Design of the neuro-like learning control system for a vehicle

VALERY FINAEV ISKANDAR KOBERSY DENIS BELOGLAZOV
IGOR SHAPOVALOV EVGENY KOSENKO VICTOR SOLOVIEV
Department Automatic control systems
Southern Federal University
Rostov-on-Don, 344006, Bolshaya Sadovaya Str., 105 / 42
RUSSIA
finaev_val_iv@tgn.sfedu.ru http://sau.tti.sfedu.ru/en

Abstract: - The paper is devoted to design of the neuro-like learning control system for a vehicle or an autonomous mobile robot with a use of artificial neuro-fuzzy networks advantages. Operation of the vehicle control system is aimed to solve the obstacle avoidance task in uncertainty conditions. We described the advantages of artificial intelligence methods in the tasks of control systems design using neuro-fuzzy approach. The structure of learning control system consisting of three modules (motion direction control module; velocity control module; obstacle identification module) is given. The stages of each module design are defined and the structures of neuro-fuzzy networks for the implementation of modules are chosen. We presented description of the operation algorithms of the motion direction control module, the velocity control module, the identification module for the obstacles on vehicle path, and the structure of neuro-like learning control system.

Key-Words: - control, uncertainty, training, neuro-fuzzy networks, vehicle, autonomous mobile robot.

1 Introduction

The tasks of effective control of technical objects and systems in parametric uncertainty conditions are topic in different domains, including robotics. The quality of such tasks solution depends on controlled object complexity and used data processing and control algorithms. The problem of the vehicle motion to a goal with the obstacle avoidance is one of the most important tasks in robotics [1 - 6].

Uncertainty is described by instability of vehicle parameters, incompleteness or lack of information about disturbances. That sets conditions for the lack of exact object model for the control tasks and impedes effective control.

The problem of the vehicle control can be solved by different methods, both by methods of the classical control theory, position-trajectory control [7, 8] and by using of hybrid controllers including neuro-like learning control systems. There is a strong interest in further researching of such systems, in alternative solutions with the use of artificial intelligence methodology.

In this paper we propose using of the artificial neuro-fuzzy networks (NFNs) of modified architecture [9, 10] to solve the problem of the vehicle control. The task of the vehicle (autonomous mobile robot) control system design can be represented in the form of a specific sequence of subtasks (decomposition of the common task) [11 - 15]: the creation of idea about the environment state through transmitted and received sensor signals; the identification of situations based on the sensor data about the environment state; the decision making for the vehicle velocity and motion direction control.

As a result of the proposed approach to the vehicle control, we developed the model of neuro-like control system, which should be regarded as a contribution to the development of topic trends in the modern control theory.

Application of the fuzzy-set theory and fuzzy logic allows operation of the neuro-like control system with incomplete data about the state of the control object and its environment [13 - 16].

2 Artificial intelligence in control systems

If motion is accompanied by stochastic changes of parameters, distribution functions of stochastic processes are known, and quality criteria can be explicitly defined, the stochastic problem of the vehicle control has no difference from deterministic. Dynamic programming is equally applicable for both deterministic and stochastic problems. An example is the well-known stochastic problem of Wiener-Kolmogorov filtering: synthesis of a linear system, which is optimal in terms of the minimum mean-square error; analytical design of the controller, i.e. synthesis of linear system, which is optimal by the minimum integral square error.

If the distribution function is a priori unknown, adaptive approach is necessary, that would solve the control problem without prior determination of the probability characteristics, when a priori information is insufficient [17]. The adaptation can be implemented as a control system training process during operation of the object. The stages of the adaptive control system development are shown in fig. 1. A similar block diagram describes the design of control systems using artificial intelligence (neural network systems).

There are a lot of approaches to the design of adaptive control systems. One of the classic models is the model using feedback with real-time controlled parameters, for example Astrom's self-tuning controller [10, 18].

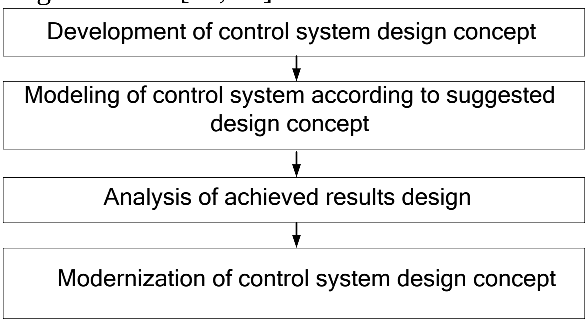

Fig. 1. Stages of adaptive control system development

Adaptive control systems with reference model are designed so that the output signal of controlled model is corresponded to the output signal of a predetermined model, which has the desired characteristics. Y. Z. Zypkin [19] proposed an approach to the adaptation problems solution, which is based on probabilistic iterative methods of the objective functional optimization. These iterative methods are used to solve technical problems. "Algorithmic" approach to the synthesis of control algorithms in real time initiated a lot of works on the theory of adaptive systems using probabilistic iterative algorithms [20]. An iterative adaptation process is described in the works of R. Bellman [21].

Control systems using artificial neural networks are one of the possible alternatives to the classical control methods.

Now architectures of intelligent control systems are well developed and widely applied [20-23]. The purpose of the intelligent (fuzzy, neural, neuro-fuzzy) controller is calculation of the sufficient signal to control the dynamics of the object state. Organization of the object state control and implementation of the intelligent controller depend on chosen learning algorithm and used control structure.

3 Neuro-like learning control system for a vehicle

The structure of learning control system is given in fig. 2. The intelligent control system consists of three modules: the module of motion direction control was implemented on the basis of neuro-fuzzy network 1 (NFN_1); the velocity control was implemented on the basis of NFN_2; the module of obstacles identification based on the distance between obstacles and the vehicle was implemented by NFS_3.

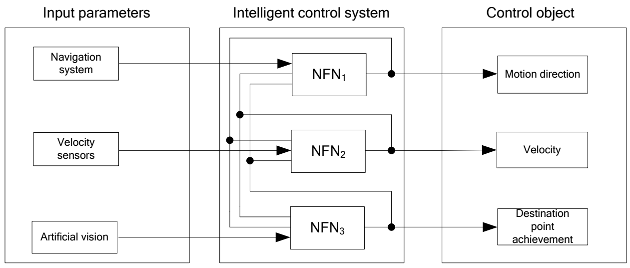

Fig. 2. Structure of hybrid vehicle control system

The overall structure of adaptive neuro-fuzzy control system is similar to a simple feed-forward neural network (FFNN) (individual neurons are the neuro-fuzzy networks). Distinctive feature of each from above listed neuro-fuzzy networks (NFN_1, NFN_2, NFN_3) is the use of artificial neural networks as a defuzzification subsystem in their structure.

The design of system modules consists of the following stages: selection of module architecture; development of module structure; development of module training algorithm; development of hybrid system training algorithms. The process of parameters adaptation in individual modules and in the control system as a whole depends on the algorithms determining the quality of training.

3.1 Motion direction control

Information about the vehicle position in space is received from sensor system. Data from the navigation system, the modules of velocity (NFN_2) and obstacle identification (NFN_3) is received at the input of motion direction control module (NFN_1). The NFN_1 with three inputs and one output allows control only “direction” parameter.

The algorithm of NFN_1 design consists of the following steps.

Step 1. In order to solve the vehicle motion direction control task, it is necessary to define input and output parameters of the module in the form of linguistic variables and their term sets. The triangular form of membership functions is used as a basic form of fuzzy variable term sets, because this versatile form is the most commonly used by developers [23, 24].

The first linguistic variable T_{11} defines the obstacle position in space relative to the vehicle and has the term set ={front area: in a center, far from center - near to right area, very far from center – very close to right area, far from center – near to left area, very far from center – very close to left sight, close to center, very close to center; left area: in a center, far from center – close to front area, very far from center – very close to front area, far from center – close to back area, very far from center – very close to back area, close to center, very close to center; right area: in a center, far from center – close to front area, very far from center – very close to front area, far from center – close to back area, very far from center – very close to back area, close to center, very close to center; back area: in a center, far from center – closer to right area , very far from center – very close to right area, far from center – closer to left area, very far from center – very close to left area, close to center, very close to center}. The term set $T_{11} = \{t_1^1, t_2^1, t_3^1, ..., t_{26}^1\}$ includes twenty six fuzzy variables defining the linguistic variable "obstacle position".

The distribution of environment areas for the definition of fuzzy variables of the linguistic variable T_{11} is shown in fig. 3.

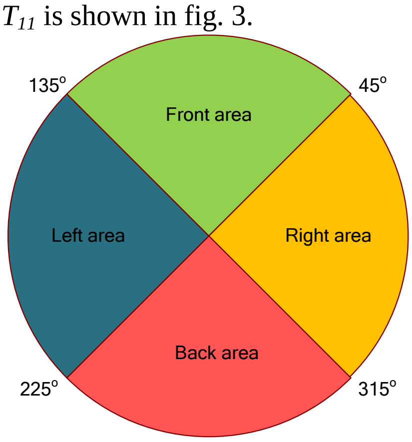

Fig. 3. The separation of external space

The measured vehicle velocity value T_{12} enters to the second input of NFN$_1$ and is defined by the fuzzy variables from the term set $T_{12} = \{t_1^2, t_2^2, t_3^2, ..., t_5^2\}$ ={high velocity; very high velocity; low velocity; very low velocity; stop}.

The input linguistic variable T_{13} describes the distance from the vehicle to the destination point. This linguistic variable has the term set $T_{13} = \{t_1^3, t_2^3, t_3^3, ..., t_7^3\}$ ={very far from destination; far from destination; middle of route; not very far from destination; not very close to destination; very close to destination; destination}. The term set T_{13} includes seven fuzzy variables.

Step 2. At this step the parameters of membership functions are defined. The number of fuzzy neurons in the first layer of NFN$_1$ is calculated. The number L_1 of fuzzy neurons in the first layer of NFN$_1$ is equal to the sum of cardinal numbers of the input linguistic variables term set: L_1=T_{11}+T_{12}+T_{13}=38.

The membership function of fuzzy neurons is described by expression

$$\mu_{A_i^k} = \begin{cases} 0, & x \in]-\infty, a_i^k], \\ \dfrac{x_i - a_i^k}{b_i^k - a_i^k}, & x \in [a_i^k, b_i^k], \\ \dfrac{x_i - c_i^k}{b_i^k - c_i^k}, & x \in [b_i^k, c_i^k], \\ 0, & x \in [c_i^k, +\infty[. \end{cases} \quad (1)$$

The following parameters define the shape of membership function: a_i^k, b_i^k and c_i^k, where b_i^k is the center; a_i^k and c_i^k are the boundaries of membership function. $T_{11} = \{t_1^1, t_2^1, t_3^1, ..., t_{26}^1\}$

Step 3. The number of fuzzy neurons in the second layer of NFN$_1$ is calculated. The output block defining the degree of fulfillment of the fuzzy rules conditions is implemented in the second layer of NFN$_1$

$$\tau_k = \min_{i=1,...,n} \{\mu_{A_i^k}(\bar{x}_i)\} \quad (2)$$

The number of elements in the second layer is equal to the number of fuzzy rules: L_2=N_1×N_2×N_3. In our case L_2=5Ч9Ч24=1080.

Step 4. The quantity of fuzzy sets defines the number of elements in the third layer by formula

$$L_3 = \frac{L_2}{M} \quad (3)$$

As the number of rules in the second layer is L_2, the number of fuzzy neurons is L_3=360.

All layers have weights of connections. These weights are equal to 0 when there is no connection or to 1 when there is connection. Such approach is convenient for connection of the third and the second layer according to a principle "each with each". If the third layer contains r elements, we can write

$$y_r = \max_{i=1,...,n} \{\tau_k, w_{kr}\}, \quad (4)$$

where r1,…..,m is the number of element in the third layer, 1,…..,N is the rule number, w_{kr} are the weights of connections between element k in the second layer and element r in the third layer.

In the NFN_1 each element of the second layer is connected to only one element of the third layer. The same condition cannot have several conclusions in the base of fuzzy rules, but the same conclusion can be drawn based on different conditions. The second, the third and the fourth steps are the solution of fuzzification and fuzzy rule base development tasks.

Fig. 4 shows the structure of the process of fuzzy rules conclusions goodness calculation based on conditions.

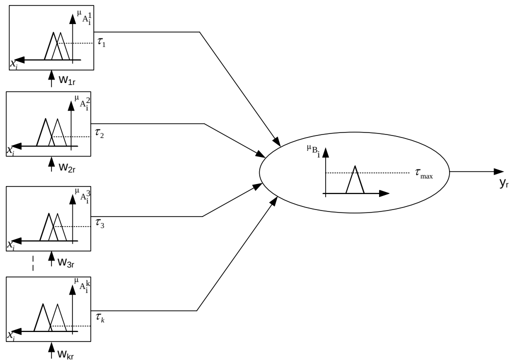

Fig. 4. The structure of goodness calculation

Step 5. Fuzzification task. We face the problem of the vehicle rotational displacement relative to a current motion trajectory in the task of the motion direction control.

We use the rotational displacement with the range of value (-a, a) as an output variable. If we have the membership functions «-*a*, 0, 0, 0, 0, *a*» as a result of output block operation, we would expect the numerical value of control signal close to *a* or to -a^o. The majority of fuzzification methods cannot handle this condition and give the angle value equal to 0^o.

To solve the problem of defuzzification block implementation [25], we use neural networks, which are capable to implement different mathematical dependencies.

The input layer of neural network from the fuzzification block is connected to the last, the third layer of previously mentioned module. Let's denote weight vectors of these *i*-th neurons connection as $W_i^{(1)}$. The number of elements in this layer is defined by the number of previous layer fuzzy rules. Values from the first layer of defuzzification neural network enter to inputs of the second hidden layer of defuzzification neural network.

For the calculation of the neurons number in the hidden layer the next rules can be used [26]: the number of hidden neurons should be in a range of the input and output layer size; the number of hidden neurons should be 2/3 of the input and output layer size; the number of hidden neurons should be twice less than the output layer size. We chose the number of hidden neurons equal to 180.

We denote the connection between input and hidden layers as $W_i^{(2)}$. The neurons number of output (last) layer is equal to 1. This layer produces control signal which is defuzzificated fuzzy conclusions.

The NFN_1 module training consists in tuning of parameters of the neural network responsible for control signal defuzzification. The complete structure of NFN_1 is shown in fig. 5.

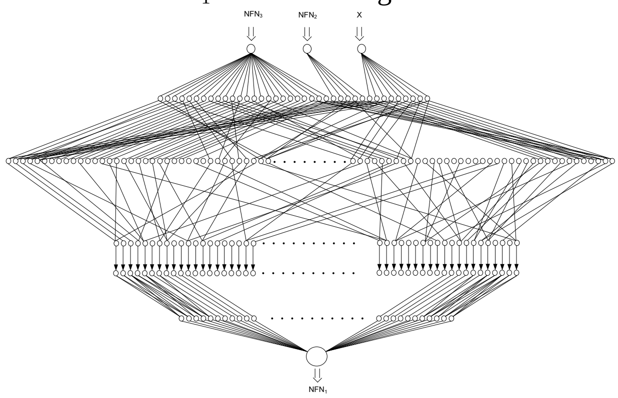

Fig. 5. Complete structure of NFN_1

The NFN consists in a definition of degree of input data compliance with each inference rule. Different learning algorithms are used in order to adapt this network to given task. These algorithms define the difference between the given (reference) value and the real value of output signal.

3.2 Velocity control

The second stage of the learning vehicle control system design is related to the development of the velocity control module. The fuzzy control system is described by the membership function of fuzzy set B_k

$$\mu_{\bar{B}_k}(\bar{y}_k) = \prod_{i=1}^{n} \exp\left[-\left(\frac{\bar{x}_i - \bar{x}_i^k}{\sigma_j^k}\right)^2\right] \quad (5)$$

The membership function describing defuzzification operation has a form

$$\bar{y} = \frac{\sum_{k=1}^{N} \bar{y}^k \exp\left(h^k\left(\sum_{i=1}^{n} \bar{x}_i \bar{x}_i^k - 1\right)\right)}{\sum_{k=1}^{N} \exp\left(h^k\left(\sum_{i=1}^{n} \bar{x}_i \bar{x}_i^k - 1\right)\right)} \quad (6)$$

The structure shown in fig. 6 is a modification of neuro-fuzzy control system with an artificial neural network as a defuzzificator.

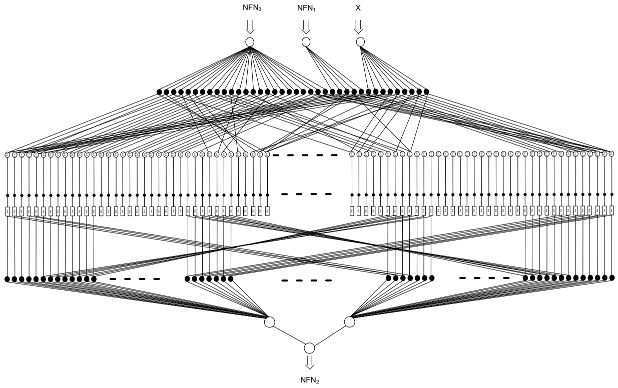

Fig. 6. Complete structure of NFN_2

The inputs of NFN_2 are the following: X_2 is the signal from sensors of distance to obstacle; Y_1 is the output of NFN_1 controlling the vehicle direction; Y_3 is the output of NFN_3 classifying obstacles based on their distance to the vehicle. The output of NFN_2 module is the velocity control signal Y_2.

Classical neurons with a weighted sum of inputs and an exponential activation function form the first layer. Each neuron of the first layer corresponds to one fuzzy rule.

The distance from obstacle to the vehicle, the vehicle direction and the obstacle identifier data are defined by linguistic variables.

The first input linguistic variable “distance between vehicle and obstacle” T_{21} has the term set $T_{21} = \{t_1^2, t_2^2, t_3^2, ..., t_7^2\}$ ={very large distance; large distance; medium distance; not very large distance; not very small distance; very small distance; almost collision}.

The second linguistic variable «vehicle direction» T_{22} has term set $T_{22} = \{t_1^2, t_2^2, t_3^2, ..., t_7^2\}$ ={to the left; sharply to the left; smoothly to the left; keep direct course; to the right; sharply to the right; smoothly to the right}.

The third linguistic variable «type of obstacle» T_{23} has the term set $T_{23} = \{t_1^3, t_2^3, t_3^3, ..., t_5^3\}$ ={high degree of need to change the direction of motion; very high degree of need to change the direction of motion; low degree of need to change the direction of motion; change the direction of motion; stop}.

The size of fuzzy rule base of the velocity control module is defined by expression $L_1=T_{21}$ЧT_{22}Ч$T_{23}=245$ on the basis of size of linguistic variable term set.

The second and the third layers of neural network perform the defuzzification operation. These layers consist of neurons with a linear activation function.

Weights of the first neuron of the second layer are interpreted as centers of fuzzy set membership functions and they are modified by the training process. Weights of the second neuron are the constants equal to 1.

The last layer of the NFN_2 module contains one neuron that outputs the final value of vehicle velocity correction.

3.3 Obstacle identification

The third stage of the vehicle control system design consists in the obstacle identification module development on the basis of NFN. We suppose the NFN_3 having the same structure as the NFN_2. The inputs of NFN_3 are the following parameters: X_3 is the signal from navigation systems determining distance between obstacles and the vehicle; Y_1 is the output of NFN_1 controlling the vehicle direction; Y_2 is the output of NFN_2 controlling the vehicle velocity. The output Y_3 of NFN_3 is the obstacle type defined on the basis of distance to the vehicle.

The input variables of NFN_3 are defined by the following linguistic variables. The first linguistic variable T_{31} «distance from vehicle to obstacle» has the term set $T_{31} = \{t_1^1, t_2^1, t_3^1, ..., t_7^1\}$ ={in central area; far from center, near to vehicle; very far from center, very close to vehicle; close to center, far from vehicle; very close to center, very far from vehicle; close to area borders; very close to area borders}.

The second linguistic variable T_{32} «vehicle direction» has the term set $T_{32} = \{t_1^2, t_2^2, t_3^2, ..., t_7^2\}$ ={to the left; sharply to the left; smoothly to the left; keep straight course; to the right; sharply to the left; smoothly to the left}.

The third linguistic variable T_{33} «vehicle velocity» has the term set $T_{33} = \{t_1^3, t_2^3, t_3^3, ..., t_5^3\}$ ={very high velocity; high velocity; middle velocity; low velocity; very low velocity }.

The first layer of fuzzy module NFN_3 consists of the $L_1=T_{31}$ЧT_{32}Ч$T_{33}=245$ fuzzy rules. The second module consists of $L_2=2$ neurons. Parameters of the NFN_3 are calculated as in NFN_2 module. The training algorithm of the vehicle state control modules consist in a reduction of previous weight by the value of error derivative. This process continues while the output error of the system is greater than a priori given minimal value.

3.4 Neuro-like learning control system

The developed modules NFN_1, NFN_2, NFN_3 are the basis of the control system shown in fig. 7.

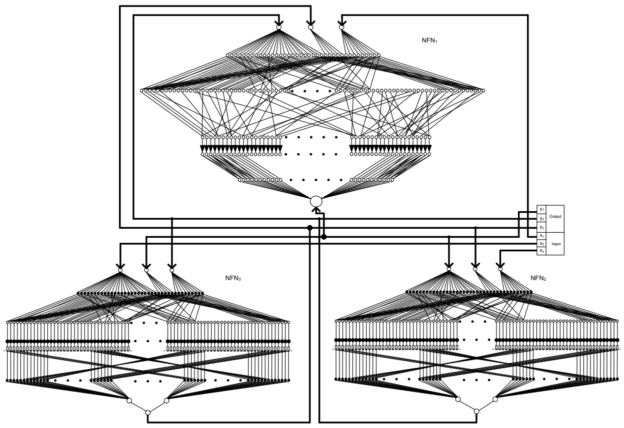

Fig. 7. Structure of neuro-like learning vehicle control system.

The data from the sensors about the environment is transmitted to the control system input. Further the data is distributed between the control modules (NFN_1, NFN_2, NFN_3) of the learning control system.

Operation of the first module NFN_1 begins from a fuzzification of the vehicle velocity values and parameters of obstacles. The forming of output signal on the basis of fuzzy rules and fuzzy inference takes place on the next step. Then defuzzification is performed using the neural network consisting of three layers. Control signals correcting the vehicle motion direction are formed at the output of neural network.

The obtained value comes to the input of the second control module. Information about obstacles and the vehicle position in space also come to the input of NFN_2.

The input data is fuzzificated and processed on the basis of fuzzy rules. The fuzzy output of module is defuzzificated, and the vehicle velocity control signals are formed at the output of NFN_3 module.

The data received from NFN_1 and NFN_2 is transmitted to the input of the third module. Information about the obstacle location comes to the third input of NFN_3. The module output and defuzzification are provided after the fuzzification procedure on the base of fuzzy rules. The information received on the output of NFN_3 is transmitted to inputs of NFN_1 and NFN_2.

The neuro-like learning system would operate while sensor information about the parameters of environment, vehicle and obstacles is received or until the desired location is achieved.

4 Conclusion

To solve the autonomous mobile robot control problem in the data incompleteness conditions, the structure of the adaptive hybrid control system was proposed. This structure is similar to feed-forward neural networks by the operation principles. We implemented the operational modules of the adaptive hybrid control system on the basis of neuro-fuzzy networks.

We developed the algorithms of modules operation for the control of motion direction, velocity and the obstacle identification. Also we designed the structures of modules in the form of NFNs. The input parameters as linguistic and fuzzy variables were defined.

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