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Design of modified movement planning system as a component of an intelligent planning system for robot manipulator

D. Nemeikšytė and V. Osadčuks*

Latvia University of Life Sciences and Technologies, Faculty of Engineering, 5 J. Cakstes blvd., LV-3001 Jelgava, Latvia
*Correspondence: nemeiksyte.daiva@llu.lv, vitalijs.osadcuks@llu.lv

Abstract. Different fields of industry and in-service support widely use robots, mechatronic and robotic technology systems in their activities. This is related to growing functionalities that result from using more advanced control systems the development of which is based on available achievements in the technical measures of computing. Therefore, the subject of study in this article was movement of a robot manipulator in using a fuzzy logics and neural network, and the goal of the study was to develop methods for designing combined intelligent planning and control systems for robot-manipulator movement in static dynamic environments based on the combined use of fuzzy logic apparatus and artificial neural networks to reduce the possibility of robot-manipulator's joints colliding into unknown obstacles located in its operating area. Based on this, the robot arm model has been developed after calculating in the article the missing parameters of the experimental robot manipulator in order to analyze the peculiarities of using the fuzzy logics device as well as the specifics and challenges of using neural network. As a result of the study performed in the article, significant data were obtained based on which a method was offered for an intelligent system for planning robot manipulator movement in static environment using a fuzzy blocks, which was characterized by the use of neural network corresponding each block, and localization of each solution to the task of planning robot manipulator movement in each specific situation, which enables to improve the accuracy and efficiency of movement planning.

Key words: static environment, intelligent planning system, neural network, robot manipulator, fuzzy logic.

INTRODUCTION

The method of designing an intelligent real-time planning system for robot-manipulator movement in an unknown static environment consisting of three stages of trajectory formation based on using the two fuzzy blocks of robot's each joint as well as the detailed classification model describing the locations of unknown obstacles in the operating area and the corresponding directions and types of movement in a form of multi-layer neural network perceptron allows for taking into account during each iteration the distance between the robot's joints and to the closest obstacles located on the right and on the left, and ensures the robot reaches the destination point.

In practice, use of geometric methods is unnecessary when the shortest distance is measured by the use of sensors. At the same time, unknown obstacles can have any shape, and the manipulator's operating device is equipped with a certain number of infrared distance sensor pairs separated one from another. Sensors are installed on the operating device in the places where it can have a contact with an obstacle. The density of distance sensors must ensure there are no 'blind zones' (Laurs & Priekulis, 2011; Osadcuks et al., 2014; Osadcuks & Pecka, 2016; Zhang, K. et al., 2016; Zhang, X. et al., 2016; Li, 2018; Matějka et al., 2019).

While calculating the shortest distances between manipulator's joints and the closest obstacles, only those obstacles which are within the sensory range of the distance sensors on the robot joints shall be taken into account. The shape of this range resembles a cylinder with its axis being the manipulator's joint, At the same time, the length of this range coincides with the length of the robot's joint, and the very range can be analysed as a simplified model of the environment scanned with the ultrasound distance sensors on both sides of each joint. Within the scope of computer simulations, readings of all the sensors comprise the known parameters of the function for calculating the shortest distance between each joint and the closest obstacle. It must be noted that analysis of this problem has not been included into the list of the main tasks of this dissertation research project (Sakai et al., 2002; Laurs & Priekulis, 2010; Yujie et al., 2010; Osadcuks, et al., 2014; Zhang et al., 2016).

The largest value in the range of the possible shortest distances between robot's each joint (joint number-one – d_{1max}, joint number-two – d_{2max}, joint number-three – d_{3max}, joint number-four – d_{4max}, joint number-five – d_{5max}, joint number-six – d_{6max}) and the closest obstacles can be calculated by the use of a graphical analysis with the model presented in Fig. 1. At the same time, the following must be taken into account (Laurs & Priekulis, 2008; Zou, et al., 2017; Ndawula et al., 2018; Zhou et al., 2018; Valjaots et al., 2018; Nemeikšis & Osadčuks, 2019; Obasekore et al., 2019).

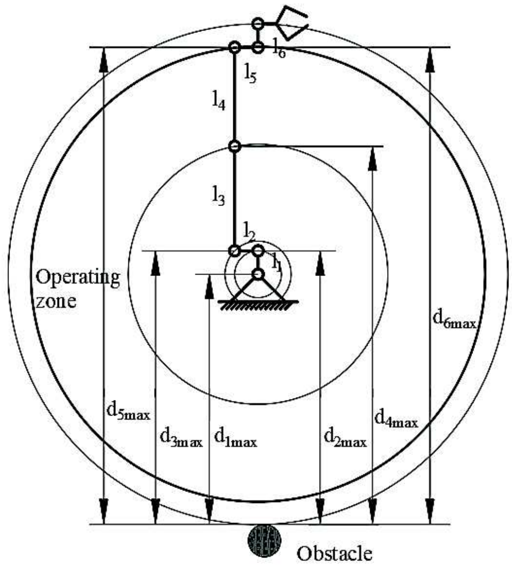

Figure 1. Graphical model for determining the largest value in the range of the possible shortest distances between the robot's joints and the closest obstacles (Yung et al., 2019).

$d_{1max} = l_1 + l_2 + l_3 + l_4 + l_5 + l_6$; $d_{4max} = 2l_1 + 2l_2 + 2l_3 + l_4 + l_5 + l_6$;
$d_{2max} = 2l_1 + l_2 + l_3 + l_4 + l_5 + l_6$; $d_{5max} = 2l_1 + 2l_2 + 2l_3 + 2l_4 + l_5 + l_6$;
$d_{3max} = 2l_1 + 2l_2 + l_3 + l_4 + l_5 + l_6$; $d_{6max} = 2l_1 + 2l_2 + 2l_3 + 2l_4 + 2l_5 + l_6$.

Note that d_{1max}, d_{2max}, d_{3max}, d_{4max}, d_{5max} and d_{6max} are used to design the diagrams of fuzzy dependency functions as the largest range (d_{nmax}) of the robot manipulator's n-link.

MATERIALS AND METHODS

A method was prepared for designing an intelligent planning system for robot manipulator real-time movement in an unknown static environment based on the process of processing information about the robot and and the surrounding static environment consisting of tree stages. The use of the method was described using a model of six-joint robot manipulator (Fig. 2).

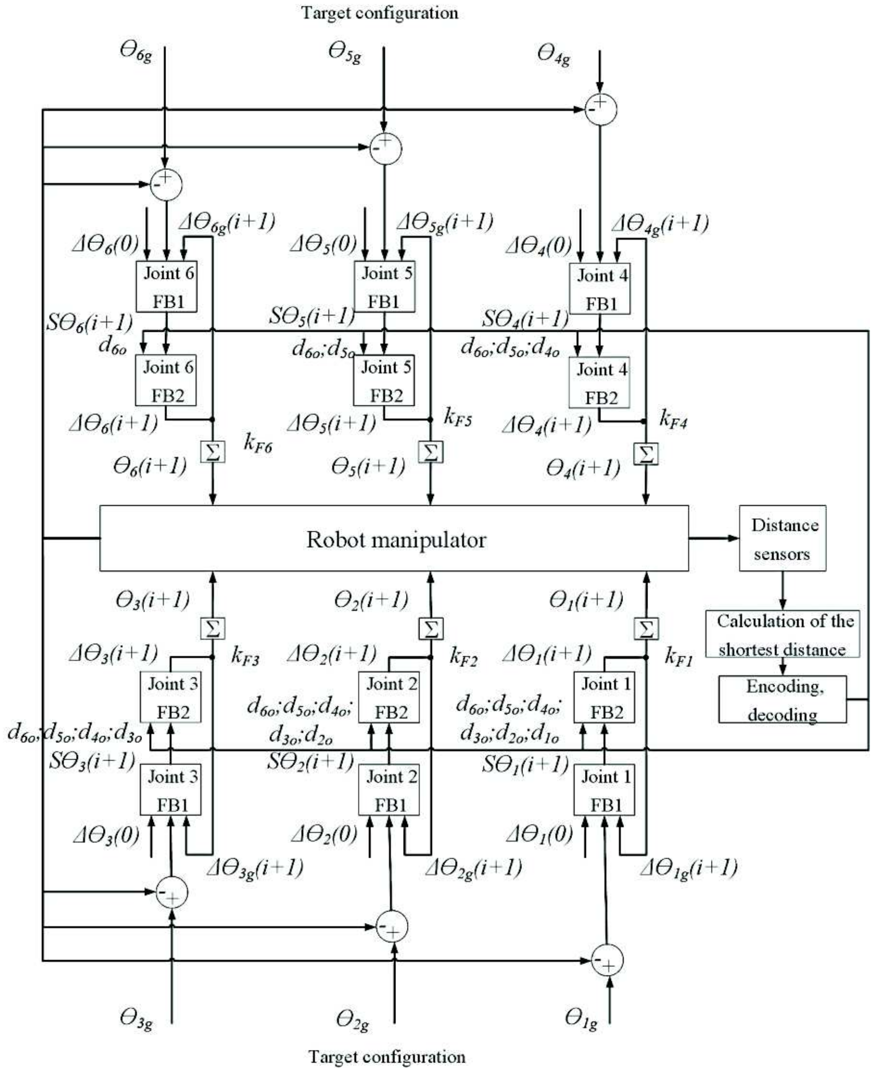

Figure 2. Intelligent planning system for six-joint robot manipulator real-time movement in an unknown static environment.

During the first stage, the final value of the distance between the robot's n-joint and an obstacle located in its operating zone (d_{no}) based on the information obtained from distance sensors, using the arrangement of the unknown obstacles in the robot's operating zone and a model of classifying the directions and movements of the respective joints as well as types of neural network multilayer (NNM).

During the second stage, the value of the initial step of the robot's n-joint movement ($S\theta_n(i+1)$which is the output of the fuzzy block number-one (FB1) with its input being the former values of changes in n-joint movement angle ($\Delta\theta_n(i)$), also the difference between the n-joint target (θ_{nd}) and current ($\theta_n(i)$) configurations ($\Delta\theta_{nd}(i+1) = \theta_{nd} - \theta_n(i)$). At the same time, the initial condition for system functioning is $\Delta\theta_n(0) = 0$.

During the third stage of the method in question, the final value of the output of the manipulator's n-joint fuzzy block number-two (FB2) - change in the movement angle - is determined based on the result parameters from the stage one and two ($\Delta\theta_n(i+1)$), when in a new iteration (i+1), the movement angle is determined as $\theta_n(i+1) = \theta_n(i) + \Delta\theta_n(i+1)$. Inputs to the FB2 are $S\theta_n(i+1)$ and d_{n0}. Internal feedback implemented in this system allows for calculation of $S\theta_n(i+1)$ depending on the $\Delta\theta_n(i)$ value, which helps to avoid robot collusion with an unknown obstacle and reach the final destination.

Designing a neural network for simulation of classifications

Designing a neural network for simulation of classifications of possible situations related to manipulator's movement starts from definition thereof. Classifications of such situations consists of systematization of unknown obstacles in the operating zone and the respective directions and types of robot's movement in each iteration.

The classification of unknown static obstacles suggested in the present thesis for six-joint manipulator consists of 16 possible situation variants with obstacles located on the right, on the left and both on the right and on the left with respect to each joint of the robot. Classification of manipulator's joint movement directions and types also has 16 possible options depending on the nature of movement: multi-step movement to the left; multi-step movement to the right; one step to the left and one step to the right.

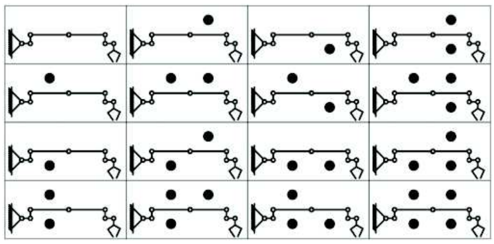

Figure 3. Classification of the closest obstacle arrangement in the operating zone of the robot manipulator.

Thus, a detailed table of classifications contains 16 items describing the positions of the possible manipulator movement in the operating zone and the related decision to be made during each iteration during the process of planning. Detailed outputs of the classification table model are the acceptable final distances between the joints of the robot and the closest obstacles on the left and on the right.

Fig. 3 presents classification of the possible arrangement of obstacles. The circles to the left and to the right of the manipulator's joint indicate obstacles located at the shortest distance, whereas a single circle can both represent a single obstacle as well as a set of obstacles.

The simulation of the classification of obstacle arrangement in the robot manipulator's operating area can be pictured as follows:

1. $D_{nR} = 0$ – no closest obstacle present to the right of the n-joint;
2. $D_{nL} = 0$ – no closest obstacle present to the left of the n-joint;
3. $D_{nR} = 1$ – an obstacle is present at the shortest distance to the right of the n-joint;
4. $D_{nL} =1$ – an obstacle is present at the shortest distance to the left of the n-joint.

Fig. 4 shows the classification of robot manipulator's directions and types of movement, where dashed arrows mark separate steps to the right or to the left, and solid lines mark multi-step movement to the right or to the left, respectively.

Simulation of the directions and types of robot movement:

1. $D\theta_n = 0$ – n-joint multi-step movement;
2. $D\theta_n = 1$ – n-joint multi-step movement;
3. $D\theta_n = 2$ – one step of the n-joint to the left;
4. $D\theta_n = 3$ – one step of the n-joint to the right.

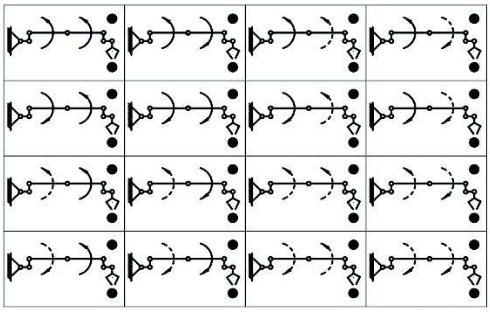

Figure 4. Classification of robot manipulator movement directions and types.

In total, the model of a detailed classification consists of 16 possible variants. Table 1 explain the functioning of a detailed classification model, where $D\theta_n$, D_{nR}, D_{nL}, D_{no} – movement directions of the manipulator's n-joint.

It should be noted that d_{nmax} is the largest value of the distance between the n-joint and an obstacle from the fuzzy range; d_{nL} – actual distance between the n-joint and the closest obstacle on the left; d_{nR} – actual distance between the *j*-joint and the closest obstacle on the right; OSR – one step to the right, OSL – one step to the left, that are calculated as the final difference between the target and actual configurations.

Table 1. Classification of the locations of obstacles and the directions and types of the related robot-manipulator movements in the operating area

No.	$D\Theta_n$	D_{nR}	D_{nL}	D_{no}
1.	0	0	0	d_{nmax}
2.	0	0	1	d_{nL}
3.	0	1	0	d_{nmax}
4.	0	1	1	d_{nL}
5.	1	0	0	$-d_{nmax}$
6.	1	0	1	$-d_{nmax}$
7.	1	1	0	d_{nR}
8.	1	1	1	d_{nR}
9.	2	0	0	OSL
10.	2	0	1	OSL
11.	2	1	0	OSL
12.	2	1	1	OSL
13.	3	0	0	OSR
14.	3	0	1	OSR
15.	3	1	0	OSR
16.	3	1	1	OSR

The designed structure of a neural network with the encoding and decoding blocks, where the values of the encoded outputs D_1, D_2, D_3, D_4, D_5, D_6 are used to determine the values of the final distances between the manipulator's joints and obstacles. In turn, d_1, d_2, d_3, d_4, d_5, d_6 are the wanted final distances – inputs to the fuzzy structure.

The neural network consists of two hidden layers and one output layer. The first hidden layer consists of forty neurons, the second consists of twenty five neurons, while the output layer consists of two neurons. The suggested structure of neural network was trained by backpropagation.

Detailed classification model based on neural network consists of three stages. During the first stage, manipulator's movements are transformed into codes according to the following classification variants: $D\theta_1$, $D\theta_2$, $D\theta_3$, $D\theta_4$, $D\theta_5$, $D\theta_6$, D_{R1}, D_{L1}, D_{R2},

D_{L2}, D_{R3}, D_{L3}. D_{R4}, D_{L4}, D_{R5}, D_{L5}, D_{R6}, D_{L6}. An encoding unit was developed to implement this process.

During the second stage, the encoded parameters get into the multilayer perceptron of the multilayer network. And finally, during the third stage, the outputs of the neural network are decoded (decoding unit) into the final values of the distances between robot joints and obstacles. Later, these values are used as inputs into a fuzzy structure with the decision-making process implemented within the limits of functioning thereof.

Designing a modified fuzzy movement planning system as a component of an intelligent planning system

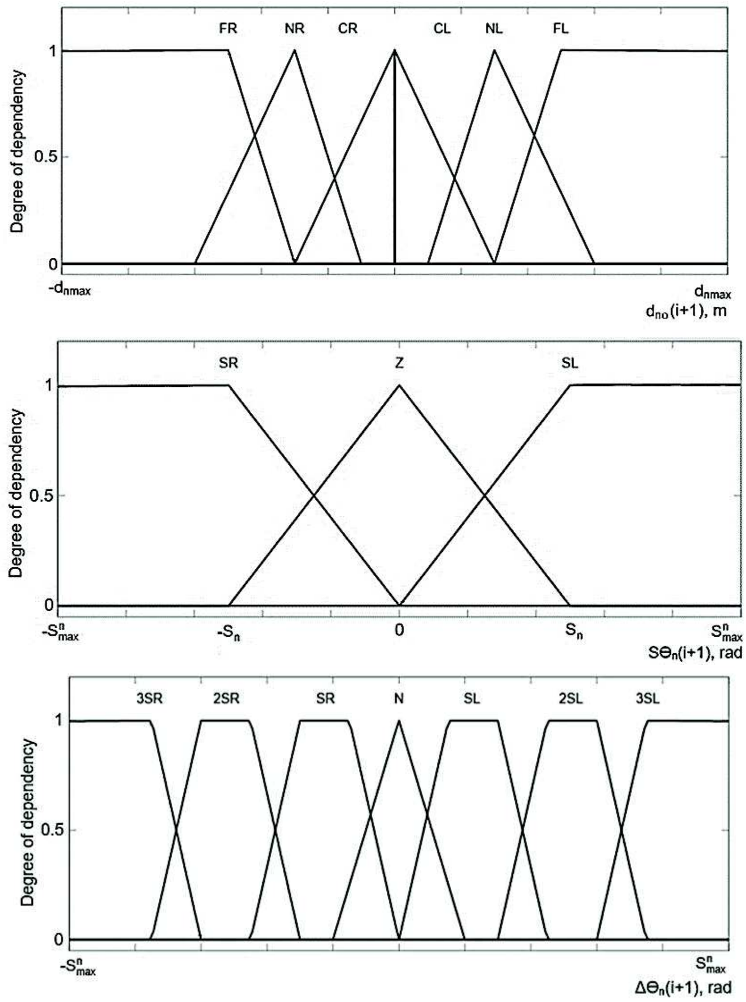

Figure 5. Dependence functions of FB2 inputs and outputs of a robot manipulator's n-joint.

The structure of a manipulator's real-time movement modified fuzzy planning system presented in the Fig. 2. In this system, the first fuzzy block (FB1) of the robot manipulator's n-joint is used to determine the $S\theta_n(i+1)$ value.

As a result of using in the planning system a detailed classification model functioning on a basis of three-layer neural network the number of inputs to FB2 for the n-joint has reduced. Therefore, the structures of FB2 for the n-joint are identical.

FB2 of the n-joint, have two inputs – movement step initial value $S\theta_n(i+1)$ and the output of the decoding unit d_{no}. Output from is $\Delta\theta_n(i+1)$. The dependence functions thereof are presented in Fig. 4.

The system of fuzzy basic rules used for FB1 and FB2 of the n-joint is presented in Table 1, which have been designed by the robot manipulator real-time movement in an unknown static environment fuzzy planning system FB2 (n-joint) (Fig. 5).

RESULTS AND DISCUSSION

N-joint robot manipulator described in Fig. 1 was also selected for computer simulation of an intelligent planning system for real-time movement in an unknown environment.

During test one, manipulator was moving from start point A configuration to target configuration point B (Fig. 6). After 2263 software iteration (set time 5.4637 s) error for θ_n was equal to 0.000°. No swinging movements in the area of target point were observed. This was obtained thanks to the functioning of the detailed classification model based on neural network.

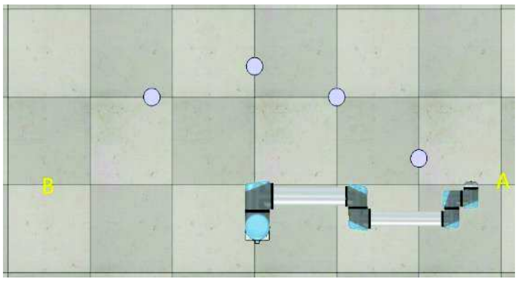

Figure 6. Results of the first test of an intelligent planning system for two-joint robot manipulator real-time movement in an unknown static environment.

Fig. 7 presents results of the test two when the robot was moving from the starting configuration point A to target configuration point B. Planning error related to the robot's joint θ_3, θ_4, θ_5 and θ_6 reaching target configuration after 2180 software iterations (set time 5.686 s), was equal to 0.000°. Moreover, no swinging movements were observed in the area of target configuration. It must be noted that there were no error of $\theta_1$and θ_2 as movement of the joint number one and two was successfully interrupted before potential collision to an obstacle. In this way, the manipulator reached the final configuration.

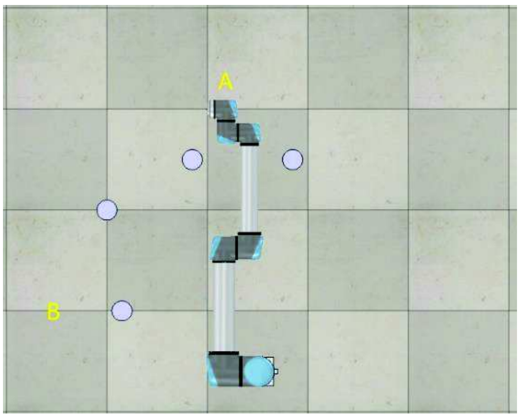

Figure 7. Results of the second test of an intelligent planning system for two-joint robot manipulator real-time movement in an unknown static environment.

Figs 8, 9, 10, 11, 12 and 13 presents the diagrams of test parameters, including D_{2o}, D_{3o}, d_{2o}, d_{3o}, $S\theta_2$, $S\theta_3$, $\Delta\theta_2$, $\Delta\theta_3$, θ_2, θ_3. It must be noted that the testing conditions provided for a situation where a robot's joint starts moving between two obstacles on the right and on the left at a short distance from one another.

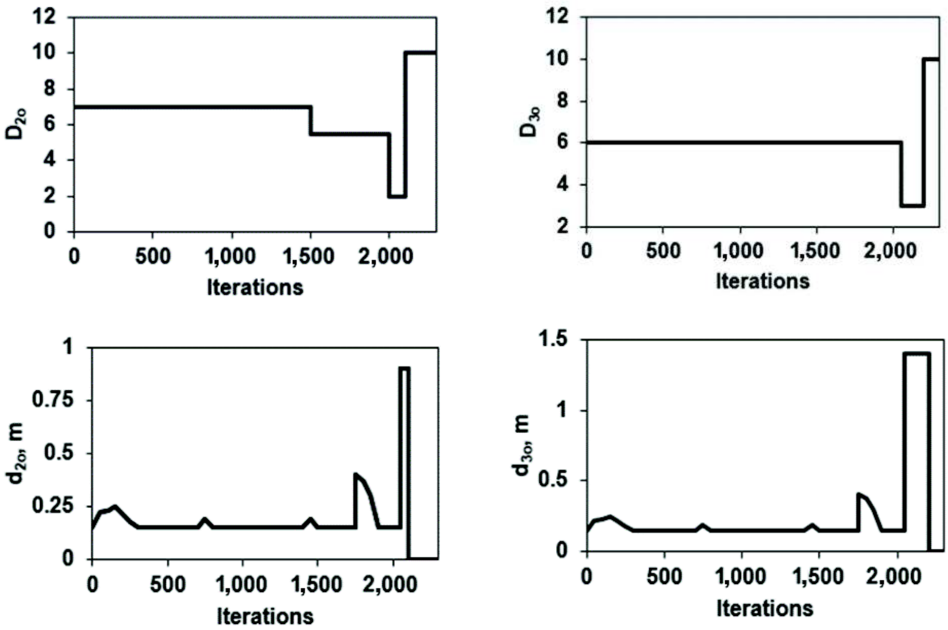

Figure 8. Parameters of the intelligent system test one results.

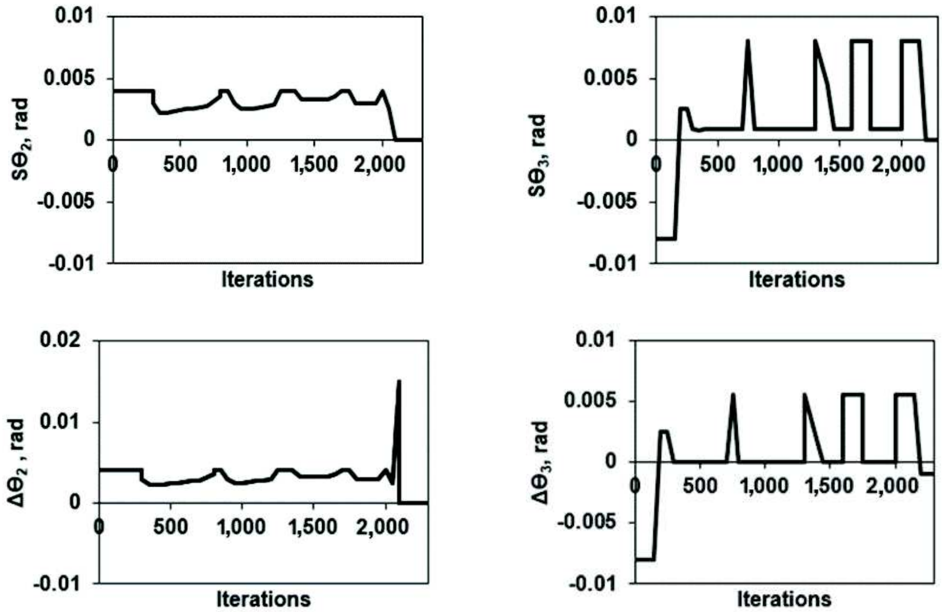

Figure 9. Parameters of the intelligent system test one results.

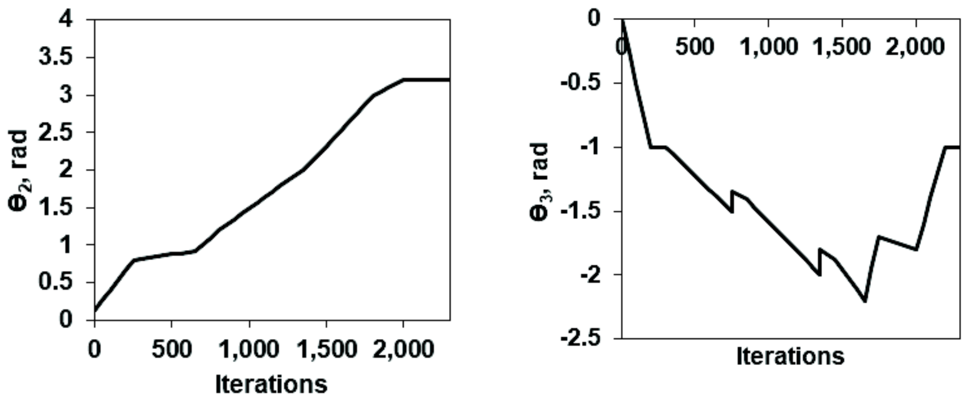

Figure 10. Parameters of the intelligent system test one results.

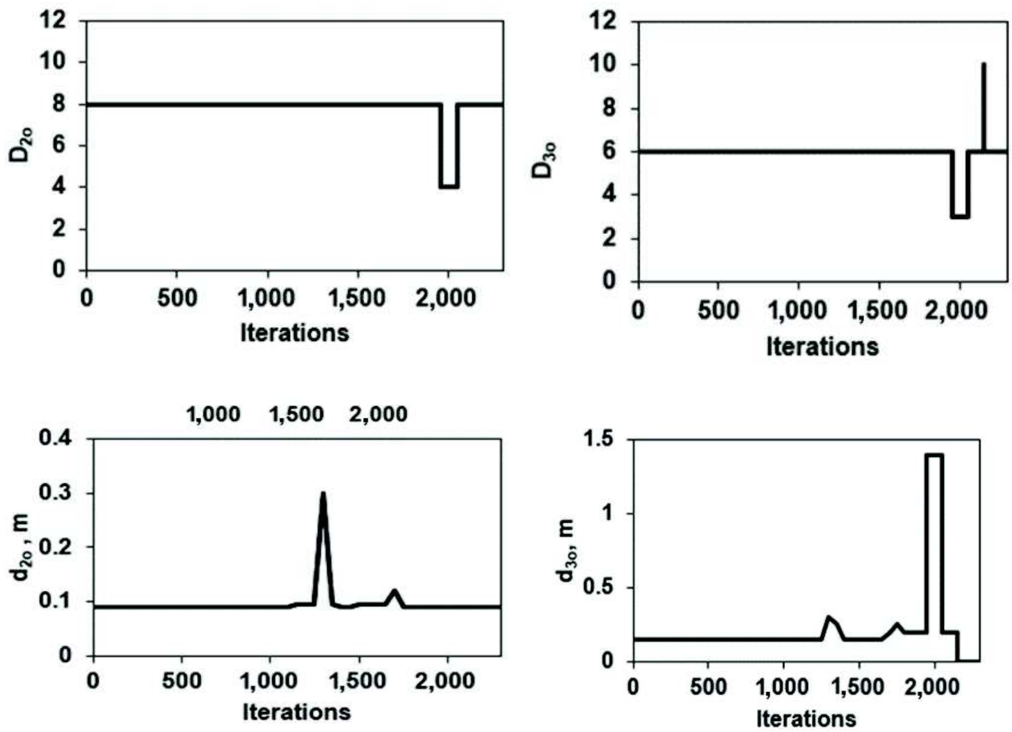

Figure 11. Parameters of the intelligent system test two results.

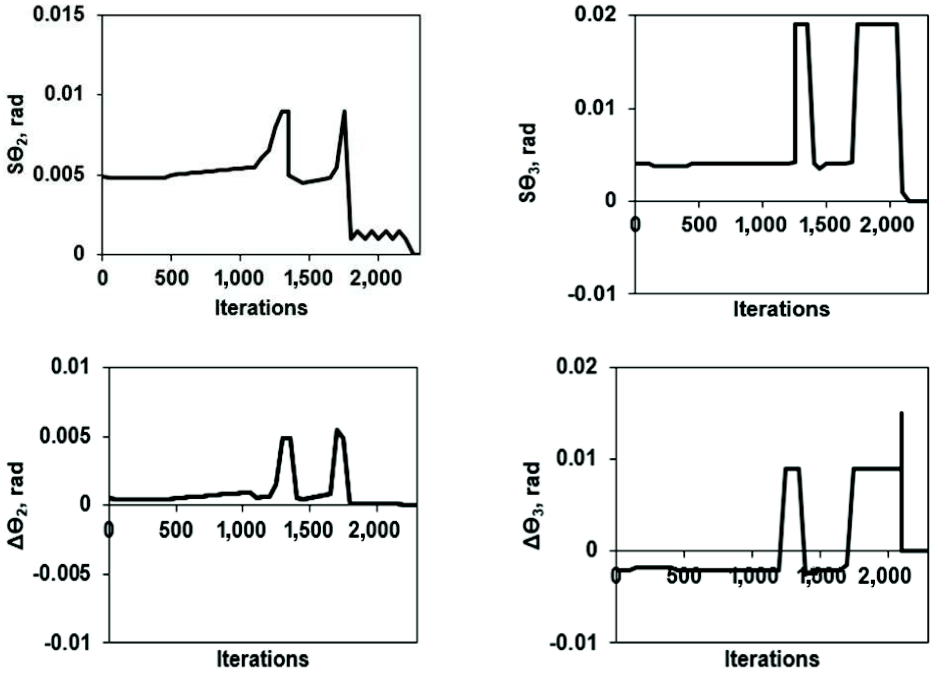

Figure 12. Parameters of the intelligent system test two results.

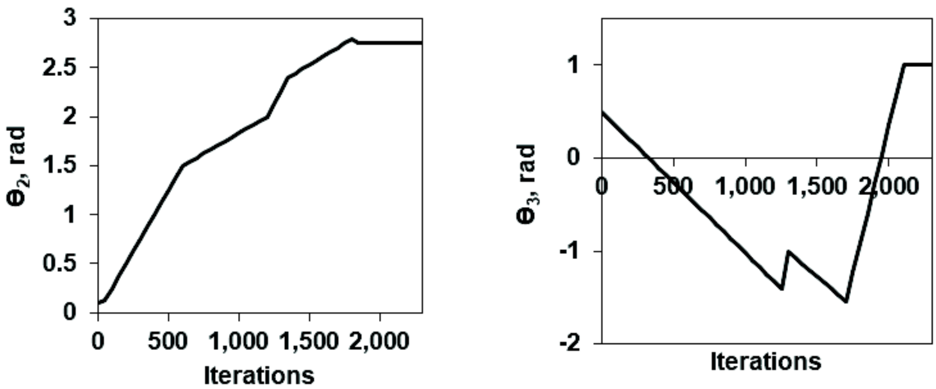

Figure 13. Parameters of the intelligent system test one results.

CONCLUSIONS

Neural network as a component of the intelligent planning system is used to simulate the 16 designed classifications of unknown obstacle arrangement in the operating zone as well as the 16 related classifications of the directions and types of movement of the two joints of the robot manipulator (the detailed classification table consists of 16 items).

A method was suggested of designing an intelligent real-time planning system for robot manipulator's movement in an unknown static environment based on the process of processing information about the robot and the surrounding environment consisting of three stages with the purpose to provide a safe trajectory. During the first stage, the final values of the distances between the manipulator's joints and the obstacles located in the operating zone are determined based on the classification model describing the arrangement of the unknown obstacles in the robot's operating zone and the respective directions and types of robot manipulator's movement. During the second stage, the values of a preliminary movement step of the robot's n-joint are calculated using the first fuzzy block of the corresponding joint. During the third stage, which is entered after completion of the first two stages, the second fuzzy block of the n-joint is used to calculate the final values of its movement angles. This method used for robot manipulators with any degree of freedom allows the following:

- taking into account during each iteration the values of the shortest distance between the robot's joints and the closest obstacles on the right and on the left;
- reducing the number of input parameters during the second stage of the fuzzy planning system;
- successfully avoid collision of the robot with the unknown static obstacles, and reach the target point without any oscillatory movements in the target point area with zero planning error.

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