*Agronomy Research* **17**(5), 1993–2004, 2019
https://doi.org/10.15159/AR.19.166

# Development of intelligent system of mobile robot movement planning in unknown dynamic environment by means of multi-agent system

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**Abstract.** Through the ages the world has conceived the projects which are aimed at creating diverse models of robots that would be beneficial for exploration of different dangerous surfaces where human participation is excluded. Therefore, the main task of the study of this article is to develop the researches, the object of which is mobile robot movement in unfamiliar environment, based on multi agent apparatus system and neural networks. The aim of the research is to develop methods for creating intellectual systems for planning mobile robot movement in unfamiliar environment applying the methods of multi agent apparatus and neural networks ensuring the robot executes the planned and adjusted on the way safe trajectory in an environment with unknown obstacles. Accordingly, the entire study of the article is based on a two-stage process. The first stage involves determination of distance between the robot and the obstacles in its operating area as well as classification of the possible location of obstacles, based on the information received from distance sensors, using the model of multilayer neural networks. During the second stage bypassing obstacles, wall tracking, movement-to-destination as well as speed management agents are developed. As the result of the study, a method was suggested for creating neural network model for classification of environment into agents and their consistent switching, which, according to the classification table compiled, involves all the possible locations of obstacles occurring on the robot's movement trajectory and allows reducing the number of unfamiliar environment situations that are necessary to identify.

**Key words:** multi-agent system, unknown environment, neural network, dynamic obstacles, planned track.

## INTRODUCTION

For neural network training, scientists have been determining various robot's target positions provided movement strategies the neural network was taught under conditions of certain environment could be easily adjusted in a new dynamic environment. In the event of moving obstacles in the robot's operation zone, robot could avoid collision only when the speed of moving obstacles allowed the robot to stop and respond in a timely manner. The probability of the moving robot colliding into obstacles increased also because ultrasound distance sensors could not recognise their sharp edges. For this reason, during their experiments, scientists positioned obstacles with polished edges in the robot's operation area at the same time recognising the necessity to to improve the structure of sensors (Panigrahi & Sahoo, 2014; Ko et al., 2017).

The neural network model was directly used for trajectory formation. The space for neural network states was defined by the robot configuration space, and each neuron was described by a respective movement equation. This model allowed implementing real-time multi-target planning of robot's movement, including planning under the conditions of unpredictable changes in the environment. This process is based on variable activity of the neural network reflecting the instability of the environment. Determining the direction of robot's safe movement did not require optimising energy, advance information on dynamic environment, nor training. The complexity of the calculations had a linear dependence on the size of the neural network, where each neuron had only a local lateral relationship with neighbouring neurons (Cardenas et al., 2013; Kagan et al., 2016; Luo, 2017).

Thus, the study performed in this article is aimed at developing this area of robotics and analysing the development of an intelligent system for planning mobile robot movement in an unknown dynamic environment using multi-agent system with neural networks in more detail, which could be defined as the subject of the study. The article studies the intelligent system the essence of which lays in the combination of the possibilities offered by fuzzy system and neural networks, and the robot in question has the main structure composed of four fuzzy blocks intended for different agents. The study in the article is limited, on one side, to the analysis of a neural network as a component of an intelligent planning system used for simulating the developed classification of the positions of unknown obstacles in the robot's operation area and for switching the agents of obstacle circumvention, wall tracking, and movement towards the target, and, on the other side, analyses the method of developing an intelligent system which is based on a two-stage robot and its environment information processing system. Also, the study assesses the advantages of the combined neural networks and multi-agent method, and the accuracy of its application in an unknown dynamic environment.

## MATERIALS AND METHODS

The intelligent system for planning mobile robot movement in an unknown dynamic environment using a multi-agent system is based on processing the information concerning the robot and the surrounding unknown dynamic environment with a help of two-stage process. The structure of this system is presented in Fig. 1.

During the first stage of planning, the distance ($d_{SI}$) between the robot and the obstacles located in its operating area as well as the safe distance ($d_{safe}$) are established; also, the possible position of obstacles is classified based on the information from ultra-sound and infra-red distance sensors with their model being in a form of a multi-layer neural network trained using the method of error back propagation in autonomous mode).

During the second stage, obstacle-bypass, wall-tracking, movement-to-destination and speed control agents are developed using fuzzy blocks.

The intelligent system for planning mobile robot movement (Fig. 1) is composed of five agents. Beside the four agents, i.e. obstacle-bypass, wall-tracking, movement-to-destination and speed control, one more – safety agent – is used to ensure the mobile robot does not collide into obstacles while moving. Safety agent gives the STOP command and stops the robot when an obstacle occurs on the robot's movement trajectory in the so-called 'safety zone' ($d_{safe} = 0.10$ m). Safety agent has the highest degree of priority.

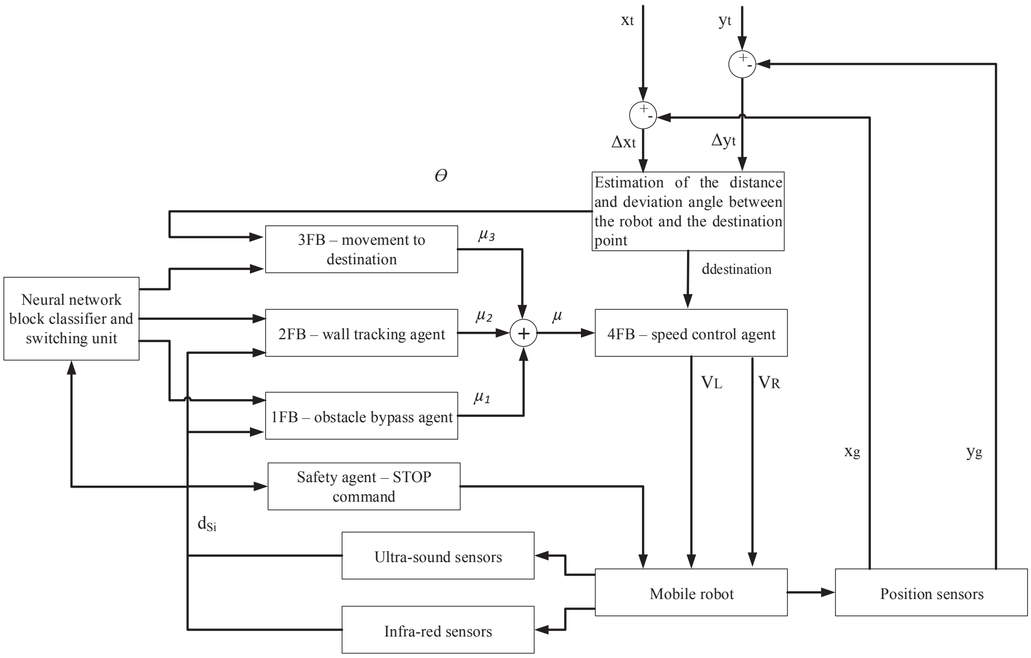



**Figure 1.** Intelligent system for planning mobile robot movement in an unknown dynamic environment using multi-agent system.

**Development of a neural network for classification and switching of environment situations**

Development of a neural network intended for simulating classification and switching of the situations related with the mobile robot movement starts from defining the situations. Classification of different situations involves systemization through each iteration of the position of unknown obstacles in the operating area and corresponding robot movement directions. Agent switching depend on the ultra-sound sensor signals.

To solve this task, operation zone of distance sensors (ultra-sound and infra-red sensors) is divided into 3 zones, as presented in the Fig. 2:

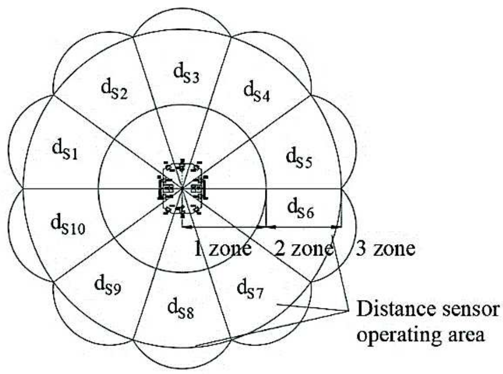



**Figure 2.** Three zones of distance sensors (ultra-sound and infra-red sensors) operation area.

Zone 1 – safe zone defined by the safe distance $d_{safe}$ (0.3 m). The safe zone does not play any role in the process of neural network classification.

Zone 2 – active detection zone restricted by 0.3 to 4 m with respect to ultra-sound sensors, and 0.3 to 0.7 m with respect to infra-red sensors.

Zone 3 – distant zone, where the distance to the obstacle is more than 4 m or 0.7 m.

Information from sensors represents one of the three situations marked by numbers 0, 1, 2, which mean:

'0' – no obstacles, i.e. they are in zone 3, and does not get into zone of distance sensor operation area;

'1' – detects any obstacle inside the zone 2;

'2' – irrelevant, which means there are no obstacles or they are located in zone 3.

Figs 3, 4 and 5 presents classification of the possible obstacle position in the movement-to-destination, wall-tracking and obstacle-bypass agents respectively.

Circles located on the left, in the front of, and on the right to the mobile robot mark the obstacles. Individual circles can mark both individual obstacles and a group of obstacles.

The movement-to-destination agent is activated when no obstacle is detected by the sensors US2-IR2, US3-IR3, US4-IR4 or US7-IR7, US8-IR8, US9-IR9, and no obstacle is at the same time detected by the sensors located on the same side (US1-IR1, US10-IR10 or US5-IR5, US6-IT6) (Fig. 3).

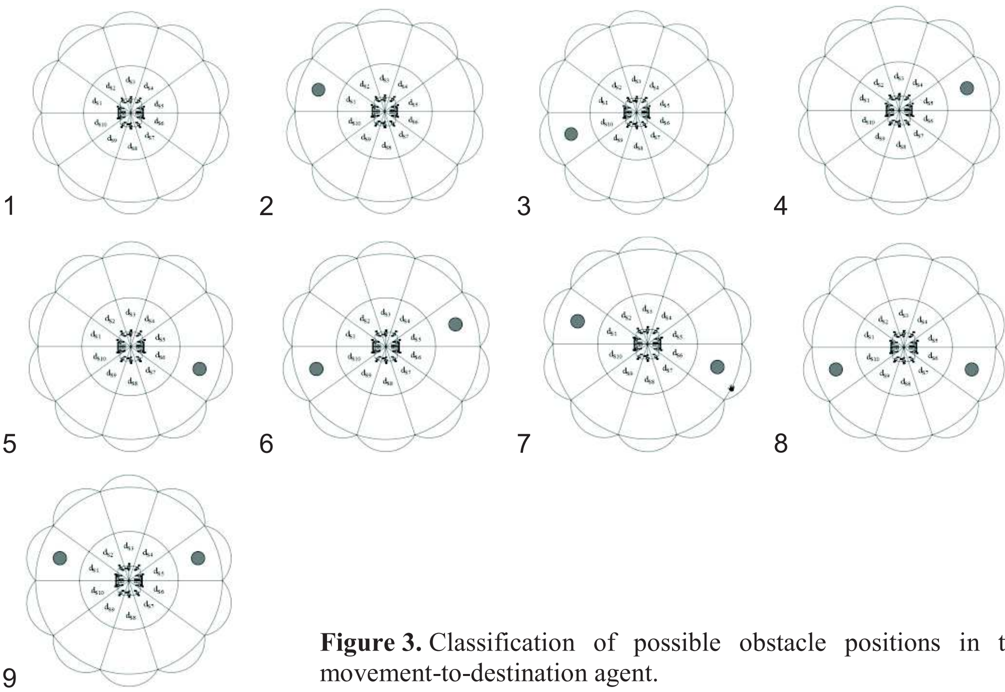



**Figure 3.** Classification of possible obstacle positions in the movement-to-destination agent.

The wall-tracking agent is activated when no obstacle is detected by the sensors US2-IR2, US3-IR3, US4-IR4 or US7-IR7, US8-IR8, US9-IR9, but obstacles are detected by the sensors located on the same side (US1-IR1, US10-IR10 or US5-IR5, US6-IT6).

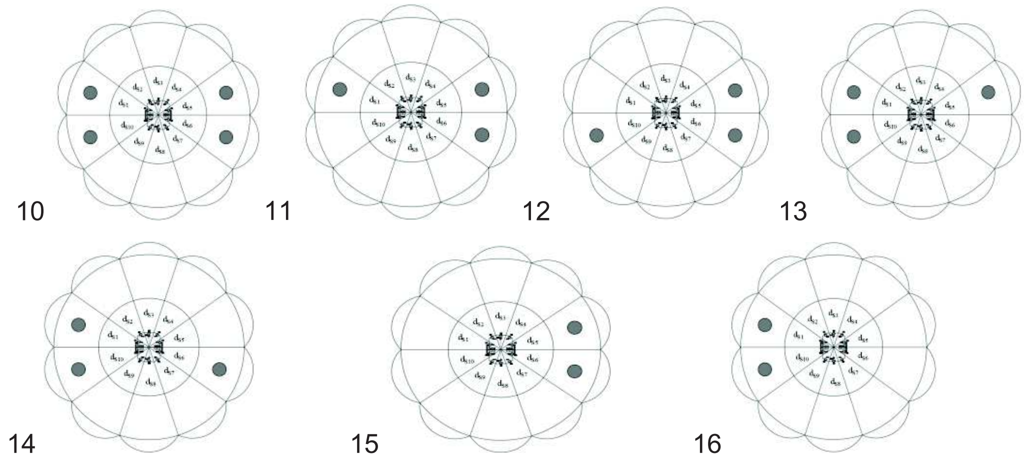
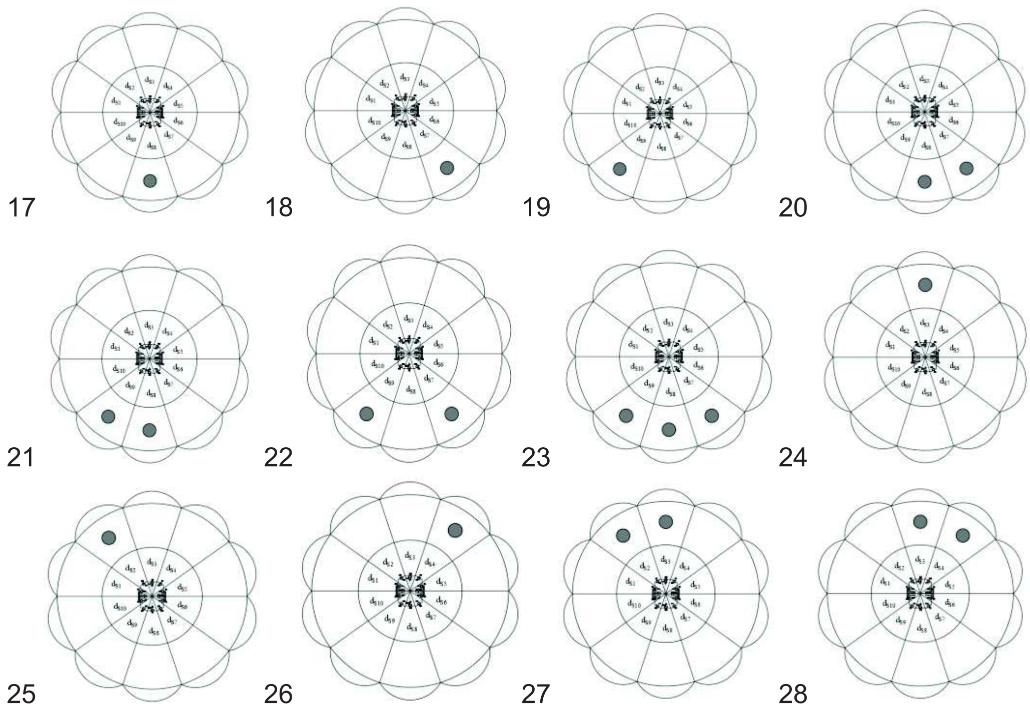



**Figure 4.** Classification of possible obstacle positions in the wall-tracking agent.

Obstacle-bypass agent is set up when one of the sensors US2-IR2, US3-IR3, US4-IR4 or US7-IR7, US8-IR8, US9-IR9 detects an obstacle.



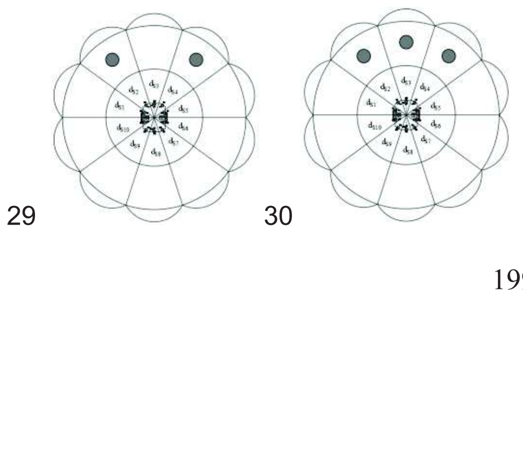




**Figure 5.** Classification of possible obstacle positions in the obstacle-bypass agent.

The classification of the positions of unknown dynamic obstacles for mobile robot presented in the present article covers 30 possible variants of situations. The detailed classification table contains 30 positions describing possible mobile robot movement in the operation zone and the situations of the related decisions made during each iteration during the planning process.

The detailed classification table model outputs are agents which are marked by numbers: 1 – obstacle-bypass, 2 – wall tracking, 3 – movement to destination.

**Table 1.** Classification of obstacles and agents

| Type | $d_{S10}$ | $d_{S1}$ | $d_{S2}$ | $d_{S3}$ | $d_{S4}$ | $d_{S5}$ | $d_{S6}$ | $d_{S7}$ | $d_{S8}$ | $d_{S9}$ | Agent |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | Movement to destination |
| 2 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | Movement to destination |
| 3 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | Movement to destination |
| 4 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | Movement to destination |
| 5 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | Movement to destination |
| 6 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | Movement to destination |
| 7 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | Movement to destination |
| 8 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | Movement to destination |
| 9 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | Movement to destination |
| 10 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | Wall tracking |
| 11 | 2 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | Wall tracking |
| 12 | 1 | 2 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | Wall tracking |
| 13 | 1 | 1 | 0 | 0 | 0 | 1 | 2 | 0 | 0 | 0 | Wall tracking |
| 14 | 1 | 1 | 0 | 0 | 0 | 2 | 1 | 0 | 0 | 0 | Wall tracking |
| 15 | 2 | 2 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | Wall tracking |
| 16 | 1 | 1 | 0 | 0 | 0 | 2 | 2 | 0 | 0 | 0 | Wall tracking |
| 17 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 1 | 2 | Obstacle bypass |
| 18 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 2 | 2 | Obstacle bypass |
| 19 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 2 | 1 | Obstacle bypass |
| 20 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 2 | Obstacle bypass |
| 21 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 1 | 1 | Obstacle bypass |
| 22 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 2 | 1 | Obstacle bypass |
| 23 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | Obstacle bypass |
| 24 | 2 | 2 | 2 | 1 | 2 | 2 | 2 | 2 | 2 | 2 | Obstacle bypass |
| 25 | 2 | 2 | 1 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | Obstacle bypass |
| 26 | 2 | 2 | 2 | 2 | 1 | 2 | 2 | 2 | 2 | 2 | Obstacle bypass |
| 27 | 2 | 2 | 1 | 1 | 2 | 2 | 2 | 2 | 2 | 2 | Obstacle bypass |
| 28 | 2 | 2 | 2 | 1 | 1 | 2 | 2 | 2 | 2 | 2 | Obstacle bypass |
| 29 | 2 | 2 | 1 | 2 | 1 | 2 | 2 | 2 | 2 | 2 | Obstacle bypass |
| 30 | 2 | 2 | 1 | 1 | 1 | 2 | 2 | 2 | 2 | 2 | Obstacle bypass |

The neural network consists of two hidden layers and one output layer. The first hidden layer covers 10 neurons, while the second covers 6, and the output layer contains 3 neurons. The proposed structure of neural network is trained using the method of error back-propagation, and the calculations for the error back-propagation method to train the neural network are expressed by the following equations:

Output layer (1):

$$\begin{gathered} \delta_k(i) = \left(y_{dk}(i) - O_k(i)\right) \cdot f'(net_k) \\ f'(net_k) = 1 \end{gathered} \tag{1}$$

Neural network output layer uses linear activation function (Khnissi et al., 2018; Wang et al., 2018) (2; 3):

$$\delta_k(i) = \left(\delta_{dk}(i) - O_k(i)\right) \tag{2}$$

$$w_{kh}(i) = \eta \cdot \delta_k(i) \cdot O_h(i) \tag{3}$$

The second hidden layer (4):

$$\begin{gathered} \delta_k(i) = \left(1 - O_h^2(i)\right) \sum_k \delta_k(i) \cdot w_{kh}(i) \\ w_{kh}(i) = \eta \cdot \delta_h(i) \cdot O_j(i) \end{gathered} \tag{4}$$

The first hidden layer (5):

$$\begin{gathered} \delta_j(i) = \left(1 - O_j^2(i)\right) \sum_h \delta_h(i) \cdot w_{hj}(i) \\ w_{jm}(i) = \eta \cdot \delta_j(i) \cdot O_m(i) \end{gathered} \tag{5}$$

New weight matrix value (6; 7; 8):

$$w_{kh}(i+1) = w_{kh}(i) + \Delta w_{kh}(i) + \alpha \cdot \Delta w_{kh}(i-1) \tag{6}$$

$$w_{hj}(i+1) = w_{hj}(i) + \Delta w_{hj}(i) + \alpha \cdot \Delta w_{hj}(i-1) \tag{7}$$

$$w_{jm}(i+1) = w_{jm}(i) + \Delta w_{jm}(i) + \alpha \cdot \Delta w_{jm}(i-1) \tag{8}$$

During the first iteration (i = 1) (9; 10; 11):

$$\Delta w_{kh}(i-1) = 0 \tag{9}$$

$$\Delta w_{hj}(i-1) = 0 \tag{10}$$

$$\Delta w_{jm}(i-1) = 0 \tag{11}$$

where $\delta_k(i)$ – is the error propagated in the k^th neuron of the output layer; $y_{dk}(i)$ – normalized desired neural network output; $\Delta w_{kh}(i)$ – updated matrix values of the weights between the output and the second hidden layer; η – training speed coefficient; α – inertia coefficient; $\Delta w_{kh}(i-1)$ – previous weight matrix value update; $\Delta w_{kh}(i+1)$ and $\Delta w_{kh}(i)$ – new and current values of the weight matrix; $y_h(i)$ – propagated error in the second hidden layer; $\Delta w_{hj}(i)$ – updated matrix values of the weights between the second hidden and the first hidden layers; $\Delta w_{hj}(i-1)$ – previous weight matrix value update; $\Delta w_{hj}(i+1)$ and $\Delta w_{hj}(i)$ – new and current values of the weight matrix; $\delta_j(i)$ – propagated error in the second hidden layer; $\Delta w_{jm}(i)$ – updated matrix values of the weights between the second hidden and the first hidden layers; $\Delta w_{jm}(i-1)$ – previous weight matrix value update; $\Delta w_{jm}(i+1)$ and $\Delta w_{jm}(i)$ – new and current values of the weight matrix (Zhao & Wang, 2018; Dewi et al., 2017; Omrane et al., 2017).

The model of classification and agent behaviour determination model on the basis of neural network involve three stages. During the first stage, mobile robot movement is replaced by codes according to the classification variants: 0, 1, 2. 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. Finally, during the third stage, the outputs of neural network are the variables 1, 2 and 3, which mark the respectively obstacle-bypass, wall-tracking, and movement-to-destination agents. These are used in the process of dynamic switching of agent fuzzy blocks.

## RESULTS AND DISCUSSION

Based on the information from the distance sensors (ultra-sound and infra-red sensors), neural network classifies the operating area located in a complex environment based on three specific situations by three respective agents: obstacle-bypass, wall-tracking, and movement-to-destination. Taking into account the current situation of the environment, neural network switches and activates one specific agent. Later, using the fuzzy blocks 1FB, 2FB and 3FB (to determine the mobile robot rotation angle $\mu_{1}, \mu_{2}, \mu_{3}$ in the respective obstacle- bypass, wall-tracking and movement-to-destination agents) and 4FB (to control the $V_{average}$ = 0.2343 m $s^{-1}$ speed), the neural-fuzzy system performs the task with the selected agent. Thus, during the process of planning mobile robot movement, agents are being constantly switched to other agents, and the movement trajectory is a combination of movement sub-trajectories in agents.

Simulation of an intelligent system for planning mobile robot movement in an unknown dynamic environment using multi-agent system involves four pilot testings.

During the first testing, mobile robot moves from the starting point A($x_1$ = 2 m; $y_1$ = 1 m) to the destination point B ($x_2$ = 6 m; $y_2$ = 4 m) Fig. 6.

Dynamic obstacle moves past the robot and affect its movement towards the destination (Fig. 6). After 464 iterations of the program (the set time is 11.95 s) the mobile robot reached the destination without colliding with a dynamic obstacle.

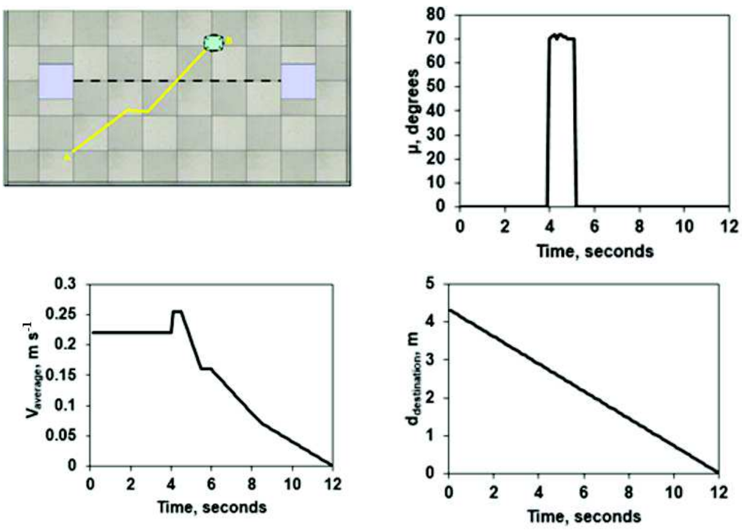



**Figure 6.** Results of the testing of the intelligent system for planning mobile robot movement in an unknown dynamic environment.

Variations of the mobile robot parameters – rotation angle $\mu$, mobile robot average velocity $V_{average}$, distance between the robot and the destination point $d_{destination}$ – are presented by diagrams in the Fig. 6. At first, robot moves forward towards the destination and the angle $\mu$ remain the same (equal to 0) until the distance sensors US2-IR2, US3-IR3, US4-IR4 or US7-IR7, US8-IR8, US9-IR9 detects a dynamic obstacle. Value $\mu$ changes rapidly and substantially with the help of 1FB, which is dedicated to bypass the moving obstacle. Later, the value of $\mu$ decreases to zero and remains unchanged.

When using the fuzzy block 1FB, the average velocity $V_{average}$ of the mobile robot remains stable, and reduces to zero after circumventing the obstacle. The distance between the robot and the destination point $d_{destination}$ also is approaching zero.

During the second testing, mobile robot was moving in the operating area with the obstacle being the surface of a wall, from the starting point A($x_1$ = 6 m; $y_1$ = 4 m) to the destination point B ($x_2$ = 3 m; $y_2$ = 0.5). After 1,389 iterations of the program (over 33.79 s) the mobile robot reached the destination point. Mobile robot movement trajectory and variations of the mobile robot parameters – rotation angle $\mu_3$, mobile robot average velocity $V_{average}$, distance between the robot and the destination point $d_{destination}$ – during the second testing are presented in the Fig. 7.

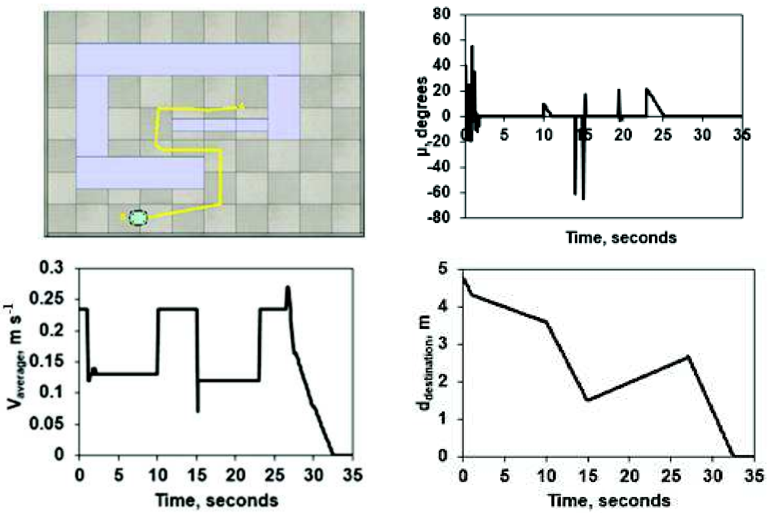



**Figure 7.** Results of the second testing of the intelligent system for planning mobile robot movement in an unknown environment.

During the third testing, mobile robot was moving from the starting point A($x_1$ = 5 m; $y_1$ = 4 m) to the destination point B ($x_2$ = 2 m; $y_2$ = 0.5 m). After 1,574 iterations of the program (the set time is 38.31 s) the robot reached the destination without colliding with a dynamic obstacle. Variations of the robot trajectory and the mobile robot parameters – rotation angle $\mu$, mobile robot average velocity $V_{average}$, distance between the robot and the destination point $d_{destination}$ – based on the results of the third testing are presented in the Fig. 8.

During the fourth testing, mobile robot was moving from the starting point A($x_1$ = 5 m; $y_1$ = 4 m) to the destination point B ($x_2$ = 2 m; $y_2$ = 0.5 m). In the operating area, there were a wall and one dynamic obstacle, which affected the robot's moving trajectory. After 1482 iterations of the program (the set time is 36.29 s) the mobile robot reached the destination without colliding with a dynamic obstacle. Variations of the robot trajectory and the mobile robot parameters – rotation angle $\mu$, mobile robot average velocity $V_{average}$, distance between the robot and the destination point $d_{destination}$ – based on the results of the fourth testing are presented in the Fig. 9.

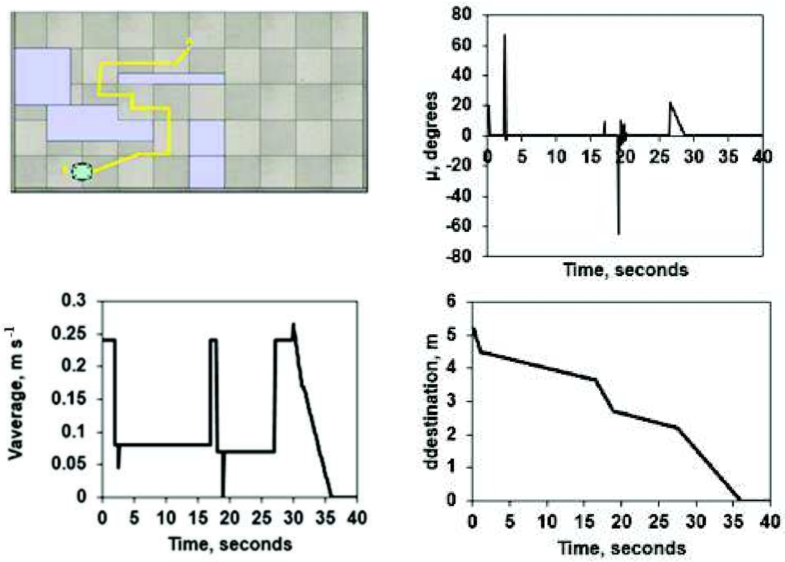



**Figure 8.** Results of the third testing of the intelligent system for planning mobile robot movement in an unknown environment.

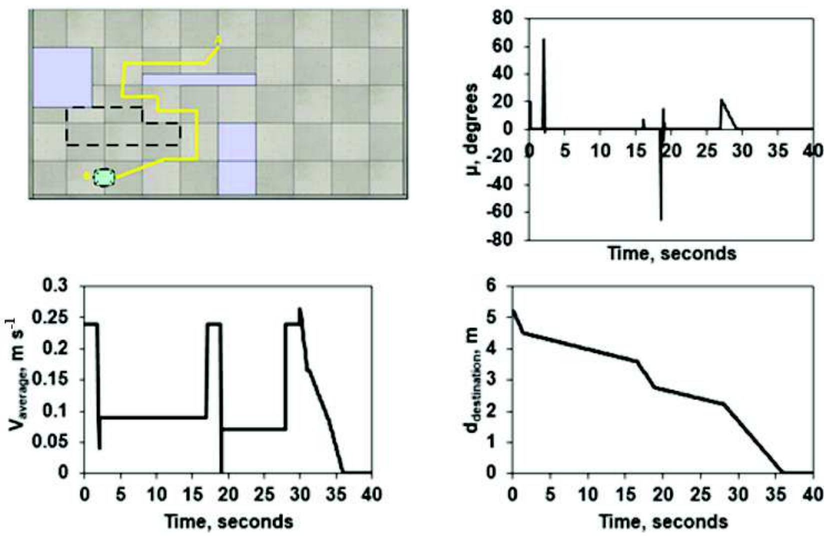



**Figure 9.** Results of the fourth testing of the intelligent system for planning mobile robot movement in an unknown environment.

## CONCLUSIONS

Based on the simulation performed in this article and the analysis of the obtained results, the following conclusions can be made:

Moving in an unknown environment mobile robot performs three tasks: circumvent obstacles, tracks wall, and moves towards the destination point. Therefore, a combination of four fuzzy blocks dedicated to different agents was offered as a method of developing an intelligent system for planning the real-time mobile robot movement in an unknown dynamic environment. The first three blocks, according to the behaviour of each agent, perform the preliminary estimation of the robot's rotation angle in the direction of the surrounding obstacles. The fourth block deals with the problem of how to prevent collision of the robot with unknown dynamic obstacles located in the operating area. The computer simulation shows that the mobile robot managed to reach the destination point in all the situations.

A neural network, as a component of the intelligent planning system, was used for simulation of the developed classification of unknown obstacles in the robot's operating area and switching the obstacle-bypass, wall-tracking, and movement-to-destination agents.

The presented method of developing the intelligent system for planning robot movement in an unknown dynamic environment is based on the two-stage process of processing the information about the robot and its environment in order to plan a safe trajectory. The first stage involves determination of the distance between the robot and the obstacles located in its operating area, and classification of the possible positions of obstacles based on the information from the distance sensors using the model of multi-layer neural network. During the second stage, obstacle-circumvention, wall-tracking, movement-to-destination and speed control agents are developed. Based on the results obtained during the first stage, the value of the mobile robot rotation angle $\mu$ is determined. Mobile robot rotation angle and the distance between the robot and the destination point are the inputs of the fourth fuzzy block. Outputs – controlled gear signals, which enable the robot to avoid collisions with unknown obstacles and reach the destination point.

This method applied to mobile robots allows the following:

- simplify the analysis of the dynamic environment, dividing the environment into a few simple and specific situations;
- take into account each specific situation in the operation area and position of the obstacles around the robot during every iteration;
- reduce the number of the fuzzy planning system input parameters;
- successfully avoid collision of the robot with the unknown obstacles and reach the destination point with high accuracy.

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