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DEVELOPMENT OF AN AUTOMOBILE ROBOT SYSTEM MODEL BASED ON SOFT COMPUTING IN AN UNSTEADY ENVIRONMENT

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ABSTRACT

This publication is dedicated to development of a simulation model of controller for an automobile robot as part of a convoy, based on soft computing. During the work a reference adaptive control model was developed, the rules of constructing the fuzzy rule base were described, an optimizer of the number of features of fuzzy linguistic variables based on soft computing was proposed. The application of fuzzy model rule base allows controlling the assigned parameters of an automobile robot under uncertainty and rapidly changing external environment (loss of the front automobile robot, automobile robot system failure, road obstacles). A system of automobile robot modelling was conducted, the efficiency of the fuzzy rule base using genetic algorithms to control the direction and distance was shown.

Keywords: driving, automobile robot controller, soft computing, fuzzy regulator, fuzzy rules base, genetic algorithms, mathematical modeling, control without human, reference adaptive control.

INTRODUCTION

Motor vehicles with remote and autonomous control for cars, "in-plant" and trucks, agricultural machinery and military vehicle are being developed since the 1980s [1, 2, 3]. Most of the work is being done in the United States, Germany, Japan, Italy, China, Britain, France, South Korea, in such companies as "General Motors", "Ford", "Mercedes Benz", Volkswagen, "Audi", BMW, "Volvo" "Saddilac" and others. At the moment, the world leader in this area is the United States, in particular, Darpa [6, 7].

Current challenges are related to the establishment of management systems. Conventional control systems behave badly under changing environments, and do not consider such problems as instability of road markings and the poor quality of the road surface. Also the usual methods cope badly in a non-stationary environment. In order to obtain a smooth trajectory that is close to optimal, as well as for the organization of the native management of a complex technical system, the fuzzy logic could be used. On the one hand, the precondition for the application of fuzzy control systems is the uncertainty associated with both the lack of information and the complexity of the system and impossibility and impracticality of its description by conventional methods and, on the other hand, the existence of the object, the necessary control actions, disturbances, etc, and the availability of qualitative information [8].

THE SIMULATION MODEL

In the fuzzy sets theory any value is specified by a set of its possible values, characterized by varying degrees of affiliation to the object (through the so-called membership function) that is described by this fuzzy set.

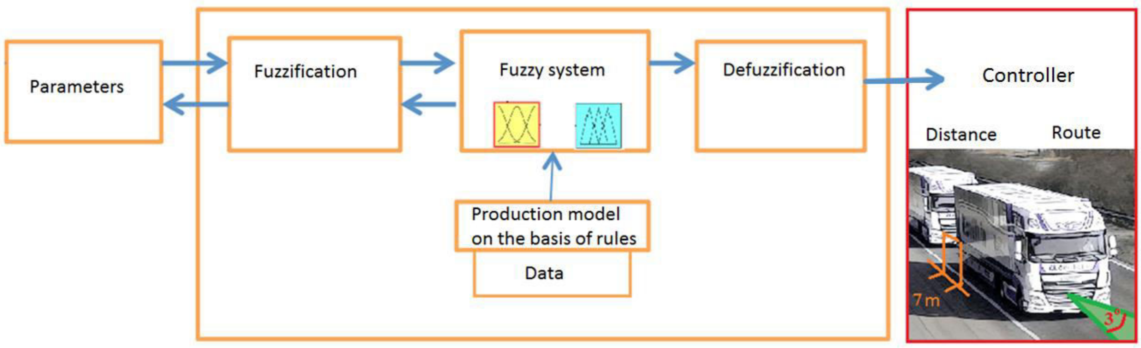

Figure-1. Automobile robot fuzzy control system.

Membership function can range from 1 ("fully belongs") to 0 ("fully doesn't belong"). To describe the objects and phenomena of the real world from the perspective of theory of fuzzy sets the concept of linguistic variable is used [9]. In addition to convenient formalization of complex data processing, fuzzy approach achieves several additional objectives, such as:

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- the usage of fuzzy model makes it possible to specify the behavior of the agent (automobile robot) in the form of a single rule base that unifies the solution and enables convenient modifications in the future;
- in application to the motion of the agent, fuzzy control circuit can be constructed so that the output is ready to issue a control action without the need for processing (i.e., not a turn corner, and, for example, velocity). If we consider the task of creating a fuzzy agent management system in relation to the automobile robot structure under consideration (unmanned cargo vehicle).

Linguistic variables are generated from listed characteristics, the membership functions must be formulated so as to ensure a smooth transition between the classes of situations, and the rules database should include rules to determine the basic direction and speed, and the rules of correcting direction and speed, including, specific to the detected obstacles in the way.

Let us introduce circuit transfer functions for fuzzy control system of an automobile robot, based on the reference adaptive control.

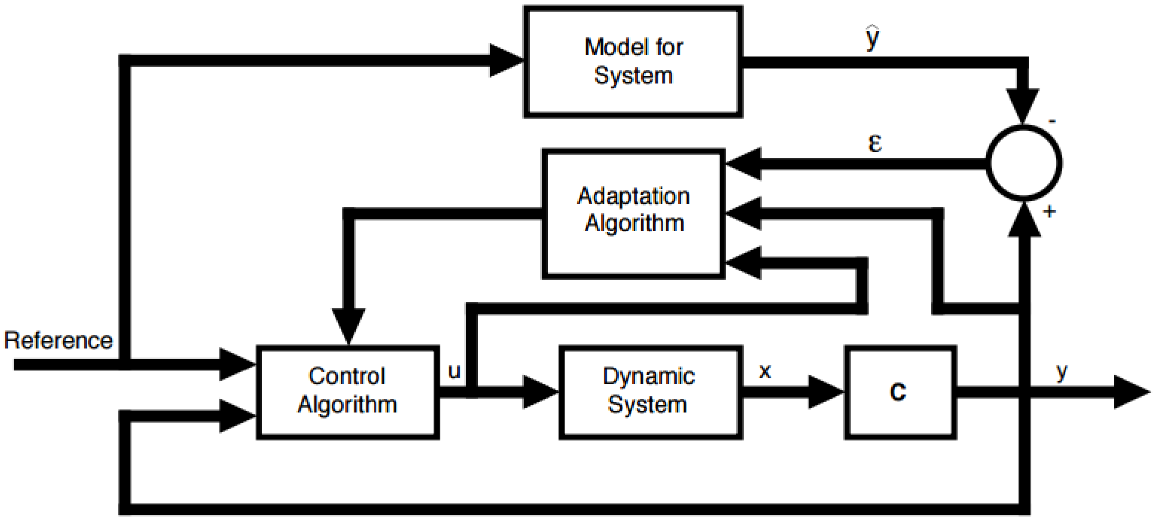

Figure-2. Model reference adaptive control.

The transfer of the controller functions are expressed below.
Control error:

$$\varepsilon = y - \hat{y} \quad (1)$$

where
ε = value of control error;
$\hat{y}$ = measurement standardof the automobile robot speed;
y = actual automobile robot speed.
Control signal to output transducer (signal):

$$\frac{dx(t)}{dt} = F_x(t) + G_u(t) \quad (2)$$

where $\frac{dx(t)}{dt}$ value of changes of output variable of automobile robot speed control

$F_x(t)$ = adapting signal;
$G_u(t)$ = control signal;

Output signal to the executive controller (Output):

$$y(t) = C_x(t) \quad (3)$$

where
$y(t)$ = control system output;
$C_x(t)$ = weight gain coefficient;

Control function (Control):

$$u = k(\Theta, R, Q) \quad (4)$$

u = control input;
Θ = adapting parameter;
R = measurement standard;
Q = value of the transfer function of management model;
K = gain constant.

Performance index:

$$J = \int_0^t x'(\tau)R_x(\tau) + u'(\tau)Q_u(\tau)d\tau \quad (5)$$

where x =output value of automobile robot control system;
J = performance coefficient;
$R_x(\tau)$ = the value of measurement standard at timeτ ;

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$Q_u(\tau)$ = the value of the control parameter of the model in timeτ.

We use the package Fuzzy Logic Toolbox for modeling, which is part of MatLab software product. Unlike SIBMAD, this which provides software tools to design robots to describe their impact on the surroundings, as well as the use of sensors, MatLab provides more fine-tuning for the mathematical model [8].

The modelling starts with naming the input and output variables [10]:

- Speed
- Distance
- Deviation of distance
- Deviation of the longitudinal axis
- Dividing line
- Danger Level
- Speed difference
- Bypass direction
- Removal
- Direction of deviation
- Best direction
- Acceleration.

The construction of a model of the controller in Fuzzy Logic Controller is shown bellow. For the linguistic variables "Deviation of distance» is x1, «Deviation of the longitudinal axis» is x2 and "Speed» is x3.

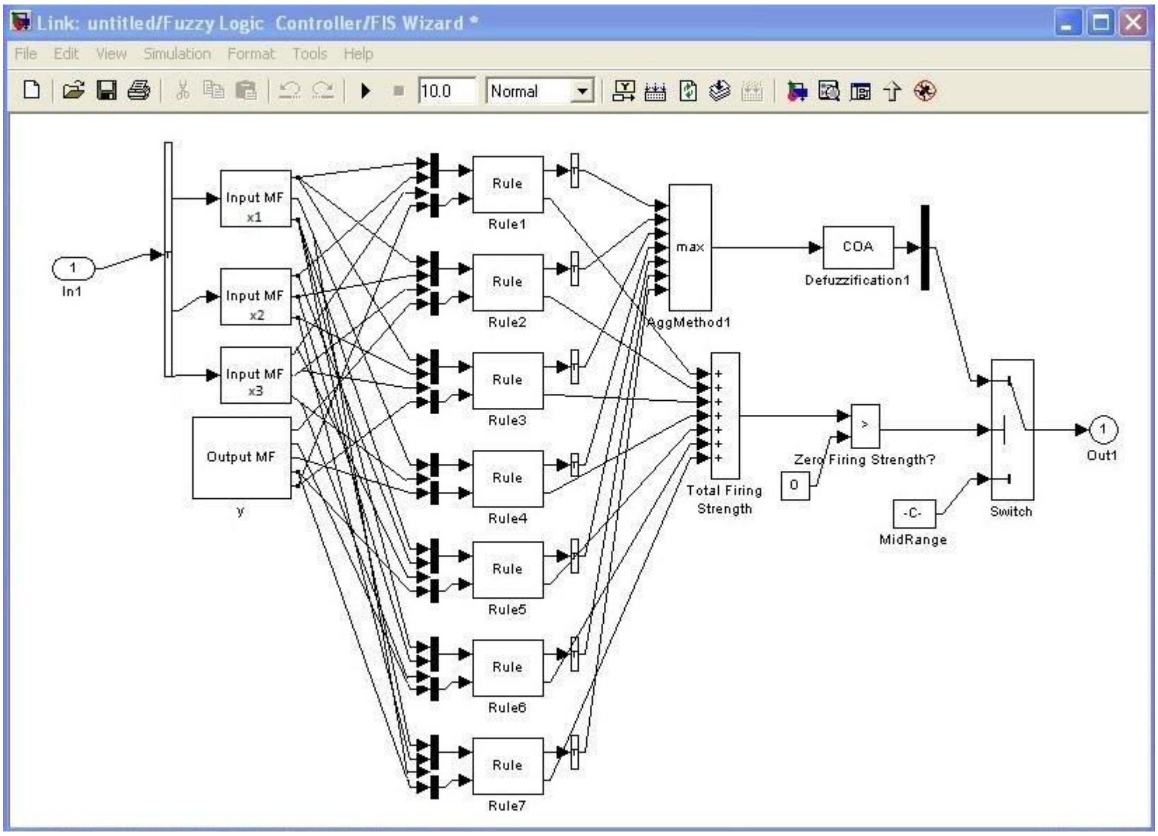

Figure-3. Automobile robot controller made from FIS WIZARD blocks.

While modelling it is necessary to to choose the number of terms of a linguistic variable and compare them by output criterion.

Let us develop several options with different numbers and types of modifiers and see how the resulting surface is constructed in the test rule base.

Let us consider the example of the construction of the membership function "the distance deviation".

The variable (S) - the deviation from the desired distance. The deviation from a predetermined distance characterizes the absolute distance in the up or down from a predetermined distance when driving in a convoy.

Variable modifiers are: "Small", "Medium", "Increased", "Big".

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The maximum deviation in the subject area analysis and expert rules were adopted on 5% of the distance.

Final model chart for the variable "Deviation from a predetermined distance" shown in Figure-4.

Linguistic terms "Small" and "Big" take the form of a double-sided Gaussian function according to the formula:

$$if, c_1 < c_2, \text{то} \mu(x) = \begin{cases} \exp\left(\frac{(x-c_1)^2}{-2a_1^2}\right), & x < c_1 \\ 1, & c_1 \le x \le c_2 \\ \exp\left(\frac{(x-c_2)^2}{(-2a_2^2)}\right), & x > c_2 \end{cases} \quad (6)$$

$$if, c_1 > c_2, \text{то} \mu(x) = \begin{cases} \exp\left(\frac{(x-c_1)^2}{-2a_1^2}\right), & x < c_2 \\ \exp\left(\frac{(x-c_1)^2}{-2a_1^2}\right) * \exp\left(\frac{(x-c_2)^2}{(-2a_2^2)}\right), & c_2 \le x \le c_1 \\ \exp\left(\frac{(x-c_2)^2}{(-2a_2^2)}\right), & x > c_1 \end{cases} \quad (7)$$

where

c_1 (c_2) = minimum (maximum) value of a fuzzy setcore;
a_1 (a_2) = concentration coefficient of the left (right) part of the membership function;
x = value;
$\mu(x)$ = value of the degree of verity functions fuzzy variable.

Formula related to terms:

- «Small»

$c_1 = -0.2;\ a_1^2 = 0.3;$
$c_2 = 0.2;\ a_2^2 = 0.3;$

$$\mu(x) = \begin{cases} \exp\left(\frac{(x-(-0.2))^2}{-2*0.3^2}\right), & x < -0.2 \\ 1, & -0.2 \le x \le 0.2 \\ \exp\left(\frac{(x-0.2)^2}{(-2*0.3^2)}\right), & x > 0.3 \end{cases} \quad (8)$$

- «Big»

$c_1 = 4.7;\ a_1^2 = 0.3;$
$c_2 = 5.2;\ a_2^2 = 0.3;$

$$\mu(x) = \begin{cases} \exp\left(\frac{(x-4.7)^2}{-2*0.3^2}\right), & x < 4.7 \\ 1, & 4.7 \le x \le 5.2 \\ \exp\left(\frac{(x-5.2)^2}{(-2*0.3^2)}\right), & x > 5.2 \end{cases} \quad (9)$$

Linguistic terms "Small" and "Big" take the form of a double-sided Gaussian function according to the formula shown above.

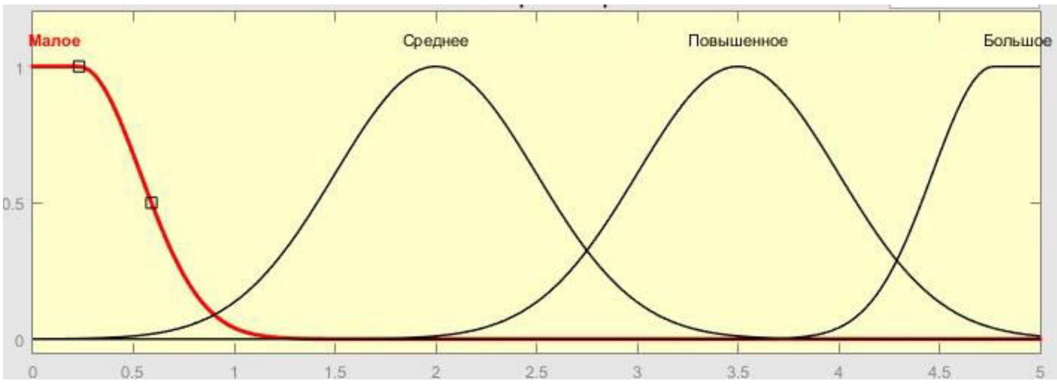

Figure-4. Membership function of the variable "Deviation of distance".

Rule base

The objective is to build an expert system of fuzzy rules to control the automobile robot with the method of controlling the speed and direction of movement. The rule base is expertly build on real data set for each parameter.

The rule base has the property of self-learning (self-appending within acceptable scales). A system of rules goes into 500 rules saturation, followed by replacement only. The rule formation carries out via training on the existing set of rules that defined by expert. The recommended number of initial rules is 20-30 pcs.

To test all the variables a test rule base should be developed.

Rule base rule model is described as follows:

R1: IF x1 IS μ(u)11 … AND …xn IS μ(u)1n,THEN y IS B1 ...
R2: IF x1 IS μ(u)21 … AND … xn IS μ(u)2n, THEN y IS B2 ...

Правило для ситуации выглядят следующим образом:

R1: IF speed ISbigAND distance deviation IS significant, THEN speed IS small increase

R2: IF low speed ISsmall ANDdistance deviation IS significant
AND deviation of of the longitudinal axis IS significant, THEN speed IS greatly increase

Following we use the Mamdani's method of inference.

Figure-5 shows the visualization of the output variable dependence on the input variables in the form of three-dimensional surface. In this case, the displayed surface stands for input variables, "Speed", "Distance Deviation", as well as their dependent output variable "Deviation from the longitudinal axis."

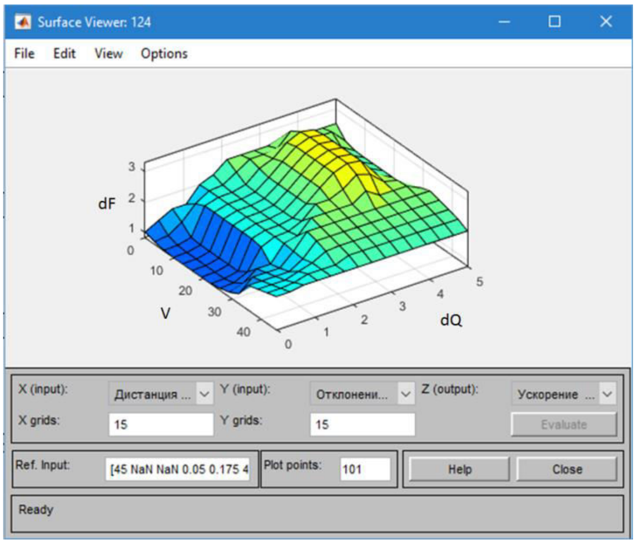

Figure-5. Visualization of the output variable dependence on the input variables.

This chart gives the normal values for all input indicators. Mamdani's method is applicable for these input data.

Optimization of fuzzy rule base using genetic algorithms

The genetic algorithm is at the moment best known representative of evolutionary algorithms and in fact is an algorithm used for searching for the global extremum of multiextremal function. It consists of parallel processing multiple alternative solutions. The search is concentrated on the most promising ones. This suggests the possibility of using genetic algorithms in solving any problems of artificial intelligence, optimization, decision-making [4, 5, 8, 12 - 16].

Genetic algorithms for adjusting the number of fuzzy variable functions are used as follows [2]. Each chromosome (solution, sequence, identity, "parent", "descendant", "child") is a vector of the number of functions (weights are read from the neural network in the established order - from left to right and top to bottom).

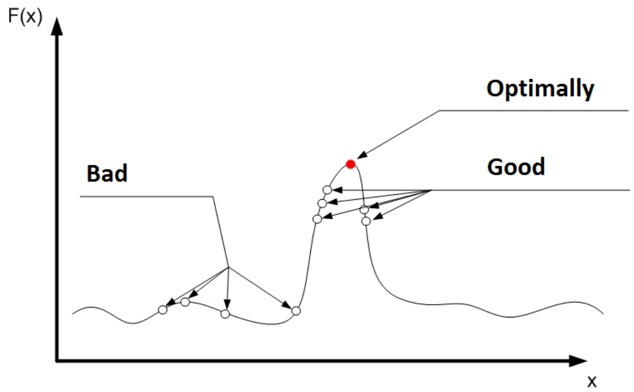

Figure-6. Typesofalleys.

Chromosome $a=(a_1, a_2, a_3, \ldots ,a_n)$ consistsofgenes a_i, that may have numerical values, called "alleles". The allele types are shown ong Figure-6.

The initial population is randomly selected, the values of the weights lie in the interval [-1.0, 1.0]. For net learning simple operations are used to the initial population: selection, crossover, mutation - causing generation of new populations.

Selection operator (reproduction, selection) selects chromosomes according to the values of specialiation function. Here, the method roulette is applicable (roulette-wheel selection), through which the selection is carried. The roulette wheel contains one sector for each member of the population. The size of the i-th sector is proportional to the corresponding Psel (i) value calculated by the formula:

$$P_i = \frac{f_i(x)}{sumf(x)} \qquad (10)$$

where *fi(x)* - value of the objective function of i-th chromosome in a population;
sumf(x) - sum objective function value of all chromosomes in the population;

Crossover operator (crossover operator), sometimes called a crossing-over, is the main genetic operator (Figure-3), through which parts of chromosomes are exchanged between the two (maybe more) chromosomes in the population [11]. It may be a one-point or multipoint. Crossover is called one-point, if it parental chromosomes are cut at only one random point.

The objective function in our case is to minimize management errors:

$$f(x_r) = \frac{1}{1+\int_0^t \varepsilon^2 dt} \qquad (11)$$

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where ε - deviation from the specifying signal, t - time of solution validation (integration range).

Genetic algorithm evaluates the previous decisions and creates the outputs for the following solutions.

Table-1. The genetic algorithm parameters.

Parameter name	Value
Number of generations	25
Population size	50
Crossing coefficient	0,62
Mutation coefficient	0,15
Time for one decision	5 sec

Theprobabilityofcrossoveristhehighestamonggeneticoperatorsandisequalto 60% ormore.

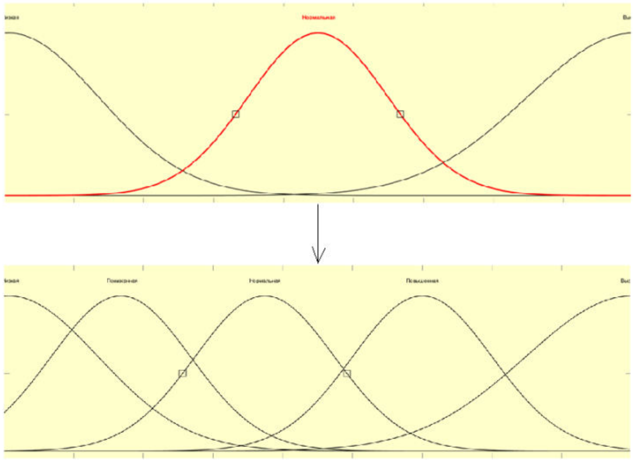

Figure-7. Optimal quantity of functions Оптимальноеколичествофункцийof fuzzy variables.

In this paper, the optimal value of the number of functions of fuzzy variables equals 5.

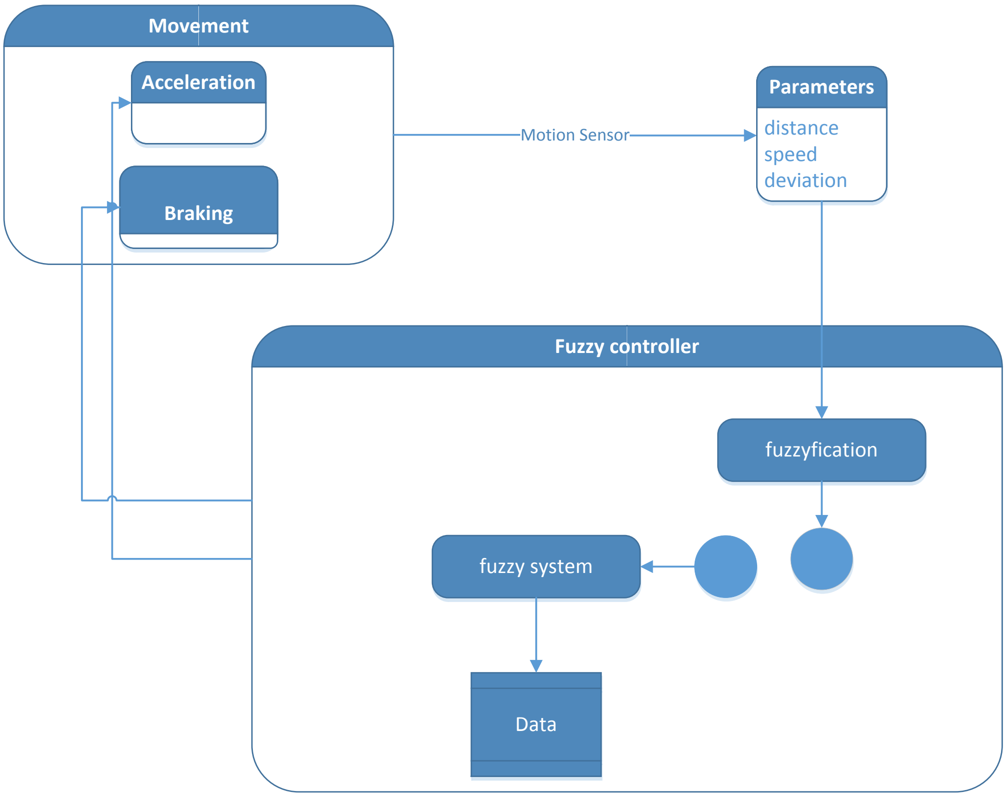

Figure-8. UML-chart of automobile robot speed control.

CONCLUSIONS

The problems automobile robots intelligent control systems in a non-stationary environment were considered. The model control system with reference information was developed. The model controller based on fuzzy rule base in the Fuzzy Logic Controller environment was submitted.

Mathematical model of the functions of fuzzy variables and coefficients of its settings was shown. Membership functions for fuzzy variables "Distance deviation" "Reject the longitudinal axis" and "Speed" was designed.

A base policy of Mamdani's inference method and a graph of surfaces on the variables depending on each other were shown. Rule base model allows editing the rules automatically, implementing the function of learning reinforcement. Rule base modification occurs, when unforeseen situations such as dusty or faulty sensor.

Genetic algorithms were used to optimize the rule base. Optimized parameter is the number of modifiers fuzzy variables with the objective function, minimum of control error integral.

The combination of fuzzy rule base and genetic algorithms allows solving the problem of optimal speed and distancing control of the automobile robot in non-stationary environments. The controller model developed solves automobile robot management problems in real time.

Simulation model control system allows creating convoys of automobile robots of more than 80 units. Multiagent convoy control principle makes it possible to manage the entire convoy as a single mechanism, with automobile robot making autonomous decisions.

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