Intelligent Navigation of a Mobile Robot within a Robot Population in Complex Unknown Environments*

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Abstract

This article describes the intelligent navigation of a mobile robot within a robot population in a complex unknown environment by using soft computing based technique. The paper is confined to controlling and navigation of mobile robots. The fuzzy control system outlined here is designed for steering and speed control of the mobile robot. Navigation in a complex unknown environment is achieved by self learning method which is a type of neuro – fuzzy navigation system. As an outcome, a robust and flexible robot navigation system is obtained.

Keywords

autonomous robots; coordination; neural networks; genetic algorithm; heterogeneity

1. Introduction

This article describes the intelligent navigation of a mobile robot within a robot population in complex unknown environments. The purpose behind this article is to present the new Neuro-Fuzzy navigation approach, which provides mobile robots with more autonomy and intelligence, such as recognition, learning and decision-making and further actions related to principal navigation problems. The following phases are related to recognition: inaccurate sensor data processing, construction of knowledge base and an environment map and orientation techniques for mobile robots.

Currently available relevant classical approaches are not aligned with such robot requirements as real-time, autonomy, and intelligence, which is why the newly developed approaches based on the fuzzy logic (FL), Artificial Neural Networks (ANN) or a combination of the two are considered. In fact, the combination of FL and ANN has been proved to improve the capacity for learning and adaptation related to variations in environments in cases when information is either qualitative and uncertain or inaccurate and incomplete. Additionally, the need and thus interest in ANN has been long as it's important to understand principles that help in exploring ways the human brain functions in order to be able to build machines to perform complex tasks that require massive parallel computation [1, 2, 3, 4].

Abstract understanding of natural concepts which are linked to the level of danger and proximity are related to the admittance of environment structure and interacting with it. The specific natural language is demonstrated via fuzzy sets embracing classes with incrementally diversifying transition

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points. Special orientation technique help to provide robots from one point to another. Actually, classical two valued logic is not the phenomenon on which human reasoning is depended, as this process embraces fuzzy realities, deduction and so on. Therefore, FL is nearer to human reasoning and natural language than standard logic [5, 6, 7, 8, 9].

In general, most of Soft Computing systems currently in use are based on fuzzy rules, which implies that ANN techniques are used to induce rules from observations. Yet, the tendency in the opposite direction is observed, i.e, FL techniques are used in the design of ANN, which in term leads to Fuzzy ANN [10, 11, 12, 13]. In particular, it appears that it is possible to significantly enhance ANN capacity by providing it with the ability to process fuzzy information. Overall, an intelligent control system should be able to learn and act in a way similar to human being behavior, as well as be able to take into account fuzziness and uncertainty present in reality [14-23].

It is more beneficial to use ANN for processing uncertain or high noise data, in comparison to the classical techniques, because it doesn't have as much high noise tolerance level as the classical techniques [24, 25, 26, 27]. This argument is also supported by the fact that the use of the FL to handle uncertainty due to environment and sensors is much more efficient than using the usual deterministic techniques [28, 29, 30, 31, 32].

It can be defined by FL being demonstrated via fuzzy membership functions and the state space that is discretized into a linguistic vocabulary. It has a great importance in terms of navigation because the flimsy data is processed in order to realize the environment. In fact, there is a challenge in the foundation of an environment map that lies in the knowledge representation. In terms of the navigation seen in a dynamic environment, it can be stated that it is much more beneficial to use a complete representation rather than incomplete one, as it is highlighted by the two different representations linked to the FL argued in. Therefore, the approach of NN theory is assigned as well as the one of FL to imperfect data processing and composition of knowledge base. It is because of their properties including parallelism, classification, help to make decisions, optimization, adaptation volume, which includes both learning and auto-organization, generalization capacity, allocated memory and simplicity of establishment. In order to sort out the problems seen in navigation, ANN certifies intriguing and inevitable when the classification criteria or generalization regulations are not known because they can learn and generalize from samples without knowledge regulations. However, the application of FL theory in order to sort out the similar troubles also demonstrates intriguing and efficient when the classification criteria or generalization regulations are presented by an expert. Within this framework, NN related to cognitive components including learning, adaptation generalization which are really suitable when knowledge oriented Systems are included. Therefore, many ANN oriented approaches are based on the design and achieve robots that resemble the human decision making process in inattentive environments [28, 29, 31, 32, 33].

On the other hand, a specialty of the fuzzy rule-oriented works can be their quality to categorize fuzzy rules, i.e., according to the level of security or any danger [34, 35, 36, 37, 38, 39], acknowledgement or control rules [40, 41], and also complication avoidance and leading rules. Within this framework, the interest of the approaches which are based on FL, locates in their capacity in order to make human like decisions for a smart movement that uses the fuzzy inference mechanisms. Moreover, the interest seen in the establishment of relations between the FL and NN can be, in part, based on the notions including both cognition and generalization. Also, the knowledge can be highlighted in the rules thanks to the FL, while the NN can be stressed the knowledge implicit in the weights. Actually, fuzzy system can clarify the knowledge, yet cannot comprehend, although NN has this capacity. The relation seen between FL and NN is mainly complementary rather than competitive. Such a technology can be stated as one of the unusual concepts that uses at once both an explicit and implicit knowledge [41, 42, 43].

The sequence seen in the fuzzy operators is produced as a result of the work of a smart robot's planner. They all applied thanks to guidance of navigation and also pilotage subsystem. Furthermore, the presumption is made that Fuzzy Mobile Smart Robot functions can be classified as two dimensional Cartesian space S=X×Y where both X and Y are the universal sets with distances

$$\rho_i^t(X,Y)=\sqrt{(x_i-x^t)^2+(y_i-y^t)^2}, i=\overline{1,k}$$

where k refers to the number of robot motion's steps. All FMIR's state is qualified with a function $z^t=f(x^t,y^t)$ which is $z_i=f(x_i,y_i)$, and the state of all initial goal- by a function , when $t\in\{T\}$. In addition to this fact, another presumption is made which FMIR moves by discrete steps. The space of FMIR habitation is defined as S=L×U×H, when LH=∅, L⊆S, H⊆S; L – space of FMIR motion; H is inhibited space, i.e. the space of troubles.

The procedure applies the fuzzy operators that lead FMIR from a local target to another target and so on since the sought global target is achieved. The target aims to reduce the difference seen between current robot's coordinates and coordinates of target. The action of this grade of general hierarchical control system of FMIR is related the neuro-fuzzy technology [44, 45, 46, 47], i.e. a smart combination including neural networks and fuzzy logic.

Actually, the robot we regarded has got many sensors which are located in its sides. The control system in discrete time moment (duration between the moments depends on environment change intensity) reads information related to the environment's current state from these sensors, and information on goal and current robot location and orientation from other supplied devices in order to drive the robot efficiently to the target.

Offered navigation system utilizes from neural networks to:

- comprehend system behavior;
- generate fuzzy rules and membership functions;
- perform logical inference.

On the basis of these facts, we utilize from separate neural network for each linguistic value that is used in rules to achieve required shapes of membership functions, and a single network in order to make fuzzy rules and apply logical inference. Furthermore, an extra neural network can be used, when requirements on speed are quiet important, in order to decide on the direction to targets in terms "on the left", "in front", "on the right" and "reached".

2. Subjects and Methods

The system consists of two main control subsystems, namely, the fuzzy drive control system and navigation system. They are described in the following subsections.

3. Fuzzy Control System

In our work, we describe the fuzzy drive control, including steering control and speed control of an autonomous mobile robot [14, 15, 16, 17, 18, 19, 20, 21]. The fuzzy control system consists of the following 5 sub-systems:

- Fuzzy Drive Expert Sub-System (FDES),

- Sensor (Vision) Sub-System, which is an Image Processing and Recognition System (IPRS) with Recognition Rules Base;
- Operator Interface, which is an operator console;
- Motor Drive Sub-System (MDS) as it's shown on Fig. 1.
- Manager System

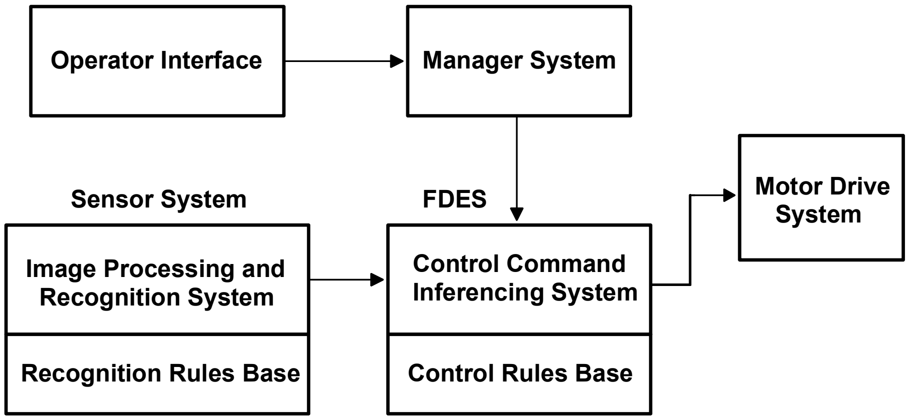

Figure 1: Fuzzy drive control system

The overall system is supervised and managed by the Manager System, with an aim of performing the plan from the operator. The driving plan provided by an operator contains a set of the following 5 commands, namely, "start", "go forward", "turn left", "turn right" and "stop". The plan is first converted into an appropriate representation by the Operator Interface and then applied to the FDES. The decision to perform the plan is then made by the FDES by using the information coming from the Vision Sub_System and the Control Rules Base. This information is then presented from Control Command Inferencing System to Motor Drive System in the form of particular driving signals. The robot executes the necessary actions by these signals.

The mobile robot has to process the image that is needed to estimate the surrounding situation and decide its motion. The image is obtained by a CCD-camera. It is then processed for elimination of the noise and is represented as a rectangular field consisting of white and black colored areas by the IPRS. The Vision System then uses this image data to calculate the approximate position of obstacles relative to the robot and the road. This operation is done by the Recognition Rule Base. The Recognition Rule Base contains the following three rules in order to get the right distance to an obstacle in front of the robot, some walls on either side of the road, and some corners of crossroads.

The Control Command Inference System generates the set of commands, which will then be passed to the Motor Drive System in order to execute the plan by using the above data and the Control Rule Base, where the Control Rule Base is basically a group of rules for determining the robot motion according to the driving plan. The fuzzy values of the robot (Fig. 2) motion used in these rules are the following: ST (straight), LS (left small), RS (right small), LM (left middle), RM (right middle), LB (left big), and RB (right big). The distance is measured by fuzzy terms: S (short), M (middle), L (long). The membership functions of the fuzzy sets are discrete. Table 1 shows an example indicating the membership functions for fuzzy sets used for defining the road width.

Figure 2: Mobile Robot

The driving rules are represented in the IF-THEN form:

IF x_1 is A_{11} and ... and x_m is A_{1m} THEN y_1 is B_{11}, ..., y_k is B_{1k}
IF x_1 is A_{21} and ... and x_m is A_{2m} THEN y_1 is B_{21}, ..., y_k is B_{2k}
...
IF x_1 is A_{n1} and ... and x_m is A_{nm} THEN y_1 is B_{n1}, ..., y_k is B_{nk}

where x_1, ..., x_m are input variables, y_1, ..., y_k are output variables; A_{ij} are fuzzy sets and B_{ij} are non-fuzzy values.

For example, here is the typical rule for driving forward:

IF "distance to obstacle" is "about 30 cm" and "deviating angle" is "left" THEN "course" is RB and "distance to move" is M.

For a particular input x_1, ..., x_n, the truth value of the premise of the i-th rule will be

$g_i = min(A_{i1}(x_1), ..., A_{im}(x_m)), \quad i = \overline{1,n}$.

The *output* y_j then can be inferred using the center of gravity method:

$$y_j = \sum_{i=1}^{n}(g_i B_{ij}) / \sum_{i=1}^{n} g_i .$$

Table 1
Membership functions for road width

Road width (cm)	20	25	30	35	40	45	50	55	60
Narrow road	1.	1.	1.	0.8	0.5	0.3	0.	0.	0.
Wide road	0.	0.	0.	0.3	0.5	0.8	1.	1.	1.

4. Orientation Techniques of a Mobile Robot

Image processing is an essential part of the navigation of the mobile robot. It consists of three main operations namely “bounding box”, “edge detection” and “object tracking”. These three subjects are related to each other. Also object tracking part includes some necessary calculation sections and these calculations are involved in robots locations.

One of the image processing tools is bounding box. This toolbar works on binary images. In binary image part, bounding box search necessary interval value and if there is a white color area, toolbar surrounds it as a shape of rectangle. In this project, the robots have to be taken into bounding boxes in order to determine their positions in the operation area (Fig.3) [20,21].

Figure 3: Bounding Box in Operation Area

In swarm robotics area, to control robots with camera, object tracking part is necessary. We are trying to track particular object from an environment consisting of multiple moving objects. In the environment, there are six robots and some obstacles. Robots must arrive at the desired place. The aim of object tracking is that finding the location of robots in the environment. Firstly, center of the robots must be found. When this step is done, locations of the robots on the map can be found. Object tracking is created on Emgu CV platform. The distance between desired position and current position is calculated as a vector.

Another important part is the so called centroid calculation. After object tracking, centroids of robot frames can be calculated by using basic centroid calculations. The camera perceives the red areas as the maximal length, it means that camera looks at the last pixel on the red area than take that as one point. This process continues till the four side of the robot is completed, after deciding the location of the last pixel of the four sides, it draws a red line which is perpendicular the camera sight image that passes across one of that point. By means of this operation, thinking that as 4 points, it forms 4 sides and a basic rectangular shape is created. Vision system must comprehend the intersection points of the perpendicular lines in order to obtain the length of the one side. By this way, camera observes 4 sides and the vision system begins to the centroid calculations. Basically, the vision system calculates the sides with two different lengths and connects the corners of them. It basically makes a vector summation and obtain one of the diagonals for this rectangle, after that it does the same thing for other two side. Hence, the point that the diagonals intersect with each other, is the centroid point. In Fig.4, the outputs of the centroid calculations are shown by using Emgu CV platform.

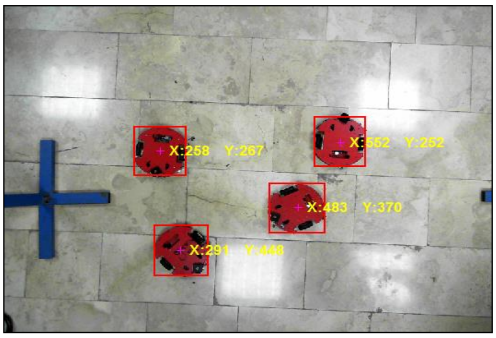

Figure 4: Centroid Calculations of Robots

Mouse position must be known to control the robots in the environment because when map is formed, robots can easily be controlled. Knowing the location of the mouse cursor on the image is necessary for giving a destination to the robot. If the coordinates of the mouse cursor is known, it will be easy to make the robot get the shortest way. Calculating the differences between the centroid and cursor coordinates, the shortest way between the robot centroid and cursor can be found. One point to be taken care of is that, if a robot tends to go to the point that the cursor lead, its centroid point will try to go to that coordinate. This may lead the robots to have some crushes.

Position analysis must be done to know position of target and robots. 800x600 pixels images are taken from camera by using Emgu CV. Centroids of robots are calculated and mouse cursor is found in 800x600 pixels real time video. Their positions of centroid and mouse cursor have two types information about their location. The 800x600 ratio means that there are 480000 pixels on an image, thinking one corner of the image as the origin of the x, y axis, there are 800 pixels on the y axis and 600 pixels on the x axis. Calculation of the distance is done by on the program, counting the number of the pixels on the x and y axis, making a vector summation, and finding the total numbers of the pixels. If length of an image is 20 cm, long side of a pixel is 20\600 cm, so by multiplying the pixel number between the cursor and the centroid, distance between them can be calculated. These location information are about x and y axis.

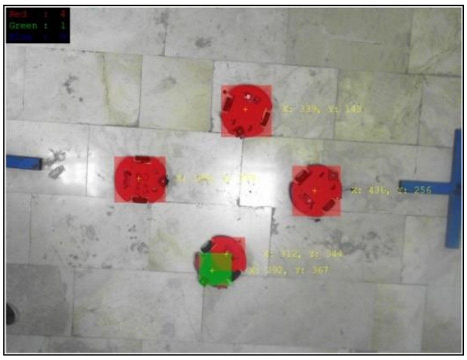

Figure 5: Orientation of Robots

The distance between robots and mouse cursor can be calculated easily. The aim of the distance calculation is to learn the distance that robots must take. For example, suppose that the robot location is [245 560] and the mouse cursor location is [15 600]. Then the distance between a robot and the mouse location is that;

for x axis, $x_d = 245 - 15 = 230, for\ y\ axis, y_d = 560 - 600 = -40, and\ d = \sqrt{230^2 + (-40)^2}. = 234$

as pixels the distance, $dp = 234 \cdot \sqrt{2} = 330\ pixels$, since one pixel is 0,03125 cm, then the distance in cm is $330 \cdot 0.3125 = 10.3\ cm.$

In 1:1 scale, distance calculation is found according to above calculations. However, since cameras are in the roof, scales can be changed so scales of measurement is significant for real distance calculation. For example, the calculation is the above is 1:1 scale, if scale is 1:5, 10,3 cm must be multiplied with 5 for real distance. In the following research the ANN navigation unit was created to fulfill the system

5. Navigation System

The structure of the offered navigation system is presented in Fig 6. In terms of generating control rules and performing logical inference neural network can be referred to as the kernel of the system on whole and the center of the Control Command Generating Unit (CCGU). Signals received from sensors initially come to distance fuzzifiers. Signals received from fuzzifiers (i.e. membership levels of inputs for linguistic values that used in rules) together with signal from the Goal Direction Searching Unit (which describes relation to target) enter CCGU that produces signals for the robots servo-motors.

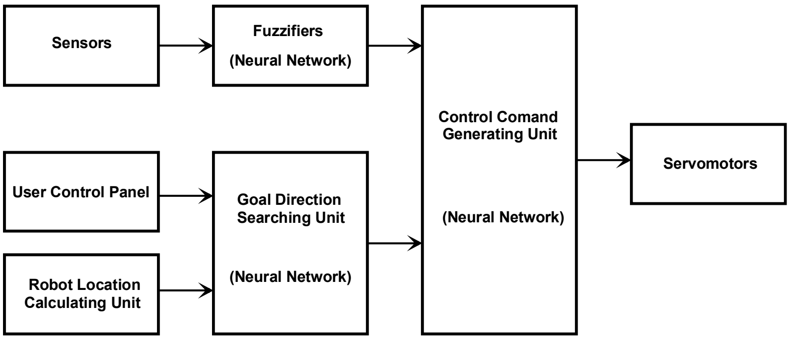

Figure 6: Structure of the FMIR Neuro-Fuzzy control system

Both CCGU network and fuzzifiers are comprehended periodically by experiences in order to adapt the environment. All linguistic values are shown by a membership function with a persistent and smooth curve produced by a corresponded fuzzifier. For simplicity, set of linguistic values that are used for all variables we describes as (“NEAR:, “FAR”). We have applied a software model of the FMIR navigation system and carried out detailed experimental investigation by a program robot simulator in an artificial fuzzy environment. Each of these five used networks is Back Propagation Feed-Forward with two different computational layers of feed-forward neurons with sigmoid activation function (Fig. 7).

6. Results of Experiments

We used about 40 rules in order to teach CCGU neural networks. Furthermore, the experiments presented very acceptable navigation ability. Except for some elaborated situations, after appropriate adaptation for many environments, the robot, having come very complex-shaped paths, successfully, without any collisions, achieved targets. (Fig. 8). Figure 9 shows the movement of the robot due to experiment on real mobile robot and Figure 10 shows the part of the experiment in which a group of robotic units swarming through the environment.

7. Navigation of a Mobile Robot and IoT

The dynamics of autonomous mobile robots are extremely complex. They become even more complicated when corners and unstructured environments are considered. Calculating the path and decisions of autonomous vehicles using accurate dynamical models is challenging even for fast computers, and in the case of embedded microcontrollers that are usually used in mobile robots, this task is impractical. This paper describes an alternative way of controlling autonomous mobile robots using a neuro-fuzzy architecture that achieves a robust and flexible navigation system. This system can be executed in microcontrollers with limited computing capabilities.

With the advent of cheap wireless communication and the emerging trend of connected devices through the internet, known as the Internet of Things – IoT, many improvements to navigation and control have become possible. Through the use of wireless connection to a central computer, the robot is connected to the internet and has access to a wide possible network of similar machines. This allows for monitoring and control of the robot from great distances and considering the adaptive nature of the neural net that is part of it’s control system, it allows for continuous improvement by combining shared experiences with other robots that are part of the network.

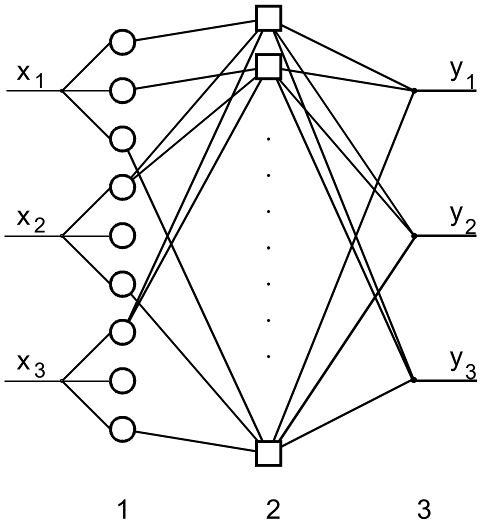

Figure 7: ANN Structure

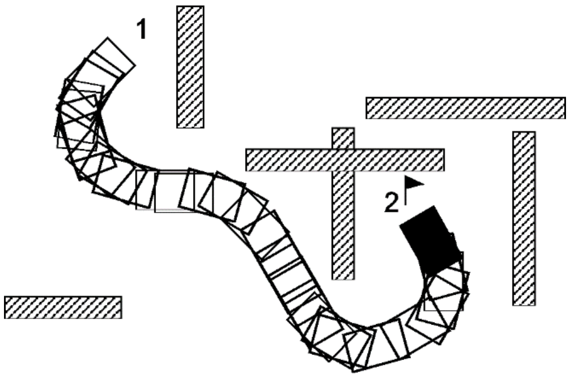

Figure 8: Trajectory Passed by the Robot (Copy From the Computer Screen)

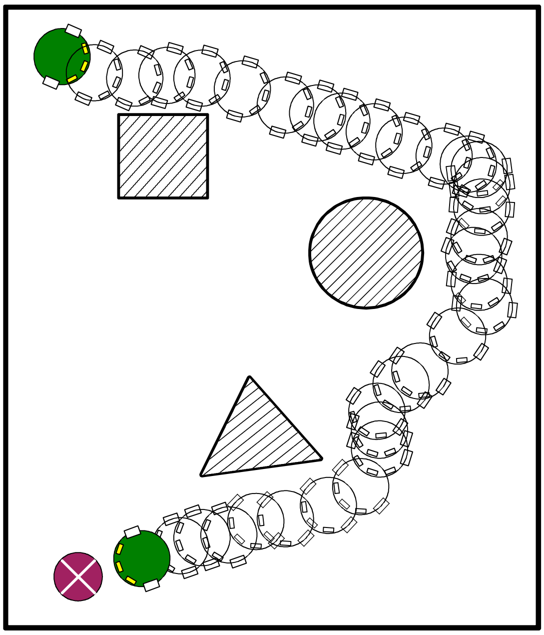
Figure 9: Navigation of Mobile Robot

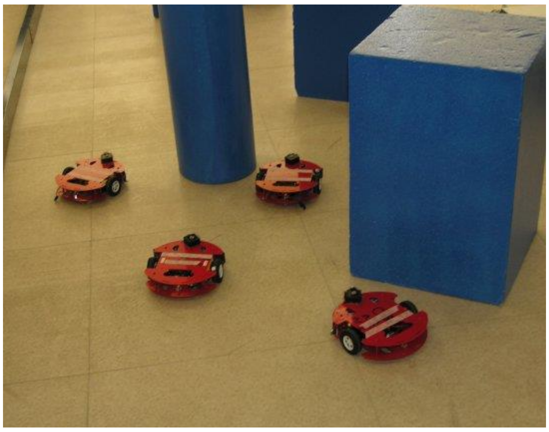
Figure 10: Robot Navigation in Swarm

8. Conclusion

In this work, we designed and implemented a mobile robot with an intelligent navigation capability within a robot population in complex unknown environments. It is composed of two main subsystems namely, a fuzzy drive control system and a neuro-fuzzy intelligent navigation system. We implemented several robots with the same capability. We carried out several experiments to test the single robot and also we tried several robots to see swarming actions. During the experiments, a single robot can be navigated through and unknown environment having obstacles. The environment is observed by a camera sensor system and the robots can follow the cursor position created in the computer screen that maps the environment. The trajectories passed by the robots were obtained in the computer screen in a real-time fashion and navigation capabilities were tested. It was observed that the fuzzy drive control system and neuro-fuzzy intelligent navigation system worked successfully. The individual robots could navigate themselves through the obstacles in an unknown environment. In addition to testing individual robots, a group of robots composed of four robots with the same capabilities were tested in swarming action. The results of the experiments were all successful.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

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