УПРАВЛІННЯ
У ТЕХНІЧНИХ СИСТЕМАХ

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CONTROL
IN TECHNICAL SYSTEMS

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A SOFT FUZZY ALGORITHM OF THE MOBILE ROBOT CONTROL

Context. The task of a mobile robot control on the base of soft algorithm fuzzy inference has been solved.

Objective is the creation of soft algorithm of the fuzzy inference which allows to provide additivity of fuzzy control system.

Method. A soft algorithm of fuzzy inference used to control the mobile robot is suggested. Given algorithm allows to compensate errors inherent to the traditional models of fuzzy inference. Errors include: the curse of dimensionality, the absence of additivity and the fuzzy partition. This soft algorithm of fuzzy inference at the expense of rational allocation of premises and conclusions in a matrix of fuzzy relations, reduces the number of operations of the fuzzy inference. Another distinctive feature of the proposed soft algorithm is that in fuzzy inference to find minima and maxima used soft arithmetic operators. The paper shows that during the work of hard formulas for the implementation of these formulas while controlling the mobile robot the situations will appear when the robot loses control. The article points out that the implementation of the possibility in soft algorithm of fuzzy inference option of changes in parameters of sigmoidal membership functions will minimize the error at fuzzy system output. Dynamics of changing RMSE ratio from the varying parameters of sigmoidal membership functions proves it. The additional simulations presented in the article shows that during varying the parameters of sigmoidal membership function, during in increasing of the parameter a, is being observed decrease in the value of RMSE. The effectiveness of the proposed soft algorithm is confirmed by numerical simulation and experiments in the researching of a mobile robot movement along a line.

Results. The specialized software for microcontroller Arduino Uno is developed and it realizes the proposed soft algorithm which allows to carry out an experimental study of its properties.

Conclusions. The software realizing proposed algorithm has been developed and used in computational experiments investigating the properties of the algorithm. The experiments confirmed the efficiency of the proposed algorithm and software.

Keywords: fuzzy inference system, fuzzy set theory, RMSE, soft computing, mobile robot.

NOMENCLATURE

RMSE is a root mean square error;
MF is a membership functions;
MISO is a multi input single output;
FR is a fuzzy rules;
FIS is a fuzzy inference system;
y is an output parameter;
x_i is an input parameter;
n is a number of input parameters;
X is a vector of the input parameters;
k is a number of fuzzy rules;
m is a number of terms;
l is a number input parameters;
a,b,c are the parameters of the Gaussian membership function;
δ is a softness operator;
γ is an operator of the parameterization;
M is the number of observations in the learning sample.

1 INTRODUCTION

Algorithms of the fuzzy-logic inference are successfully applied in modeling of difficult technological processes of the modern control systems [1, 2, 3]. The algorithms allow increasing accuracy of the control process by balancing outside effects in real-time mode.

However, in practice, implementation of the system based on algorithms of the fuzzy-logic inference has some problems concerning continuous differentiability of MF. They are curse of dimensionality [4, 5, 6]; non-observance of the condition of the partition of unity condition [7] and non-compliance of the condition of additivity [8].

The main purpose in the article is to design a soft algorithm of fuzzy inference that allows to control robotic systems in real time.

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2 PROBLEM STATEMENT

Fuzzy inference systems, based on the Zadeh rule, are used for modeling modern systems [12, 13, 14, 15]. For example, when MISO-system with n-input and one output parameter is designated, then dependence between these is defined as

$$y = f(\boldsymbol{X}) = f(x_1, x_2, \ldots, x_n),$$

where y – an output parameter, x_i – input parameters, i=1…n, n – number of input parameters.

The vector X of the input parameters is shown on the Cartesian product of the determination of input parameters $X_1 \times X_2 \times \ldots \times X_n$: $X=[x_1, x_2,\ldots,x_n]$. At the same time, the function f shows a condition multiplicity of the output parameter Y in the area of the determination of the input parameters X

$$f : X_1 \times X_2 \times \ldots \times X_n \to Y.$$

According to the Zadeh rule the fuzzy multiplicity in a MISO-system is determined as

$$Y(y) = \bigvee_{X \in X_1 \times \ldots \times X_n} \left(X_1(x_1) \wedge \ldots \wedge X_n(x_n) \right), \tag{1}$$

where $\vee$ is a symbol, which means the operation of the hard fuzzy maximum; $\wedge$ is a symbol, which means the operation of the hard fuzzy minimum.

At the same time, the membership function of the output parameter takes the form

$$\mu_Y(y) = \bigvee_{y = f(x_1,\ldots,x_n)} \left(\mu_{X_1}(x_1) \wedge \ldots \wedge \mu_{X_n}(x_n) \right). \tag{2}$$

The disadvantage of the MF relation, based on the Zade rule using hard formulas is evident. When the equation (2) $\min(x_1; x_2)=\min(0{,}7; 0)=0$, the result at the output is zero. Therefore, a fuzzy system will be non-sensitive to changes of the input parameter x_1, because its value will depend on the second parameter x_2=0; if x_1 = 0.2 and the output is 0. Thus, the FIS does not possess additivity. Therefore, values of the RMSE parameter are increasing when modeling. For example, in [16] when modeling a similar system, RMSE (without training) is more than 120.

Another huge disadvantage of ANFIS models, which are created on the Zadeh rule, is existence of empty decisions in conclusions of the fuzzy inference. They increase with the conclusion of input parameters and FR, which are the knowledge base. The growth of the conclusion of FR is so fast, that it causes an error, which is concerned the dimension damnation. In recommendation [17], the conclusion of fuzzy rules k should be the same as the conclusion of terms m. They describe a fuzzy input parameter. For example, if MISO-system has 2 input parameters and each of them is described by 3 terms, than the amount of FR will be defined as $k=m^l=3^2=9$. If the fuzzy MISO-system has 12 input parameters and each of them consists of 3 terms, than the amount of FR will be defined as k=531441. The growth of the conclusion of input parameters from 2 to 12 will increase the conclusion of fuzzy rules in 59049 times [18].

To compensate for the above drawbacks is solved the following task: the development of a fuzzy algorithm uses of soft arithmetic operations. A comparison of the proposed method with the traditional models of fuzzy inference is implemented based on the RMSE evaluation.

3 REVIEW OF THE LITERATURE

Currently, there are a large number FIS used as a decision-making system [3ч9]. However, these FIS in the composite rule Zadeh use hard arithmetic operations of finding the minimum and maximum [12, 13, 15, 16]. Typically, such systems are not additive, and are not monotone [8, 15]. Also hard fuzzy inference system may cause such error as the curse of dimensionality [4ч6]. This leads to the fact that in some cases FIS cannot learned. In some cases, FIS do not provide the condition of the partition of unity [7]. To resolve this issue we recommend to use parameterized MF for ensuring the partition of unity condition and continuity through the intersection point of the adjustment linguistic terms which equal 0.5. Also, to overcome the above errors in the studies recommended to use soft arithmetic operations [9, 10, 11, 21].

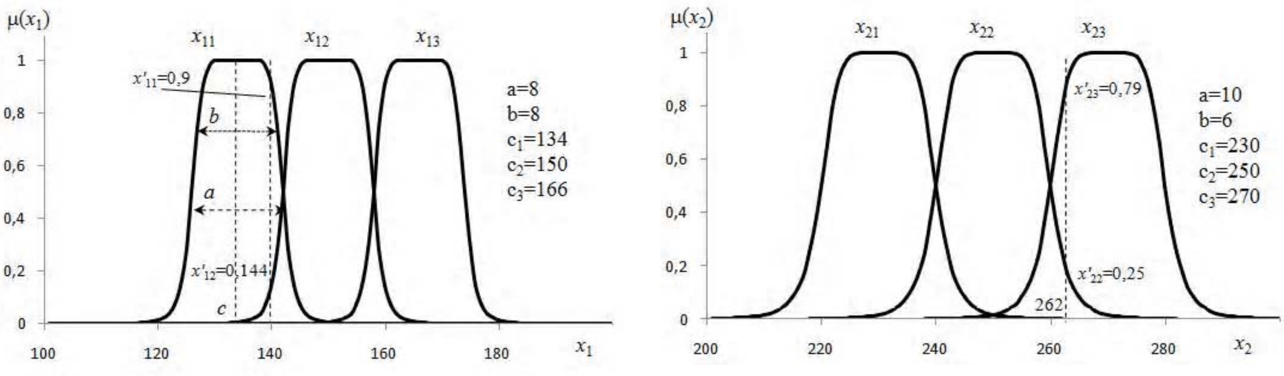
4 MATERIALS AND METHODS

A soft algorithm of the fuzzy logic inference includes the following steps:

Step 1. Fuzzification of the input parameters. The fuzzy MISO-system $\gamma=f(x_1\ x_2)$, which has 2 input and 1 output parameters should be considered. If each input parameter has 3 fuzzy terms (Fig. 1) with a MF then the output parameter has 5 fuzzy terms

$$\mu(y) = \frac{1}{1 + \left(\dfrac{x - c}{a} \right)^b}, \tag{3}$$

where a, b, c are the parameters of the MF; x is a quantitative value of the input parameter.



a b

Figure 1 – Graphics of MF: a – the first input parameter x_1; b – is the second input parameter x_2

Step 2. Determination of values of MF for every implication of the input parameters, based on the information received from sensors of active control systems, for example (Fig.1), if x_1=140 then x_2=262:

$$x_1' = (x_{11}', x_{12}', x_{13}',) = (0{,}9;\ 0{,}144;\ 0),$$

$$x_2' = (x_{21}', x_{22}', x_{23}',) = (0;\ 0{,}25;\ 0{,}79). \qquad (4)$$

Step 3. Synthesis of the knowledge base, which contains fuzzy rules of the type «If … then» (see Table 1) [19].

Step 4. Creation of a fuzzy ratio matrix. Soft arithmetic operations are used while calculating MIN and MAX [8].

The operation of determination the soft MIN is obtained as follows:

$$\min_{\delta}(x_1, x_1) = \frac{x_1 + x_2 + \delta^2 - \sqrt{(x_1 - x_2)^2 + \delta^2}}{2}, \quad \text{where } \delta = 0.05. \quad (5)$$

The Eq. (5) demonstrates that

$$\min_{\delta}(0{,}7;\ 0) = \frac{0{,}7 + 0 + 0{,}05^2 - \sqrt{(0{,}7 - 0)^2 + 0{,}05^2}}{2} = 0{,}0076.$$

Therefore, the soft MISO-system, will give the value different from zero and respond to the changing parameter x_1, if the second parameter is x_2=0. In this case the fuzzy system will be additive in the whole range of input parameters.

The equation of parameterized soft maximum capture is obtained as follows

$$\max_{\delta}(x_1, x_2) = \left|\gamma \cdot \max(x_1, x_2) + 0{,}5(1-\gamma)(x_1 + x_2)\right|, \quad (6)$$

where γ is an operator of the parameterization. If =1, then Eq. (6) will apply operations of hard-MAX. If γ =0, then Eq. (6) will apply arithmetic operations.

The Eq. (6) can be applied only with 2 operands. If there are more than 2 operands, then it is necessary to apply the soft-MAX operator

$$soft-\mathrm{MAX} = \bigvee_{i=1}^{n} (\max_{\delta}(x_{1i}, x_{2i})). \quad (7)$$

Taking into consideration the (Eqs. (5), (6), (7)) the fuzzy ratio matrix is given as in Table 2.

The conclusion of conclusions equals to the conclusion of terms of the output parameters, i.e. 5. In a hard model of the fuzzy inference the conclusion of conclusions will be equal to 9. Therefore, a rational location of elements in the fuzzy ration matrix will be of the curse dimension.

Step 5. Truncation of output parameter terms, according to the equation

$$\mu(y)_i' = soft \underset{i=1}{\overset{n}{-}} \min = (y_i';\ \mu(y)_i), \quad (8)$$

where i=1..n is the conclusion of the conclusion of the fuzzy logic inference; n is the amount of conclusions of the fuzzy logic inference.

Step 6. Integration of the transformed terms of the output parameters

$$\mu(y)' = soft \underset{i=1}{\overset{n}{-}} \max\left[\mu'(y)_1; \mu'(y)_2; \mu'(y)_3; \mu'(y)_4; \mu'(y)_5\right]. \quad (9)$$

Step 7. The obtained result is defuzzification by the weighted average method [20, 21]

$$y'' = \frac{\sum_{i=1}^{n} y_i \mu(y)_i'}{\sum_{i=1}^{n} \mu(y)_i'}. \quad (10)$$

Therefore (Eqs. (3)÷(10)) present a soft algorithm of the fuzzy logic inference.

4 EXPERIMENTS

The task of estimation of the created soft algorithm of the fuzzy logic inference assumes finding an optimal decision where RMSE is MIN [22, 23]

$$RMSE = \sqrt{\frac{1}{M} \sum_{i=1}^{n} (y - y'')} \to \min. \quad (11)$$

Experimental data $y = f(x_1, x_2, \ldots x_n)$ is given in Table 3.

Calculation of RMSE in the hard fuzzy inference system.

The data obtained from the defuzzification of the output result. Table 4 shows applying the hard algorithm of the fuzzy logic interference.

Table 4 demonstrates a non-sensitive zone. The hard fuzzy logic inference model does not react to changes of the input parameters, and it is additive.

Table 1 – Knowledge base with FR

Fuzzy rule	if		then	Fuzzy rule	if		then	Fuzzy rule	if		then
FR 1	x_{11}	x_{21}	y_5	FR 4	x_{12}	x_{21}	y_4	FR 7	x_{13}	x_{21}	y_3
FR 2	x_{11}	x_{22}	y_4	FR 5	x_{12}	x_{22}	y_3	FR 8	x_{13}	x_{22}	y_2
FR 3	x_{11}	x_{23}	y_3	FR 6	x_{12}	x_{23}	y_2	FR 9	x_{13}	x_{23}	y_1

Table 2 – Fuzzy ratio matrix

Output term	Composition			Maximum
y'_5	b_1=soft-min(x_{11}; x_{21})			b_1
y'_4	b_2=soft-min(x_{11}; x_{22})	b_4=soft-min(x_{12}; x_{21})		soft-max(b_2, b_4)
y'_3	b_3=soft-min(x_{11}; x_{23})	b_5= soft-min(x_{12}; x_{22})	b_7=soft-min(x_{13}; x_{21})	soft-MAX(b_3, b_5, b_7)
y'_2	b_6=soft-min(x_{12}; x_{23})	b_8= soft-min(x_{13}; x_{22})		soft-max(b_6, b_8)
y'_1	b_9=soft-min(x_{13}; x_{23})			b_9

Calculation of the RMSE parameter with the use of the experimental data (see Table 3) and the data, obtained from the modeling of the hard fuzzy inference model (see Table 4) is designated as $RMSE_{hf}$=247,54.

Calculation of RMSE in the soft fuzzy inference system.

RMSE of with the appliance of soft arithmetic operations is calculated in (Eqs. (3)÷(10)). The obtained data is given in Table 5.

As shown in Table 5 there are no non-sensitive zones. Thus, soft fuzzy model reacts to all changes of the input parameters and becomes additive. It helps to minimize the value of the RMSE parameter.

Calculation of the RMSE parameter with the use of the experimental data (see Table 3) and data, obtaned from the modeling of the soft fuzzy inference model (see Table 5) is defined as $RMSE_{sf}$=16,19.

It is shown that the soft model of the fuzzy logic inference is in 15,3 times more corresponded to the experimental selection in Table 3.

A graphic version of the modeling is shown in Fig. 2.

Several numerical experiments are necessary to perform to study the soft algorithm of the fuzzy inference system.

Additional imitation modeling of RMSE calculation.

Some additional experiments, which allow proving effectiveness of the introduced soft algorithm, are to be performed with the random conclusions from 430 to 470. It is necessary to fill values of the output parameter in Table 3 and to calculate RMSE for hard and soft algorithms of the FIS. It is necessary to change only the values of the coefficients a and b of the output MF y if using fuzzy logic modeling Eq. (3). The value of the parameter c is not changed (see Table 6).

MIN RMSE for the soft fuzzy logic inference is obtained in the 3rd experiment: RMSE=11.14. MIN RMSE of the hard fuzzy logic inference is obtained in the 4th experiment: RMSE=244.88, then a=40, then b=2 (see Eq. (3)).

A graphic version of the best variants for the RMSE parameter is illustrated in Fig. 3.

The data, which show dynamics of RMSE depend on the parameter a (see Table 7).

Interpretation of the data (see Table 7) is given in Fig. 4.

Table 3 – Experimental selection

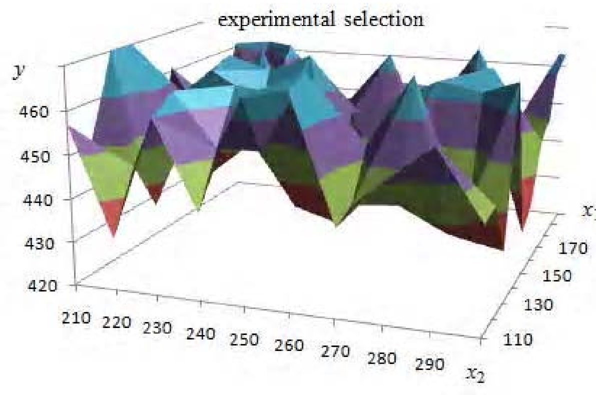
x_1 \ x_2	**210**	**220**	**230**	**240**	**250**	**260**	**270**	**280**	**290**	**300**
	y									
110	457	432	460	440	466	468	440	451	459	444
120	451	446	464	452	452	470	442	443	438	445
130	470	434	456	464	463	452	453	469	434	432
140	470	457	465	448	434	431	442	435	435	467
150	435	455	467	464	468	455	458	464	462	430
160	461	434	442	439	462	439	458	457	466	434
170	435	448	465	442	445	446	443	455	442	447
180	446	436	456	434	452	464	432	445	444	450
190	446	453	463	447	441	455	435	465	446	465
200	461	462	455	444	446	432	452	445	436	463

Table 4 – Defuzzification on the hard fuzzy model

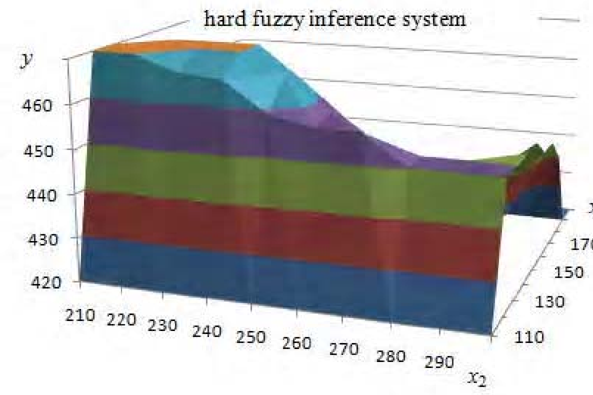
x_1 \ x_2	**210**	**220**	**230**	**240**	**250**	**260**	**270**	**280**	**290**	**300**
	y									
110	0	0	0	0	0	0	0	0	0	0
120	473.99	472.72	466.44	465.7	459.01	456.76	456.76	450.12	450.05	450.33
130	474.24	481.39	481.14	473.61	465.6	457.94	450.43	450	450	449.96
140	467.64	477.45	478.12	470.24	462.62	454.6	447.54	446.05	443.11	449.96
150	461.85	465.67	465.33	457.85	450.01	442.17	434.69	434.35	438.36	449.96
160	457.04	453.96	452.48	445.42	437.42	429.81	421.93	422.61	432.89	445.25
170	450.1	450	449.58	442.06	434.43	426.45	418.9	418.67	426.32	445.25
180	450.05	449.99	443.44	443.44	441.54	434.87	434.09	427.84	426.54	438.92
190	0	0	0	0	0	0	0	0	0	0
200	0	0	0	0	0	0	0	0	0	0

Table 5 – Defuzzification on the soft fuzzy model

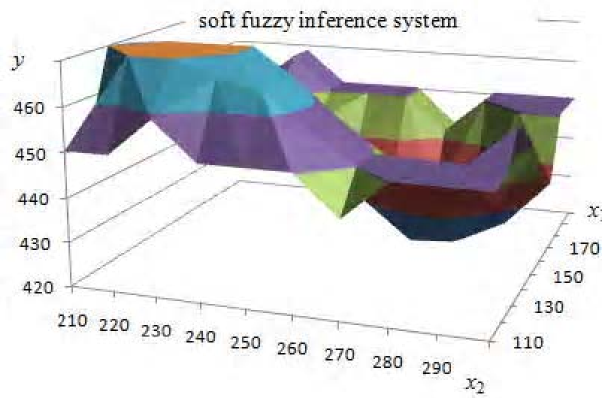
x_1 \ x_2	**210**	**220**	**230**	**240**	**250**	**260**	**270**	**280**	**290**	**300**
	y									
110	450.5	450.5	458.87	450.5	450.5	450.5	441.74	450.5	450.5	450.5
120	450.5	473.98	474.22	466.64	464.07	456.85	450.06	450.06	450.5	450.5
130	475.4	481.41	481.16	473.75	465.66	458.11	450.42	450	450.04	458.84
140	469.12	477.63	478.36	470.57	462.89	454.68	447.52	445.98	444.58	454.66
150	464.48	465.67	465.49	458.03	450.01	441.99	434.52	434.27	435.67	448.78
160	455.12	453.91	452.44	445.43	437.15	429.48	421.69	422.44	431.47	438.73
170	450.04	450	449.6	442.07	434.42	426.31	418.88	418.67	425.13	436.08
180	450.5	450.05	450.05	444.11	436.12	433.9	426.31	426.55	450.5	450.5
190	450.5	450.5	458.87	450.5	450.5	450.5	441.74	450.5	450.5	450.5
200	450.5	450.5	458.87	450.5	450.5	450.5	441.74	450.5	450.5	450.5



a

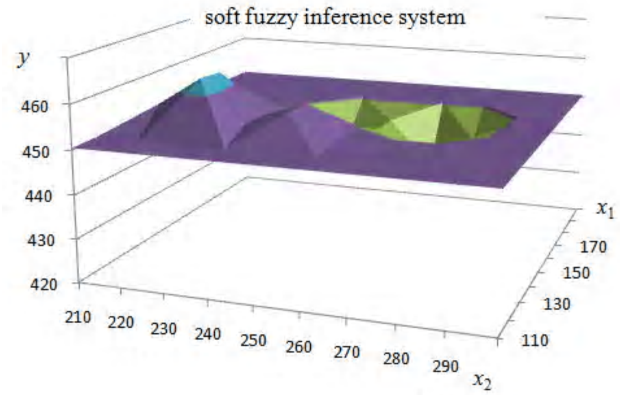


b

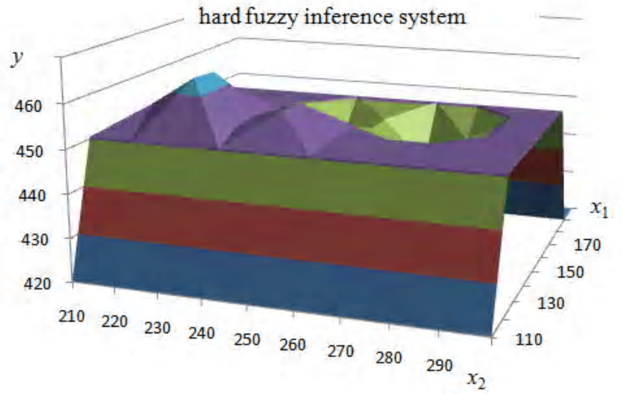


c

Figure 2 – Modeling: a – experimental selection; b – hard FIS; c – soft FIS



a



b

Figure 3 – a – 3rd experiment for the soft FIS; b – 4th for the hard FIS (experiment)

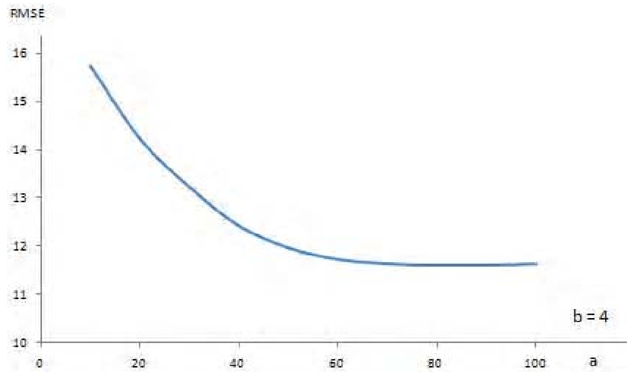


Figure 4 – Dynamics of RMSE when the parameter a is changed

Table 6 – Imitation modeling of RMSE

No. of experiment	$RMSE_{hf}$ Hard-FIS			$RMSE_{sf}$ Soft-FIS		
	a=8 b=4	a=20 b=4	a=40 b=2	a=8 b=4	a=20 b=4	a=40 b=2
1	247.54	247.42	247.3	16.19	14.21	11.99
2	247.55	247.35	247.19	17.95	14.65	11.74
3	247.65	247.46	247.33	17.1	13.8	11.14
4	245.04	244.88	244.69	18.84	15.95	12.6
5	247.43	247.26	247.1	17.07	14.37	11.42
6	247.55	247.39	247.28	17.15	14.12	11.98
7	246.78	246.59	246.45	17.87	14.52	11.9
8	247.23	247.04	246.88	19.22	15.67	12.71
9	247.33	247.2	247.09	16.44	13.73	11.44
10	247.63	247.51	247.37	16.76	14.87	12.38
Average	247.17	247.01	246.87	17.46	14.59	11.93

Table 7 – Dynamics of RMSE when the parameter a is changed

a	10	20	30	40	50	60	70	80	90	100
RMSE	15.73	14.21	13.22	12.42	11.96	11.72	11.63	11.61	11.61	11.63

5 RESULTS

The process of mobile robot control, which is moving along the line, is illustrated in Fig. 5. The decision of this task is made for 2 lengths: 2 meters and 2.5 meters.

There are a lot of ways to solve the task [27, 28]. A robot based on the two-wheeled platform mini Q, is applied in the experiment.

Scheme and the principle of the mobile robot operation.

Mobile robot includes the following elements: A microcontroller, based on the Arduino Uno scheme, made on ATmega328p processor with 16 MHz CPU speed with 32 Kb memory; A two-wheeled platform mini Q with a disc, 2 wheels 42Ч19 mm and 2 micro motors with 3–9 V; A Motor Shield card for Arduino Uno, based on L298P driver, which allows controlling two micro motors with 5–24 V voltage; Troyka Shield card connects necessary sensors to the mobile robot; Two digital line sensors. A structural scheme of the mobile robot is shown in Fig. 6.

The line sensors, which determine the colour of the surface under the mobile robot, should be used for the robot moving along the line. The output signal from the sensor is a binary signal: logical 0 or 1 depends on the colour under the mobile robot. 1 means “black”, 0 means “white”.

The use of the Troyka Shield card allows connecting to the Motor Shield. Three different signals are transmitted through the three-wire loopback: G means “ground”; V means “voltage”; S means “signal”. The Motor Shiels is used to control two wheel rotation. Its work is similar to the scheme H-bridge, for example l293d. Two pins are applied to indicate the direction of the wheel rotation. For example, if there is a signal 1:1, then the mobile robot moves straight ahead.

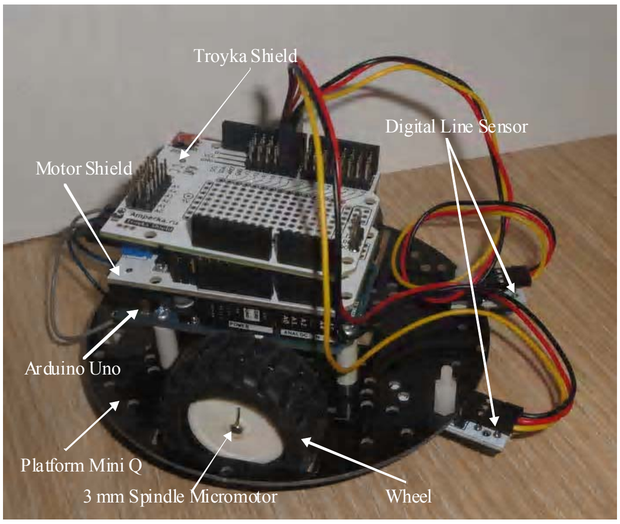


Figure 6 – Structural scheme of the mobile robot

If the signal 1:0, then the mobile robot rotates around its axis. If the signal 0:0, then the mobile robot moves back. The other two pins are used to supply the voltage to the micro motors ranging from 0 to 5 V. The process of control is implemented with the help of pulse-wide modulation. If the pin is under 5V, then the mobile robot moves at the maximum speed. If V=0, then the mobile robot does not move. The Motor Shield card is put on the Arduino Uno.

Fuzzy system of the mobile robot control.

Input parameters for the mobile robot control are linguistic variables: power supply voltage – u (V) and robot's weight – m (gr). It is possible to use the range of values of linguistic variables. If the power voltage is within the range from 6 to 9 V (see Fig. 7, a) then a FM of the linguistic variables of the power voltage is defined as $U = [u_1] + [u_2] + [u_3]$. The weight of the mobile robot depends both on the conclusion of its sensors and a type of the voltage supply. The presented weight is within the range from 180 to 270 grams. FM of the linguistic variables of the mobile robot weight is defined as $M = [m_1] + [m_2] + [m_3]$ (see Fig. 7, b). The MF is designated as Eq. (3).

The MF of the output linguistic variable *Speed*, depends on the ADC precision. Therefore its range is occurred as [0 … 255] (see Fig.7, c). This variable is also defined by the sigmoidal function Eq. (3) $Speed = [s_1] + [s_2] + [s_3] + [s_4] + [s_5]$.

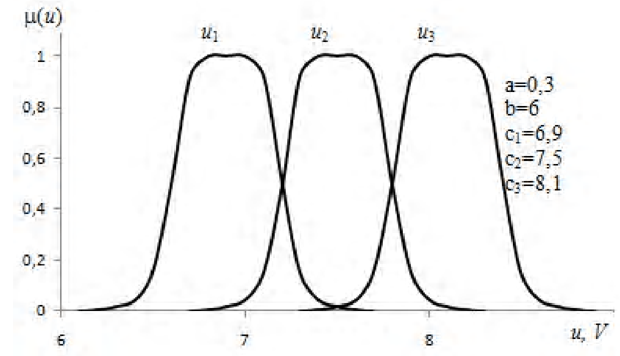
Hard and soft algorithms of the fuzzy logic inference should be used for calculation the variable *Speed*. A matrix should be created for the robot with a FIS applying the (Eqs. (5)÷ (7)) outlined in Table 8.

Defuzzification uses a method of the center of gravity to determinate the output variable *Speed* outlined in Table 9 and Table 10.

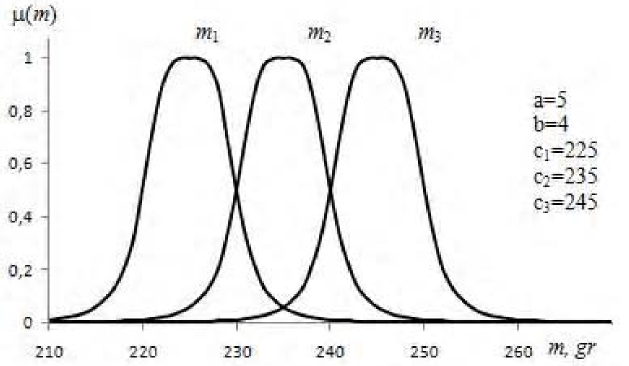
Calculation of the RMSE by the methods presented in Section 4 shows that $RMSE_{sf}$=11.93 in modeling of the soft model of the fuzzy inference and $RMSE_{hf}$=35.59 in modeling of the hard model of FIS. The area, which is grey (see Table 10), is an area of non-sensitivity of the mobile robot with a FIS. The output of the MISO system will be the same if the robot's weight is in the range from 180 to 190 grams. It will also influence its work. Therefore, the robot will not move if the variable *Speed* equals 0. The results are illustrated in Fig. 8 and in Table 9 and Tables 10.

Table 8 – Fuzzy ratio matrix

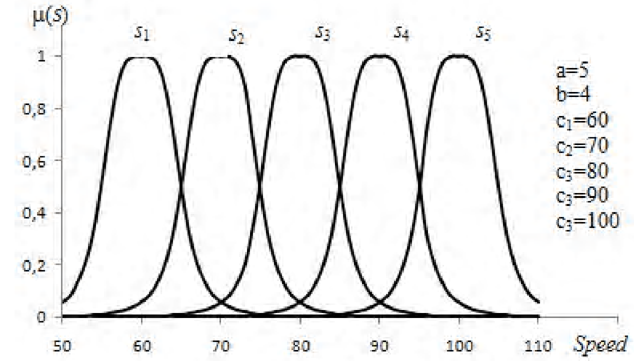
Output term	Composition			Maximum
s'_5	b_1=soft-min(u_1; m_1)			b_1
s'_4	b_2=soft-min(u_1; m_2)	b_4=soft-min(u_2; m_1)		soft-max(b_2, b_4)
s'_3	b_3=soft-min(u_1; m_3)	b_5= soft-min(u_2; m_2)	b_7=*soft*-min(u_3; m_1)	soft-MAX(b_3, b_5, b_7)
s'_2	b_6=soft-min(u_2; m_3)	b_8= soft-min(u_3; m_2)		soft-max(b_6, b_8)
s'_1	b_9=soft-min(u_3; m_3)			b_9



a

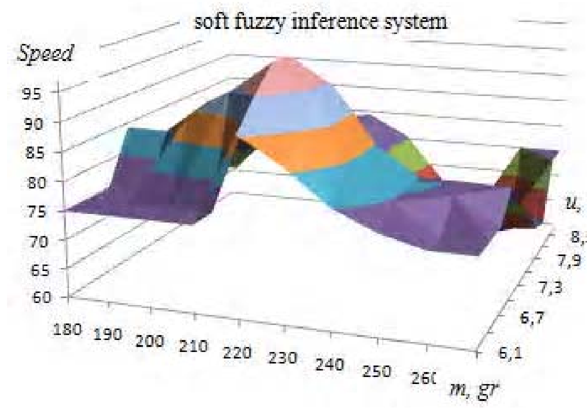


b

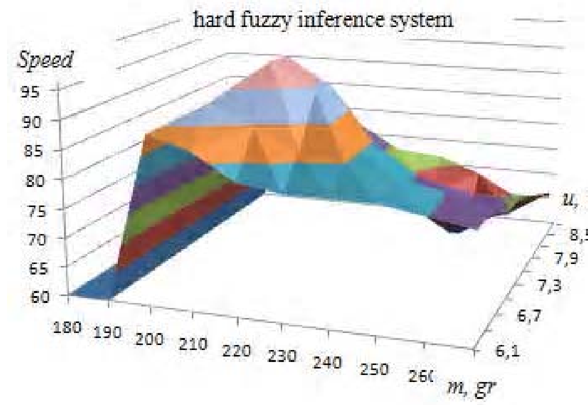


c

Figure 7 – Input MF: a – power supply voltage *u*; b – the robot's weight *m*; c – output MF *Speed*



a



b

Figure 8 – Modeling: a – soft model; b – hard model

The moving time of the mobile robot along the line *t* (see Fig. 5) and the amount of successful robot's passes are estimated withing the experiment. The experimental data of the mobile robot when it moves along the first track (see Fig. 5, a) are given in Table 11. The experimental data of the mobile robot when it moves along the second track are given in Fig. 5, b (see Table 12).

The analysis of the experimental results (see Table 11) shows that the mobile robot has not done a move along the track in the experiment no. 1, when using the hard FIS. However, the mobile robot has successfully done all the movements along the track in the all experiments (see Table 11), when using the soft FIS.

Table 9 – Defuzzification variable *Speed* based on the soft fuzzy inference algorithm

m / *u*	180	190	200	210	220	230	240	250	260	270
	Speed									
6.1	75	75	75	75	90.36	85.89	80.14	76.85	75	75
6.4	75	75	75	75	95.15	90.49	84.11	79.68	75	75
6.7	75	75	88.9	93.71	99.17	94.53	85.09	80.28	79.6	75
7	84.2	84.2	89.89	93.29	99.06	94.49	84.79	79.86	79.84	79.56
7.3	75	75	84.51	89.31	94.5	89.8	80.02	75.13	75.14	74.45
7.6	75	75	83.23	87.58	88.72	84.2	74.29	69.34	70.87	71.26
7.9	72.76	72.76	78.4	81.19	82.11	76.93	67.23	62.88	65.12	65.86
8.2	69.88	69.88	77.52	78.91	79.68	74.85	65.22	60.58	62.39	64.69
8.5	75	75	75	79.55	79.37	74.56	65.55	60.87	61.72	75
8.8	75	75	75	75	79.37	75.53	66.9	62.37	75	75

Table 10 – Defuzzification variable *Speed* based on the hard fuzzy inference algorithm

m / u	180	190	200	210	220	230	240	250	260	270
	Speed									
6.1	0	0	88.9	86.74	82.39	81.25	81.25	81.25	80.02	78.74
6.4	0	0	88.9	93.09	89.79	86.2	85.02	83.35	80.01	78.74
6.7	0	0	86	92.2	99.09	94.41	84.98	80.27	79.58	77.1
7	0	0	84.39	88.57	98.53	94.02	84.68	79.85	75.29	75
7.3	0	0	81.88	88.06	94.37	89.52	80.01	75.23	75.27	74.91
7.6	0	0	80.03	83.05	88.33	83.83	74.44	69.55	69.21	73.72
7.9	0	0	80.03	82.89	82.16	76.95	67.51	63.1	67.13	71.6
8.2	0	0	80.03	80.81	79.73	74.87	65.46	60.77	65.51	69.97
8.5	0	0	78.84	78.68	79.05	74.4	65.85	61.29	63.15	68.12
8.8	0	0	78.74	77.76	74.48	71.53	71.53	68.71	64.46	65.61

Table 11 – The robot moving along the track no. 1

Experiment no.	Hard fuzzy inference				Soft fuzzy inference			
	u, V	m, gr.	Speed	t, sec.	u, V	m, gr.	Speed	t, sec.
1	6.1	180	0	–	6.1	180	75	11.49
				–				12.46
				–				13.6
	7.5	180	0	–	7.5	180	75	6.97
				–				7.83
				–				7.94
	9	180	0	–	9	180	75	6.19
				–				5.95
				–				6.54
2	6.1	230	81	12.84	6.1	230	86	6.01
				13.81				7.54
				14.13				7.12
	7.5	230	85	5.88	7.5	230	85	5.88
				6.81				6.81
				6.64				6.64
	9	230	75	5.59	9	230	78	5.37
				6.05				6.52
				6.47				6.07
3	6.1	260	80	11.45	6.1	260	75	12.11
				13.81				13.72
				13.49				11.94
	7.5	260	71	7.53	7.5	260	71	7.14
				8.32				7.95
				8.24				8.19
	9	260	63	5.62	8.5	260	62	5.37
				6.17				6.52
				6.27				6.07

Table 12 – The robot moving along the track no. 2

Experiment no.	Hard fuzzy inference				Soft fuzzy inference			
	u, V	m, gr.		u, V	m, gr.		u, V	m, gr.
1	6.1	180	–	–	6.1	180	75	27.61
								26.15
								27.27
2	7.5	210	84	10.29	7.5	210	88	9.93
				10.85				10.45
				10.66				10.42
3	9	250	72	9.31	9	250	64	11.08
				8.81				10.35
				8.9				10.32

The result of the robot moving along the track no.2 are similar to the above mentioned result. Thus, the experiments show that the process of the mobile robot control is unstable.

Analyzing the results given in Table 12 one can conclude that if the power voltage supply of the mobile robot increases then the time of its passing the track decreases (see Fig. 9).

6 DISCUSSION

Different methods are possible to minimize RMSE. For example, ANFIS technology of finding the optimal conclusion of fuzzy rules is described in paper [24, 25, 26]. Nevertheless, the present research proves that it is possible to decrease RMSE at 30 % off if change the parameters a and b of the sigmoidal function Eq. (3). RMSE should be

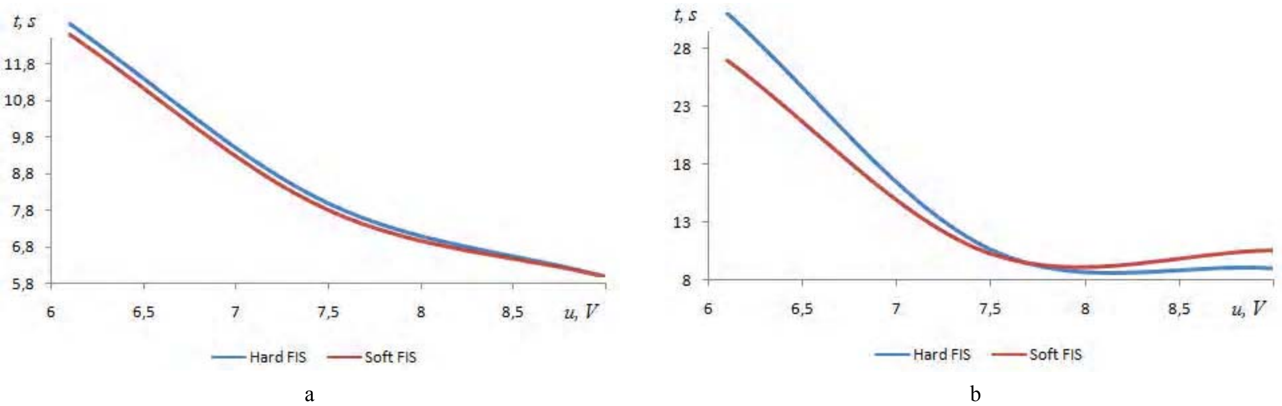


Figure 9 – Dependence of robot's decision time on the power voltage $t=f(u)$: a – track no.1; b – track no. 2

calculated for experimental values (see Table 3), if the parameters a and b of the sigmoidal function are changed (see Eq.(3)). Other parameters (see Table 3) are constant.

According to the results of the experiments, it is possible to conclude that: RMSE is 20,7 times less when using a soft fuzzy algorithm in comparison with a hard one. It is possible to minimize RMSE in 1,46 times if the parameters of the sigmoidal MF are changed. The mobile robot does not always accomplish a task if the hard FIS is used. The decision time for a track is minimized if the power voltage supply is increased. Therefore, a soft fuzzy system of decision-making is recommended to apply for a mobile robot control.

CONCLUSION

The problem of building a soft algorithm of fuzzy inference used to control a mobile robot is solved in the paper.

Scientific novelty of the results obtained in the article is that for the first time proposed soft algorithm, which in fuzzy inference to find minima and maxima uses soft arithmetic operators that provides additive of fuzzy control systems.

The practical significance of these results is that for the movement of the mobile robot along a line the specialized software based on the soft fuzzy algorithm is developed.

Prospects for further research consist in the fact that the improvement of the developed software for control of a mobile robot will allow to study given soft algorithm of fuzzy inference for a wide class tasks to control mobile robots.

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МЯГКИЙ НЕЧЕТКИЙ АЛГОРИТМ ДЛЯ УПРАВЛЕНИЯ МОБИЛЬНЫМ РОБОТОМ

Актуальность. Решена задача управления мобильным роботом на основе мягкого алгоритма нечетко-логического вывода.

Цель работы – создание мягкого алгоритма нечетко-логического вывода, позволяющего обеспечить аддитивность нечеткой системы управления.

Метод. Предложен мягкий алгоритм нечетко-логического вывода, использующийся для управления мобильным роботом. Данный алгоритм позволяет компенсировать ошибки присущие традиционным моделям нечеткого вывода. К ошибкам относятся: проклятие размерности, отсутствия аддитивности и условия разбиения единицы. Данный мягкий алгоритм нечеткого вывода, за счет рационального размещения предпосылок и заключений в матрице нечетких отношений, позволяет сократить число операций необходимых для реализации нечеткого вывода. Другая отличительная особенность предложенного мягкого алгоритма заключается в том, что для нахождения в нечетком выводе минимумов и максимумов используются мягкие арифметические операторы. В статье показано, что при использовании жестких формул для реализации этих же формул в процессе управления мобильным роботом будут возникать ситуации в которых робот потеряет управляемость. В статье указано, что реализация возможности в мягком алгоритме нечеткого вывода опции изменения параметров сигмодальных функций принадлежностей, позволит минимизировать погрешности на его выходе. Об этом свидетельствует динамика изменения коэффициента RMSE от варьирования параметров сигмодальной функции. Дополнительное имитационное моделирование представленное в статье показывает, что при варьировании коэффициентов сигмодальной функции принадлежности, в частности при увеличении параметра *a* наблюдается уменьшение значения RMSE. Эффективность предложенного мягкого алгоритма подтверждают представленное в статье численное моделирование и эксперименты исследования перемещения мобильного робота вдоль линии.

Результаты. Разработано специализированное программное обеспечение для микроконтроллера Arduino Uno, реализующее предложенный алгоритм, и позволяющее осуществить экспериментальное исследование его свойств.

Выводы. Проведенные численные и экспериментальные исследования подтвердили работоспособность предложенного мягкого алгоритм и реализующего его программного обеспечения, а также позволяют рекомендовать их для применения на практике для управления мобильными роботами.

Ключевые слова: нечеткая система вывода, нечеткие множества; RMSE; мягкие вычисления; мобильный робот.

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МЯГКИЙ НЕЧІТКО АЛГОРИТМ ДЛЯ УПРАВЛІННЯ МОБІЛЬНИМ РОБОТОМ

Актуальність. Вирішено завдання управління мобільним роботом на основі м'якого алгоритму нечітко-логічного виводу.

Мета роботи – створення м'якого алгоритму нечітко-логічного виводу, що дозволяє забезпечити аддитивність нечіткої системи управління.

Метод. Запропонований м'який алгоритм нечітко-логічного виводу, що використовується для управління мобільним роботом. Даний алгоритм дозволяє компенсувати помилки властиві традиційним моделям нечіткого виводу. До помилок відносяться: проклін розмірності, відсутність аддитивності і умови розбиття одиниці. Даний алгоритм за рахунок раціонального розміщення передумов і висновків в матриці нечітких стосунків, дозволяє скоротити, число операцій необхідних для реалізації нечіткого виводу. Інша відмітна особливість запропонованого м'якого алгоритму полягає в тому, що для знаходження в нечіткому виводі мінімумів і максимумів використовуються м'які арифметичні оператори. У статті показано, що при використанні жорстких формул для реалізації цих же формул в процесі управління мобільним роботом виникатимуть ситуації в яких робот втратить керованість. Також в статті показано, що реалізація можливості в м'якому алгоритмі нечіткого виведення опції зміна параметрів сигмодальних функцій приналежностей, дозволить мінімізувати погрішності на його виході. Про це свідчить динаміка зміни коефіцієнта RMSE від варіювання параметрів сигмодальної функції. Додаткове імітаційне моделювання представлене в статті показує, що при варіюванні коефіцієнтів сигмодальної функції приналежності, зокрема при збільшенні параметра a спостерігається зменшення значення коефіцієнта RMSE. Ефективність запропонованого м'якого алгоритму підтверджують представлене в статті чисельне моделювання і експерименти дослідження переміщення мобільного робота вздовж лінії.

Результати. Розроблено спеціалізоване програмне забезпечення для мікроконтроллера Arduino Uno, що реалізовує запропонований алгоритм, і що дозволяє здійснити експериментальне дослідження його властивостей.

Висновки. Проведені чисельні і експериментальні дослідження підтвердили працездатність запропонованого м'якого алгоритм і реалізованого програмного забезпечення, а також дозволяють рекомендувати їх для вживання на практиці для управління мобільними роботами.

Ключові слова: нечітка система виведення, нечіткі множини; RMSE; м'які обчислення; мобільний робот.

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