			Assumed output parameters		
φ [deg]	V [km/h]	L [m]	φ_v [deg]	V_v [km/h]	L_v [m]
10	20	40	20	20	40
15	30	60	25	25	50
20	40	80	35	25	50
25	50	100	10	40	80
30	60	120	5	45	90
35	70	140	5	50	110
40	80	160	10	70	140
45	90	180	5	80	160
5	100	200	5	85	200
10	110	165	5	80	120

VI. EXPERIMENTAL RESULTS

We launched the modeling process 40 times for each of 10 test examples. Each launch was independent. The output parameters with relation to desired values were determined for data at the system input (see table VII). These output parameters are the results of the control system training.

The average iteration number for the first module is equal to 7, for the second module it is equal to 10 and for the third module it is equal to 15 iterations. Results of the first module training for the vehicle steering control is shown in Fig. 7.

We implemented training of the NFN $_2$ and the NFN $_3$ module in a similar way.

The values of squared deviation of made decision from the desired value are shown in table VIII [21] – [24].

Table V

Input and desired output values of vehicle control system in the second experiment

Input parameters			Assumed output parameters		
φ [deg]	V [km/h]	L [m]	φ_v [deg]	V_v [km/h]	L_v [m]
15	120	180	10	90	135
20	20	30	25	20	35
25	30	45	45	20	35
30	40	60	35	30	45
35	50	75	25	30	45
40	60	90	15	40	65
45	70	115	10	60	75
0	80	120	10	65	80
5	90	135	5	80	95
10	100	150	5	90	135

Table VI

Input and desired output values of vehicle control system in the third experiment

Input parameters			Assumed output parameters		
φ [deg]	V [km/h]	L [m]	φ_v [deg]	V_v [km/h]	L_v [m]
10	100	150	5	85	50
15	110	110	5	85	50
20	120	120	2	90	45
25	20	20	45	20	45
30	30	30	45	20	60
35	40	40	35	20	65
40	50	50	35	30	75
45	60	60	25	40	85
0	70	70	15	60	85
5	80	80	15	80	90

Table VII

Desired (Des) and output (Out) parameters of system								
φ [degree]			V [km/h]			L [m]		
It. numb.	Des	Out	It. numb.	Des	Out.	It. numb.	Des	Out
5	20	19.8	20	20	0	7	40	0
4	25	24.9	16	25	24.9	40	50	49.7
3	35	34.9	9	25	25.2	4	50	50.3
13	10	10.1	6	40	39.9	10	80	79.8
5	5	4.9	13	45	44.7	16	90	90.3
10	5	5	8	50	49.8	20	100	98.6
1	10	10.1	7	70	79.8	10	140	140
9	5	5.0	6	80	80.2	25	160	160
9	5	0	9	85	84.8	8	200	199
10	5	0	8	80	80.1	8	80	79.9

Desired value and value at module output

Average training error

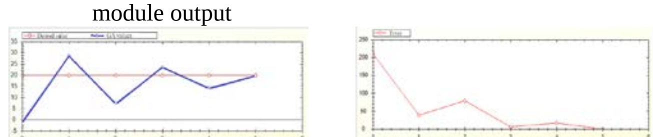
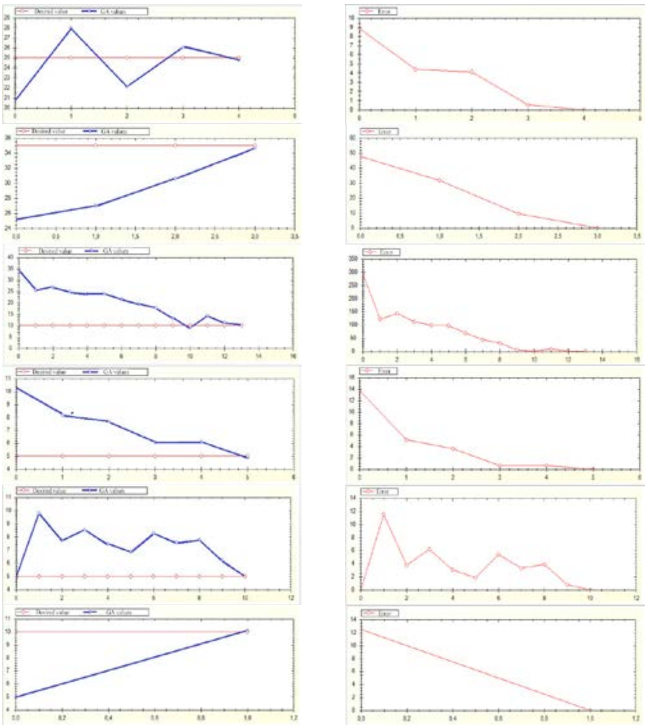


Fig. 7. Training process of the first module



Ending of Fig. 7

Table VIII

Example	1	2	3	4	5
$E_1(x)$	0.014	0.01	0.004	0.003	0.005
$E_2(x)$	0	0.005	0.01	0.002	0.045
$E_3(x)$	0	0.09	0.05	0.020	0.045
Example	6	7	8	9	10
$E_1(x)$	0	0.003	0.001	0	0
$E_2(x)$	0.028	0.020	0.014	0.0288	0.008
$E_3(x)$	0.080	0.088	0.057	0.3612	0.008

We show the process of changes in the mean square error of the control system per one motion path sector in Fig. 8. The error is within the interval from 0 to 14×10^{-3} for the first module, the error is within the interval from 0 to 45×10^{-3} for the second module, and the error is within the interval from 0 to 0.3612 for the third module.

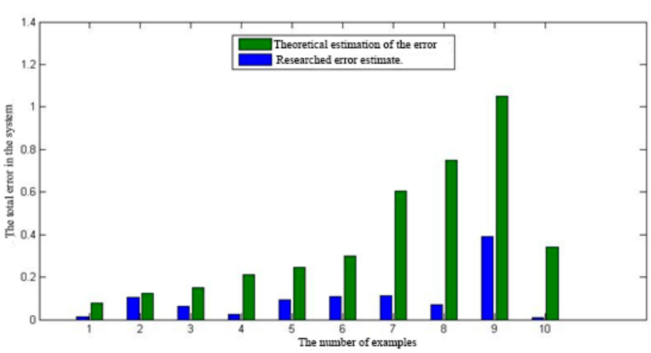


Fig. 8. The mean square error of the control system per one motion path sector

Theoretical estimation of the error is the given error limitations, which are 0.5 % of the squared sum of system desired values.

We carried out the research on system operation on the second motion path sector. For the research the following input parameters were set: the motion direction, the velocity, the distance from obstacle to the vehicle, and estimated values of the output parameters describing the vehicle relative to the obstacle. We showed the output parameters with relation to the desired values for the data at the system input in table IX.

The average iteration number for the first module is equal to 9, for the second module it's equal to 12 and for the third module it's equal to 10 iterations. Our modelling program application allows observing the training process of each system module.

Table IX

Desired (Des) and output (Out) parameters of system								
φ [degree]			V [km/h]			L [m]		
It. numb.	Des	Out	It. numb.	Des	Out.	It. numb.	Des	Out
15	10	10	31	90	89.3	17	135	134
8	25	24.9	7	20	20	8	35	35
2	45	44.7	8	20	30	2	35	34.9
7	35	35.1	7	30	29.9	4	45	45
12	25	24.1	5	30	30	12	45	44.9
6	15	14.3	5	40	40	12	65	65
7	10	10.3	4	60	60.1	3	75	75
6	10	9.85	12	65	60	13	80	80
16	5	5	30	80	79.9	8	95	94.8
7	5	5.23	7	90	89.1	17	135	134

Changing of the mean square error of the control system per one motion path sector is shown in Fig. 9. The error is within the interval from 0 to 0.245 for the first module, the error is within the interval from 0 to 0.378 for the second module, and the error is within the interval from 0 to 0.016 for the third module [19].

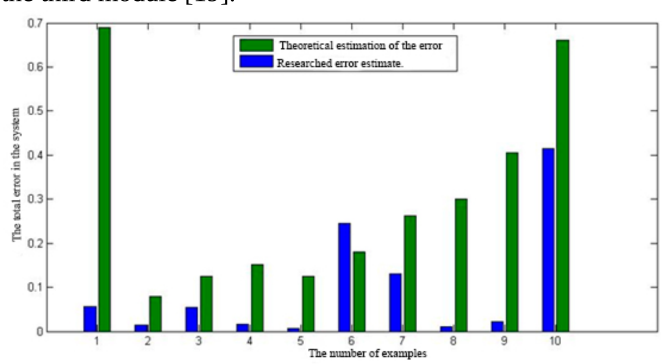


Fig. 9. The mean square error of the control system per one motion path sector

We gave the experimental results of the adaptive control system operation on the third motion path sector in table X. The average iteration number is equal to 7 for the first module, it's equal to 10 for the second module and it's equal to 10 iterations for the third module.

We showed the changing of the mean square error of the control system per one motion path sector in Fig. 10. The error is within the interval from 0 to 0.016 for the first module, the error is within the interval from 0 to 0.01 for the second module, and the error is within the interval from 0 to 0.02 for the third module.

Table X

Desired (Des) and output (Out) parameters of system								
φ [degree]			V [km/h]			L [m]		
It. numb.	Des	Out	It. numb.	Des	Out.	It. numb.	Des	Out
12	5	5.02	8	85	85	8	50	50
5	5	5	25	85	85	11	50	50.6
4	2	1.93	12	90	90	2	45	45.2
11	45	45	16	20	20	4	45	45
7	45	45.1	3	20	19.8	10	60	60
5	35	34.8	2	20	19	14	65	65
4	35	34.9	3	30	30.2	15	75	75
13	25	24.9	13	40	40	11	85	85
4	15	15.1	13	60	60	22	85	85
9	15	14.9	9	80	80	6	90	90.1

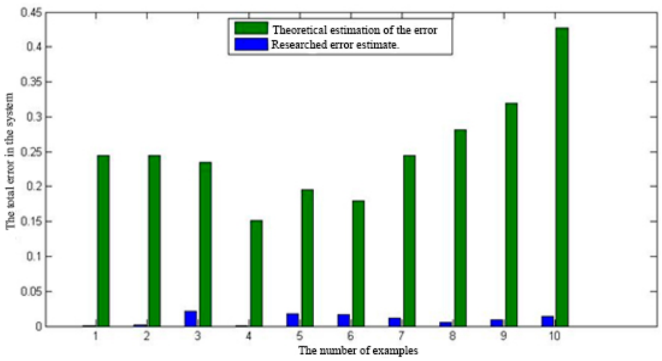


Fig. 10. The mean square error of the control system per one motion path sector

VII. CONCLUSIONS

We developed NeuroAndFuzzy program as the information support system. This information support system allows researching the training algorithms for the vehicle control system on the example of autonomous mobile robot.

We carried out some experiments and processed statistical data. The results of the system and training GA operation were received in graphical form.

The developed application can be used for design and research on the vehicle control by learning control systems with genetic tuning. The research has revealed that the intelligent adaptive learning fuzzy control system achieves the desired results with the permissible tolerance of not more than 0.5 %.

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