Applied Soft Computing Journal 89 (2020) 106088

Contents lists available at ScienceDirect

Applied Soft Computing Journal

journal homepage: www.elsevier.com/locate/asoc

Navigational analysis of multiple humanoids using a hybrid regression-fuzzy logic control approach in complex terrains

Priyadarshi Biplab Kumar *, Manoj Kumar Muni, Dayal R. Parhi

Robotics Laboratory, Mechanical Engineering Department, National Institute of Technology, Rourkela 769008, Odisha, India

ARTICLE INFO

Article history:
Received 18 August 2018
Received in revised form 11 June 2019
Accepted 10 January 2020
Available online 15 January 2020

Keywords:
Navigation
Humanoid NAO
RA-FLC
Petri-Net
Hybridization

ABSTRACT

In the current work, a hybrid navigational control architecture combining regression analysis with fuzzy logic control has been proposed for smooth and hassle-free motion planning of humanoids. In the proposed hybrid scheme, sensory information regarding obstacle distances are initially supplied to the regression controller, and an interim turning angle is obtained as the preliminary output based on the preloaded training pattern of the regression model. In the next phase, interim turning angle is again supplied to the fuzzy controller to generate the ultimate turning angle which eventually guides the humanoid to take a safe direction of turn while avoiding any obstacle present in the work environment. The working of the developed hybrid model is validated through simulation and real-time environments, and satisfactory results have been obtained from comparisons of selected navigational parameters along with a minimal percentage of deviations. To avoid possible chances of inter-collision for navigation of multiple humanoids in a common platform, a Petri-Net model has been integrated with the developed hybrid control scheme. Finally, the developed motion planning model is also assessed against another existing navigational controller, and significant performance enhancement is obtained.

1. Introduction

Humanoid navigation has always remained as one of the most prominent area of research among robotic practitioners by virtue of the complexities involved in the design of joint movements that the humanoids possess. The last two decades of robotics research has been devoted primarily towards the use of different robotic forms in easing human efforts and replacing the same in humanitarian platforms. Humanoids have become the centre of attraction of many researchers due to their unique abilities like mimicking human behaviour. To fulfil the ever growing needs of increasing population in production and automation, navigation and path planning has remained as one of the most debated topics. Depending upon the preliminary information supplied to the robot regarding environmental conditions such as the position of start, goal and obstacles, path planning approaches have been broadly categorized as model-based and sensor-based approaches. Model-based approaches otherwise known as global path planning take into consideration the environmental conditions supplied very initially to the robot before the start of the movement. On the other hand, sensor-based approaches otherwise known as local path planning take into consideration no arena conditions supplied to the robot from the beginning and ultimately it has to perform online navigation based on unforeseen arena conditions. While a model based path planning seems easy to deal with, sensor-based approaches resemble more like real life scenarios. On a whole, navigational analysis has remained as one of the most challenging areas of investigation till date. Along with that, when it comes to the navigation of humanoids, it becomes more difficult as it is quite different from the navigation of wheeled robots involving complex joint movements rather than wheel movements. Over the last few years, several researchers have attempted navigational analysis of different forms of robots. Navigational algorithms are classified as classical and artificial intelligent (AI) approaches based on their tactic in solving the problem considered. While classical approaches are inherited from basic statistical techniques, AI techniques are mostly nature-inspired. Classical techniques [1] such as regression analysis (RA), artificial potential field (APF), Voronoi Diagram (VD), Cell decomposition, etc. are known to generate converged results within limited problem space. On the other hand, AI techniques such as fuzzy logic control (FLC), genetic algorithm (GA), artificial neural network (ANN), etc. are known to solve problems with greater accuracy although they might require more time in converging towards the solution. Some of the prominent works on the navigational analysis can be highlighted over here.

* Corresponding author.
E-mail addresses: p.biplabkumar@gmail.com (P.B. Kumar), manoj1986nitr@gmail.com (M.K. Muni), dayaldoc@yahoo.com (D.R. Parhi).

https://doi.org/10.1016/j.asoc.2020.106088
1568-4946/

Benamati et al. [2] have developed a navigational controller for a mobile robot using a flat potential field based approach. Hong et al. [3] have used artificial potential field as a dynamic path planner for mobile robots. Li et al. [4,5] have used an artificial potential field based regression search technique for navigation of autonomous mobile robots in known and unknown environments. They have modified the basic algorithm to overcome the limitations like avoiding oscillations and local minima. Ong et al. [6] have used fuzzy logic to control the movement of a mobile robot in a pipe-line. They have used a PID controller to regulate the actuators of the robot and fuzzy logic to analyse and provide the sensor outputs for smooth navigation. Melendez et al. [7] have proposed a fuzzy logic based regulator system for tracking and reaction control in the navigation of an autonomous mobile robot. Faisal et al. [8] have used fuzzy logic as a navigational tool for obstacle avoidance and target reaching behaviour in a mobile robotic agent. Al-Jumaily and Leung [9] have applied a wavefront based navigational algorithm for path planning of an indoor mobile robot. They have used the possibility theory of fuzzy logic to plan obstacle avoidance. Al-Mutib and Abdessemed [10] have developed fuzzy based behaviours for indoor navigation of a mobile robot with obstacle avoidance and goal following pattern. Omrane et al. [11] have used a fuzzy based controller for trajectory tracking behaviour of a mobile robot through data collected by infrared sensors of the robot. Singh and Thongam [12] have tested a fuzzy based controller for navigation of a mobile robot in a static environment and obtained satisfactory results through simulation platform. Fernando et al. [13] have used fuzzy logic as obstacle avoidance and target tracking tool in a dynamic, hostile environment. Amiri et al. [14] have proposed a fuzzy logic based robot navigation system to capture endangered species in complicated scenarios. Van Nguyen et al. [15] have used a behaviour based fuzzy architecture for navigation of a mobile robot in an unknown environment using multi-objective optimization methods. Qin et al. [16] have used fuzzy logic for robust control of the carrier tracking loop in an inertial navigation system. Raguraman et al. [17] have proposed a fuzzy based behavioural navigation pattern for the movement of a mobile robot in an indoor environment. Pham and Awadalla [18] have proposed a fuzzy logic based approach to achieve coordination in a multi-robot system. They have verified the effectiveness of the proposed model in a simulation platform. Rovira-Mas and Zhang [19] have used a fuzzy logic controller to send steering signals to an electrohydraulic valve in order to achieve auto steering in off-road vehicles. Ibrahim et al. [20] have used fuzzy logic for motion control of a dynamical hexapod robot. Boem and Cho [21] have used fuzzy logic and reinforcement learning for navigation of a mobile robot in a complex scenario accompanied by obstacle avoidance and goal-seeking behaviour. Al-Yahmedi and Fatmi [22] have discussed regarding the use of a fuzzy based controller for navigation of mobile robots in complicated terrains. Shi et al. [23] have proposed a fuzzy based three-dimensional grid navigation model for mobile robots and tested the developed approach through simulation and experimental platforms. Jaafar and Mckenzie [24] have used fuzzy logic to decide the direction of turn in an autonomous robot navigation problem. Nattharith and Guzel [25] have used a fuzzy logic based control strategy along with machine vision for navigation of a goal-oriented mobile robot. Wang et al. [26] have recommended a fuzzy based predictor–corrector guidance scheme for entry vehicle in an aerospace system. Mendon et al. [27] have used fuzzy cognitive maps for decision taking behaviours in a mobile robot navigation problem. Dirik [28] have developed a fuzzy-based control scheme for collision-free navigation of a mobile robot in indoor environmental conditions. Sun et al. [29] have investigated the application of adaptive fuzzy control in a class of non-triangular structural stochastic switched nonlinear systems with full state constraints. They have verified the effectiveness of the developed approach through simulation outcomes. Qiu et al. [30] have discussed regarding the concept of fuzzy adaptive event-triggered control for a class of pure-feedback nonlinear systems containing unknown smooth functions and unmeasured states. To prove the efficiency of the approach, simulation results have been presented. Keshmiri and Payandeh [31–33] have used regression analysis to solve multi-robot and multi recharging station problem in a simultaneous movement process. They have used the developed approach to train the robots to use the nearest recharging station rather than to stick to a particular recharging station. Takano and Nakamura [34] have developed a human trajectory following behaviour by a humanoid robot. Bennewitz et al. [35,36] have proposed dynamic footstep plans for navigational control of humanoid robots. Clever et al. [37,38] have proposed inverse control approaches for transferring human motions to humanoids and generated smooth movement in complex terrains. Castillo et al. [39] have used fuzzy logic to tune the parameters of an ant colony and used the same in a fuzzy logic controller for navigation of a mobile robot. Kumar et al. [40,41] have designed several motion planning controllers for humanoid robots using regression analysis and fuzzy logic control. Choomuang and Afzulpurkar [42] have hybridized a Kalman filter with a fuzzy based system for position control of an autonomous mobile robot. They have used both the logic to integrate information from external and internal sensors and design the navigation pattern. Melingui et al. [43] have hybridized artificial potential field with fuzzy logic to avoid the limitations available in both the techniques and used the hybrid controller in mobile robot navigation. Zhao et al. [44] have used genetic algorithm to tune the input and output membership functions of a fuzzy logic based controller and used the hybrid model in the navigation of a mobile robot. Boufera et al. [45] have used a hybrid methodology consisting of limit cycles and fuzzy logic for the navigation of a mobile robot in an unknown environment. Azouaoui et al. [46] used a combination of neural network and fuzzy logic for the navigation of a bi-steerable mobile robot. Panda et al. [47] hybridized firefly algorithm with invasive weed optimization for navigational control of a mobile robot.

It can be observed from the extensive literature survey that most of the techniques from classical and AI fraternity are primarily applied to navigation of mobile robots only. Some of the researchers have applied several intelligent methods towards humanoid analysis. However, most of their approaches are devoted towards footstep plans, stability and posture control. Online obstacle avoidance along with goal following behaviours is rare to find in the available literature. Along with that, navigation of multiple humanoids in a common platform with incorporation of online obstacle detection has not been reported. Similarly, the use of hybrid techniques for path planning and navigation is yet to be reported in the existing work. Therefore, the current research is aimed towards design, development and implementation of a novel hybrid controller for navigation of single as well as multiple humanoids in a common platform. The hybrid architecture consists of regression analysis taken from classical methods and fuzzy logic control taken from the AI category. As already stated, the hybrid model is expected to receive advantageous properties from both the categories of classical and AI methods. Here, the obstacle distances in the form of sensor outputs are fed as initial inputs to an RA control architecture and an intermediate turning angle (ITA) is obtained as the first output based on the previous training pattern supplied to the regression model. The first output ITA is again fed as input to the FLC along with other regular inputs to obtain ultimate turning angle (UTA) as the final output. The working of the developed hybrid architecture is validated through multiple tests on simulation and real-time platforms. The results obtained from both the platforms are compared against each other with a good covenant and minimal error limits. For navigation of multiple humanoids on a common platform, a Petri-Net model has been designed to resolve conflicts in avoiding dynamic obstacles. Finally, the developed hybrid control scheme is also tested against another established navigational controller, and an enhancement in efficiency is observed.

The major contributions of the proposed investigation can be highlighted as follows. Humanoid navigation is yet far away from the automation that has been presented in fictional characters. To provide complete autonomy to a humanoid robot, a robust and intelligent controller is required that is able to make smart decisions based on environmental conditions. Along with that, simultaneous navigation of multiple humanoids on a common platform requires extra care towards avoiding possible inter-collision. Therefore, the current research has been focused on design, development and implementation of a regression-fuzzy logic control based robust hybrid navigational controller that can work smartly in complicated arena conditions achieving safe obstacle avoidance and goal reaching in an optimized manner. The developed controller has been tested on multiple simulations and experimental scenes with comparisons of selected navigational parameters from each arena and a good agreement between the results have been observed. Most of the previous works on humanoid navigation are limited to motion control without obstacle avoidance of goal reachability. However, the current research considers smooth motion control along with avoidance of both static and dynamic obstacles in complicated arena settings.

2. Control architecture of RA model

Regression is a popular classical tool in forecasting unforeseen conditions based on analysis of previous data trend. It relates reliant variables with non-reliant ones using functional relations. Out of a cluttered data set, RA generates a straight line equation which closely relates the data set. Accumulation of scattered data into a straight line is the most significant feature of the regression model. An RA model can be mathematically expressed as:

$$u_i = \delta_1 + \delta_2 v_i + \varepsilon_r \tag{1}$$

In the above equation, u_i is a reliant variable, and v_i is a non-reliant variable with δ_1, δ_2 as parameters of regression and ε_r accounts for the error in data fitting.

Likewise, a humanoid navigation problem can be fitted to a regression model by suitable consideration of the navigational parameters as inputs and outputs.

2.1. Humanoid navigational model using RA

A navigational algorithm used for obstacle avoidance purpose in complicated terrains has two major objectives to achieve such as avoiding the obstacles present in the arena and reaching the desired target location. Hence, the algorithm needs to first detect the obstacles and then process them to generate a collision-free smooth path. In the current analysis, NAO humanoid robots have been used for navigational analysis. NAO is a medium sized smart programmable robot armed with a variety of sensors [48] such as ultrasonic sensors, infrareds, cameras, tactile sensors, pressure sensors, etc. Out of all the sensors that the humanoid NAO possess, ultrasonic sensors are used in the current analysis. Here, obstacle distances such as Front Sensor Output (FSO), Left Sensor Output (LSO), Right Sensor Output (RSO) are selected as the inputs to the RA architecture, and Turning Angle (TA) is obtained as the output. Fig. 1 demonstrates the RA architecture used in the current work.

Table 1
A sample set of training pattern data used in RA model.

Sl. No.	FSO	LSO	RSO	TA	Sl. No.	FSO	LSO	RSO	TA
1	62	35	48	7	11	50	65	30	−14
2	41	46	59	11	12	62	33	45	4
3	36	72	41	−11	13	53	43	72	13
4	31	53	36	−14	14	33	34	57	15
5	74	33	47	0	15	42	74	30	−16
6	32	41	41	−27	16	45	38	51	22
7	53	41	32	−28	17	52	54	40	−18
8	42	64	44	−14	18	41	38	65	21
9	84	44	56	0	19	55	80	40	−24
10	39	57	41	−9	20	45	39	60	15

As per the basic rule of the regression model, a training data set containing sample inputs and outputs is fed to the architecture and based on the training pattern, the architecture generates output to unforeseen conditions. Basically, the regression model tries to map the unforeseen conditions of the arena to the closest data set available in the training pattern and then works accordingly. Table 1 demonstrates a sample data set that has been used in the current work. The regression model is largely dependent upon the training pattern data for solution generation. The training pattern data is completely user specific. The humanoid has been tested in multiple simulations and experimental scenarios using different settings of obstacles, start and goal positions. During the experimentation, different cases of failure and success were recorded and accordingly navigational parameters for each setting were noted. The failure cases were analysed, and rectifications were done to the parameters to achieve smooth movement.

It can be observed from the training pattern data that some of the outputs are in their negative values. It should not be confused with any negative turning. For ease of the analysis, a general sign convention has been used for the direction of turn which states that any turn towards the left periphery is taken as negative and any turn towards the right counterpart is taken as positive. The zero values indicate that the robot continues to follow the same path as was in the previous step. 500 data sets are fed to the regression model. To generate a straight line equation, the data sets are supplied to Minitab software, and an equation is generated in the following format.

$$\alpha = -0.005742 d_1 - 0.2567 d_2 + 0.794382 d_3 - 23.0975 \tag{2}$$

where, $d_1 = \text{FSO}$, $d_2 = \text{LSO}$, $d_3 = \text{RSO}$ and $\alpha = \text{TA}$.

Eq. (2) signifies that turning angle is generated as a linear combination of input parameters such as the sensor outputs. After creating Eq. (2), the humanoid can generate a safe direction of turn based on any arena condition using sensor outputs regarding the obstacle distances as inputs to the controller.

The humanoid is initially supplied with the source and target locations of the arena and with an initial turning angle set accordingly, it proceeds to reach the target. The ultrasonic sensors of the humanoid can detect the obstacles up to a range of 2.55 m. However, in the current work, a threshold of 0.3 m is set for activation of the RA controller. After detection of a potential obstacle within the set threshold range, the RA controller is activated, and sensor outputs are fed as inputs to the controller. The controller generates the turning angle as the output as per the above-stated equation. To achieve smooth navigation in the arena, some reactive behaviours such as target trailing, obstacle evading and barricade trailing are also combined with the RA controller. In target trailing mode, the robot always moves towards the target in the absence of any obstacle in its path. In obstacle evading mode, the robot escapes from the obstacle by taking some suitable turning angle. In barricade trailing mode, the robot

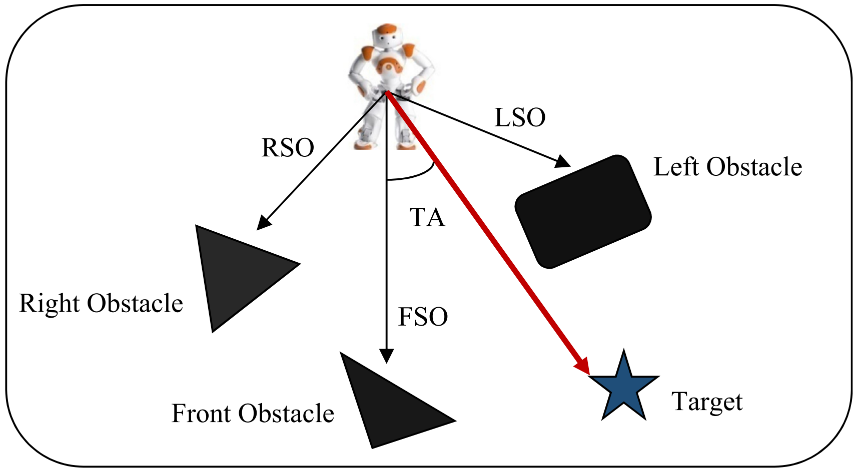


Fig. 1. Input and output parameters of RA model.

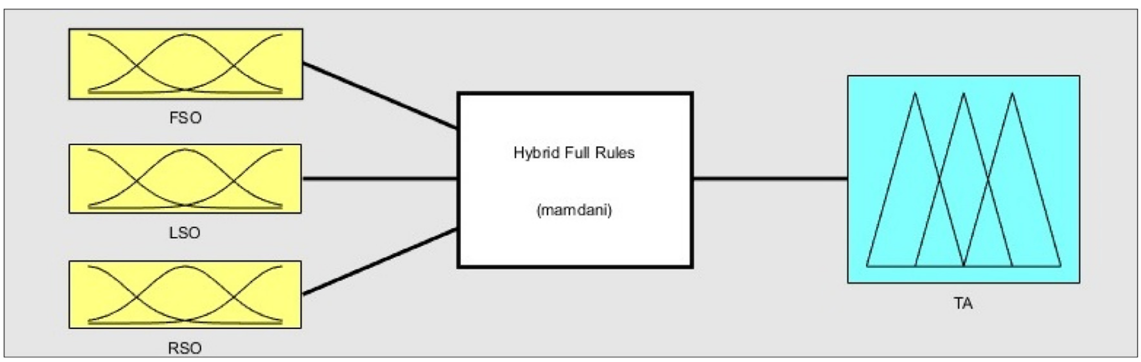


Fig. 2. Fuzzy logic architecture.

follows a long barricade to reach the target provided the target is located at the end of the barricade. By the above-discussed architecture, the humanoid can perform a smooth navigational pattern in complex scenarios.

3. Control architecture of FLC

Fuzzy logic [49] is primarily inspired by the human way of reasoning. With semantic reasoning by the use of "IF-ELSE" statements, fuzzy logic has drawn attraction from many researchers in solving a variety of engineering problems. The implementation of fuzzy logic as a problem-solving technique is progressed through a series of steps such as fuzzification of the input variables, designing the rule base for fuzzy set, generation of output as per the rules and defuzzification of the output variables. Fuzzification of the input variables symbolizes conversion of the input variables from numeric terms to fuzzy linguistic terms. The fuzzy rule base is a set of rules designed as per the human way of reasoning with "If-Else" statements. The output of the fuzzy rule base is again converted from linguistic terms to actual numeric terms in the defuzzification process.

The major advantages of using a fuzzy logic approach can be highlighted over here. Fuzzy logic is simple and flexible. It can manage trouble with inaccurate data. It is comparatively less expensive for development. Fuzzy logic can manage a large area of operating conditions. It involves more precision. It does not require a large database to train. It follows a simple human way of reasoning as a result, it requires simplified rules rather than complicated codes. Another major advantage can be; it does not require to re-train the system if some new rules are added to the controller after the initial design.

3.1. Humanoid navigational model using FLC

The design of fuzzy control architecture for a navigational problem requires careful consideration of the robot parameters. As already stated before, in the current work, NAO humanoids have been used. Therefore, as considered for the regression model, FSO, LSO, RSO are considered as the input variables and TA is taken as the output variable. The minimum sensor output is set as 30 cm, and the maximum sensor output is set as 80 cm. Here, hybrid type of membership functions (a combination of triangular, trapezoidal and Gaussian functions) are used for the analysis. The total interval of membership functions has been categorized into 7 sub-intervals. The categories are very very near (VVN), very near (VN), near (N), standard (S), extreme (E), very extreme (VE), very very extreme (VVE) for the obstacle distances (sensor outputs). The same has been categorized as very very negative (VVNE), very negative (VNE), negative (NE), no turn (NT), positive (P), very positive (VP) and very very positive (VVP) for the turning angle. Fig. 2 represents the FLC used in the current work, and Fig. 3 represents the input and output variables.

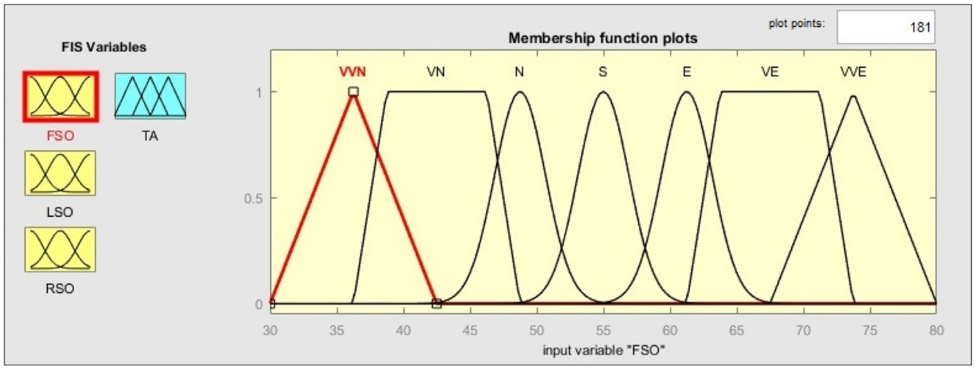
As per the input and output variables, a typical fuzzy rule can be written as:

If (FSO is FSO_a and LSO is LSO_b and RSO is ROD_c), Then TA is TA_{abc}

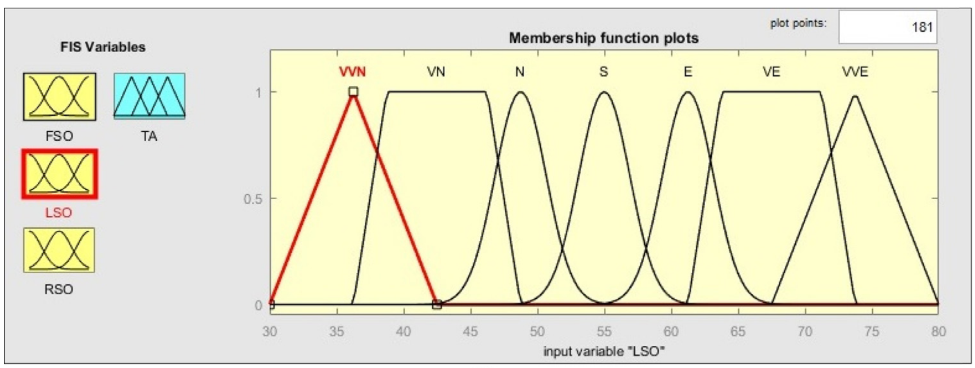
where, a, b, c may vary from 1 to 7 as each parameter has 7 membership functions.

As per general conventions of the FLC method [50], a factor K_{abc} can be defined for the rule base as follows:

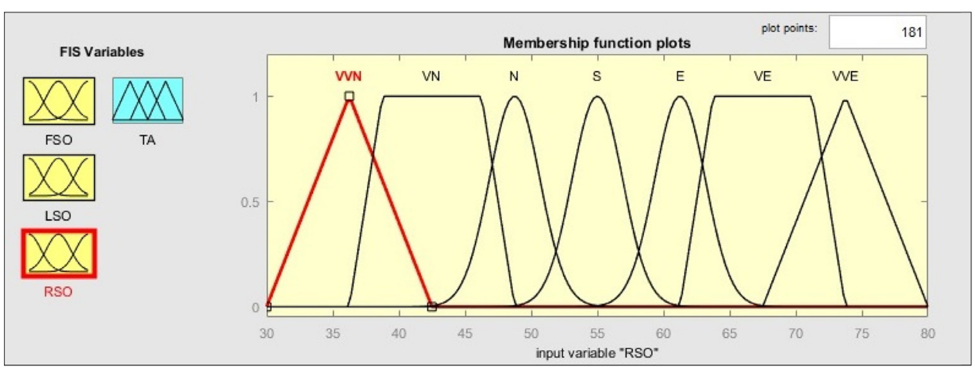
$$K_{abc} = \eta_{FSO_a}(d_a) \wedge \eta_{LSO_b}(d_b) \wedge \eta_{RSO_c}(d_c) \tag{3}$$



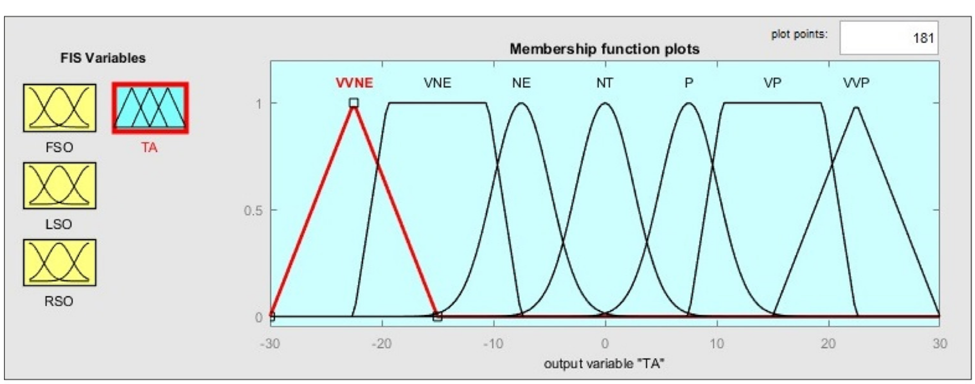
(a)



(b)



(c)



(d)

Fig. 3. (a) FSO (b) LSO (c) RSO (d) TA.

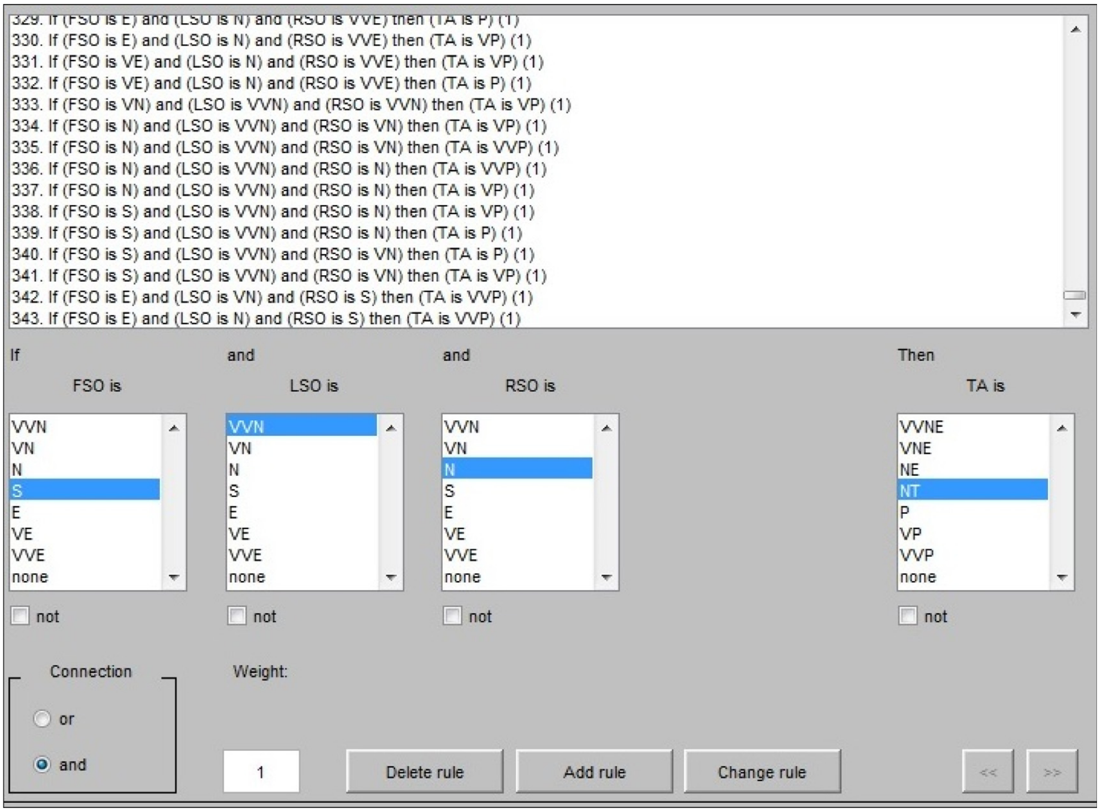


Fig. 4. Rule base sample.

Eq. (3) signifies that the factor K_{abc} is a linear combination of the inputs joined by intersection operator.

As per the rules of interference [50], turning angle membership values can be written as:

$$\eta_{TA_{abc}}(\theta) = K_{abc} \tag{4}$$

The defuzzification process for the turning angle is performed by the centre of gravity method [50] which can be represented as follows:

$$\text{Turning angle} = TA = \frac{\int \theta \eta_{TA}(\theta) d\theta}{\int \eta_{TA}(\theta) d\theta} \tag{5}$$

where θ = angle.

The defuzzification process signifies conversion of the output from linguistic fuzzy terms to standard numeric terms that can be understood by the operator. So, Eq. (5) signifies such a conversion where the required output turning angle is converted to a numerical value that the robot can use as the guiding norms to avoid the obstacle present ahead.

As there is three number of inputs and each input has seven number of membership functions, as per a general convention, 343 number of rules are used in the current analysis. Fig. 4 represents a sample of total rule base and Fig. 5 represents a sample output generated by the rule base.

Fig. 6 represents the surface plots obtained from the FLC that signifies the relationship between input and output parameters of the controller used in the current investigation.

The fuzzy architecture gets activated after the detection of a potential obstacle in its path and as per the above-discussed processes, the output is generated.

4. Control architecture of RA-FLC hybrid model

The major objective of developing hybrid architectures is to avoid the limitations of standalone methods. As already discussed, classical methods are known for providing converged results within limited problem space, and AI methods provide more accurate results. However, classical methods may sometimes face the difficulty of being trapped at local optima. Humanoid navigation has always remained as one of the most challenging areas of investigation which requires accurate results within limited problem space along with quick convergence and smart decision making. Therefore, hybridization of a classical method with an AI technique is always a stimulating area of investigation. In the current hybrid model, a two-step hybridization mode is proposed. The inputs in the form of sensory information (FSO, LSO, RSO) are initially fed to the RA model, and an interim turning angle (ITA) is obtained as the first output. In the second stage, the FLC is fed with the ITA along with other regular inputs (FSO, LSO, RSO). The FLC calculates the ultimate turning angle (UTA) which is eventually used by the humanoid to avoid the obstacles and reach a safe position. Fig. 7 represents the hybridization scheme used in the current work. It can be noted that the membership function generation for ITA is kept similar to the output of standalone FLC model as discussed before.

The proposed RA-FLC hybrid model can be summarized by the help of following steps.

- State source and target locations for the humanoid.
- Proceed towards the target until detection of a potential obstacle within the set threshold limit by the help of target trailing mode.
- Once the sensors detect an obstacle, activate the RA control architecture.
- Supply FSO, LSO, RSO as initial inputs to the RA model and attain ITA as the first output.

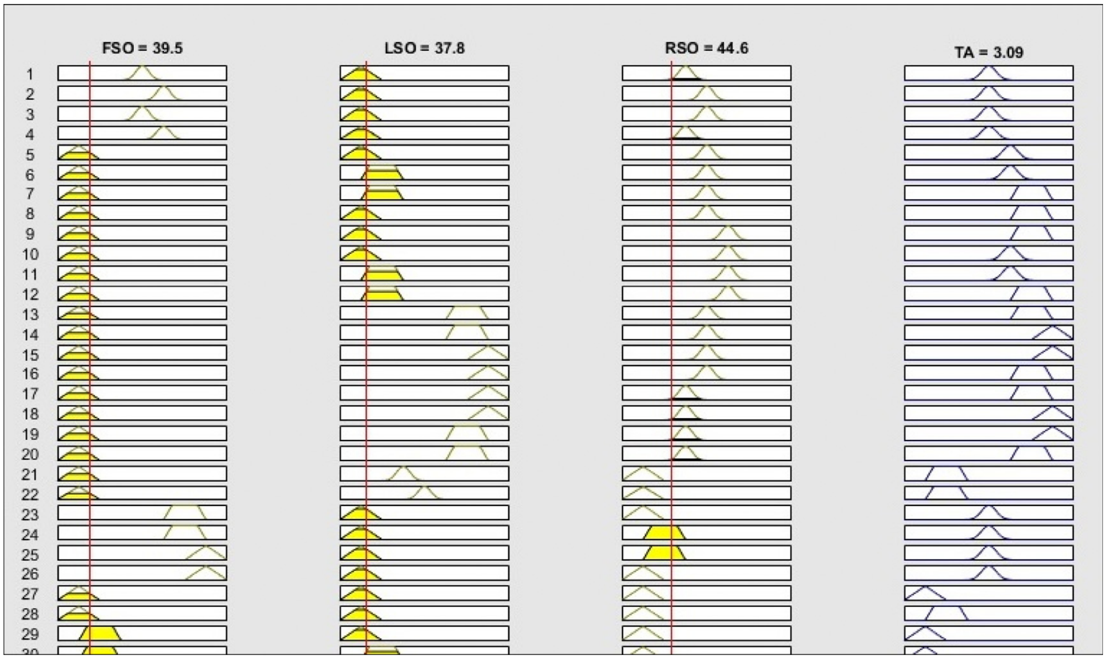


Fig. 5. Output generation by FLC.

- Supply the FLC model with ITA, FSO, LSO and RSO.
- Attain UTA as the final output as per the fuzzy rule base and provide the humanoid with the necessary turning angle required for smooth movement.

Fig. 8 represents the pseudo code of the RA-FLC control scheme and Fig. 9 represents the flowchart of the whole process.

5. Petri-net control architecture

To navigate with dynamic systems under a common platform, Petri-Net models [51,52] are used. Petri-Net is a sequential scheme designed to resolve conflicts between multiple agents when they encounter a common obstacle during their movement. In the current work, navigation of single as well as multiple humanoids has endeavoured in a common platform. The proposed hybrid navigational model works to avoid the obstacles present in the environment and reach the target location smoothly. However, if the robots encounter dynamic obstacles, the navigational model cannot decide the priority regarding motion. Therefore, a Petri-Net control scheme is integrated with the hybrid model to avoid possible inter-collisions. Fig. 10 represents the Petri-Net control architecture used in the current work.

In the above control architecture, an oval symbol denotes the current position of the robot, and the bar symbol denotes the transition from one phase to another. The architecture is designed using six levels, and each level can be understood as follows.

Level-I: Level-I represents the robots at random locations of the arena with no prior knowledge regarding the position of other robots. Here, all the robots are waiting for the start command to move towards their respective targets.

Level-II: In this level, target trailing behaviour is activated, and all the robots proceed towards their respective targets and in turn may detect obstacles present in their path.

Level-III: After detection of a dynamic obstacle, the robots enter to this level.

Level-IV: In this level, to avoid a conflict between two robots, the one having less distance left towards the target gets higher priority and moves forward while the other one behaves like a static obstacle at its place.

Level-V: In this level, the robots check for any further conflicting situation and move forward if such situations are absent.

Level-VI: This is a waiting level. If a robot comes across another set of robots already in Level-III, it has to behave as a static obstacle and wait until the first set of robots move forward. After that, the waiting robot commences its journey from Level-II.

By the use of the above-discussed control architecture, navigation of multiple humanoids can be achieved in a common platform.

6. Execution of proposed RA-FLC control architecture

The developed RA-FLC hybrid architecture has been executed in simulation and real-time environments considering NAO humanoids as the navigation platform. Here, navigation of single as well as multiple humanoids has been executed in a common platform. It can be noted that, while navigating multiple humanoids in a common platform, Petri-Net architecture is combined with the hybrid model for smooth movement and avoidance of possible inter-collision.

6.1. Navigation of a single humanoid

Although MATLAB has gained immense interest among researchers in analysing navigational problems, it is not suitable for analysis of humanoid navigation. Humanoids differ from wheeled locomotion in the movement of joints rather than wheel movements. Wheel movements can be represented as the movement of a point (circle or rectangle) in MATLAB simulation tool. Therefore, V-REP has been selected as the navigational tool for humanoid locomotion as it possesses advantageous properties like better obstacle detection, collision avoidance, enhanced motion planning, etc. Along with that, complete humanoid models can be accurately designed in the V-REP platform that helps to visualize the movements similar to the real-time arena. In the V-REP platform, an arena of size 240 x 160 units has been designated as the navigation space. Specific source and target locations are provided for the humanoid and several obstacles of random size and shape are arbitrarily kept at different locations of the arena. The logic of the developed hybrid model has been supplied to the

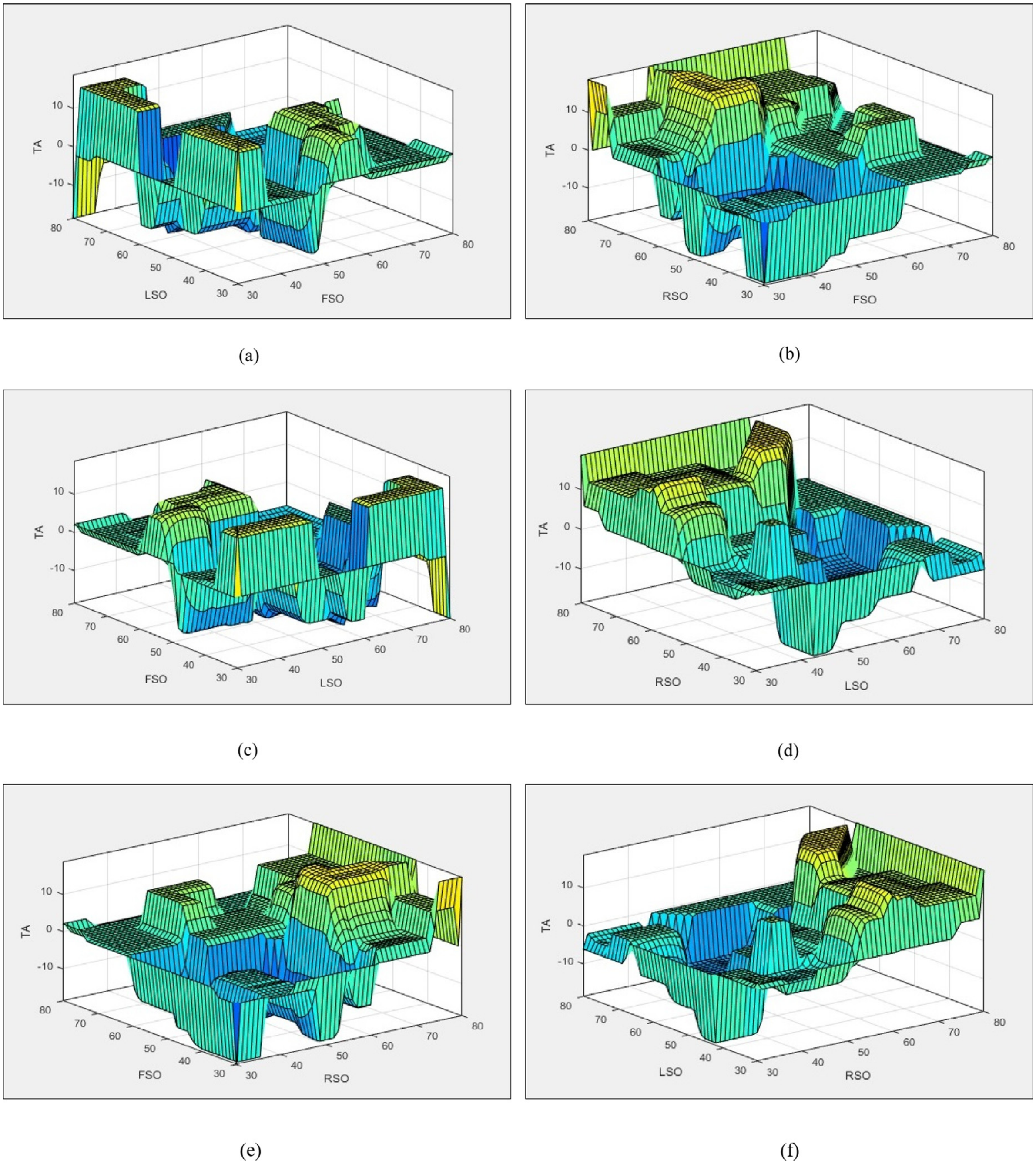


Fig. 6. Surface plots for FLC.

humanoid in the form of a code written in LUA language and the humanoid was set for movement towards the target from the source location. Figs. 11 and 12 depict the simulation results obtained for the navigation of a single humanoid in scene 1 and scene 2 respectively.

It can be observed from the simulation results that the humanoid is successful in reaching the target location by good negotiation with the obstacles and in an optimized manner.

The simulation results are validated against real-time environments prepared under laboratory conditions. A real-time platform was prepared to keep the same arena size of 240 x 160 units. Each simulation scenario has been replicated in the real-time environment with similar arena conditions such as the same sized and shaped obstacles, same position of source and target locations and obstacle positions. The humanoid in the real-time arena was operated in Wi-Fi mode through python programming language. The logic of the developed hybrid control scheme was supplied to the humanoid through code, and it was advanced towards its target. Figs. 13 and 14 depict the real-time results obtained from the navigation of a single humanoid in scene 1 and scene 2 respectively.

The assessment of the simulation results with real-time results has been performed through trajectory followed and navigational parameters. It can be observed from simulation and real-time results that, the trajectory followed in simulation and real-time arenas are almost of similar kinds. Here, navigation route length and navigation time consumed are selected as the two parameters for the above mentioned assessment. These two parameters are recorded directly from the V-REP simulation window and are calculated by the help of measuring tape and stopwatch in

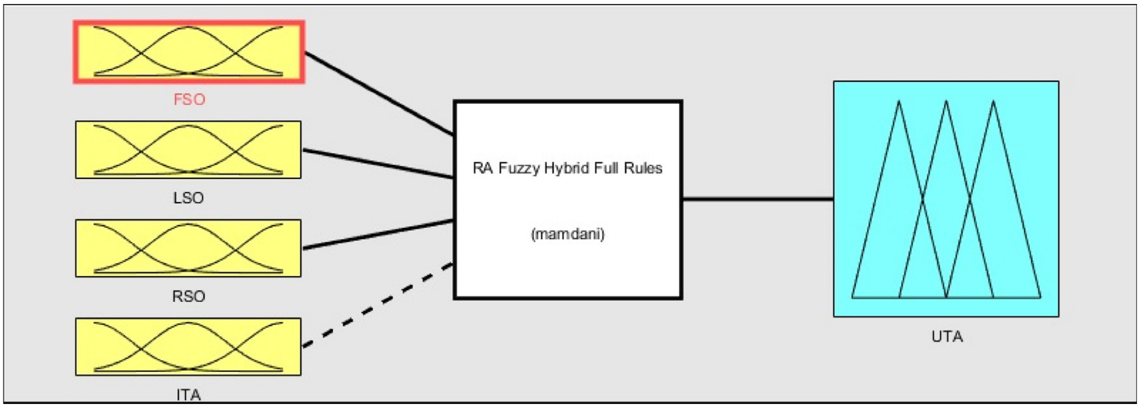


Fig. 7. RA-FLC hybrid model.

The humanoid starts heading towards the target with target-seeking behaviour

If (Target is reached)

    Stop navigation

Else if a potential obstacle is detected by the sensory network

    RA motion planning strategy is activated

    Sensor outputs regarding obstacle distances (FSO, LSO and RSO) are fed as inputs

    ETA is generated as the intermediate output

    FLC is activated

    ETA is again fed to the FLC model along with other inputs (FSO, LSO and RSO)

    Fuzzification converts the inputs from numeric to linguistic terms

    The fuzzy rule base is created using the fuzzified inputs

    The output is generated by combining membership values of all rules

    Defuzzification converts the output from linguistic to numeric terms

    UTA is generated as the final output

    The humanoid moves to the next position as per the generated UTA

    If (Target is reached)

        Stop navigation

    Else if (Obstacle is detected)

        Repeat the RA-FLC controller to find the next UTA

Else

    Keep navigating till an obstacle is detected or target is reached

Fig. 8. Pseudo code of RA-FLC architecture.

the real-time environment. Tables 2 and 3 depict the assessment of simulation and real-time results in terms of navigation route length, and Tables 4 and 5 represent the comparison of navigation time consumed in scene 1 and scene 2 respectively.

From the above assessments, it can be observed that navigational analysis using the developed hybrid model earns minimal deviation limit. It can further be noticed that the real-time platforms possess higher values for the navigational parameter compared to the simulation counterparts. The reason for the same is the presence of external factors such as slippage effect, frictional loss, data transmission loss, etc. in the real-time environment which is absent in the simulation platform.

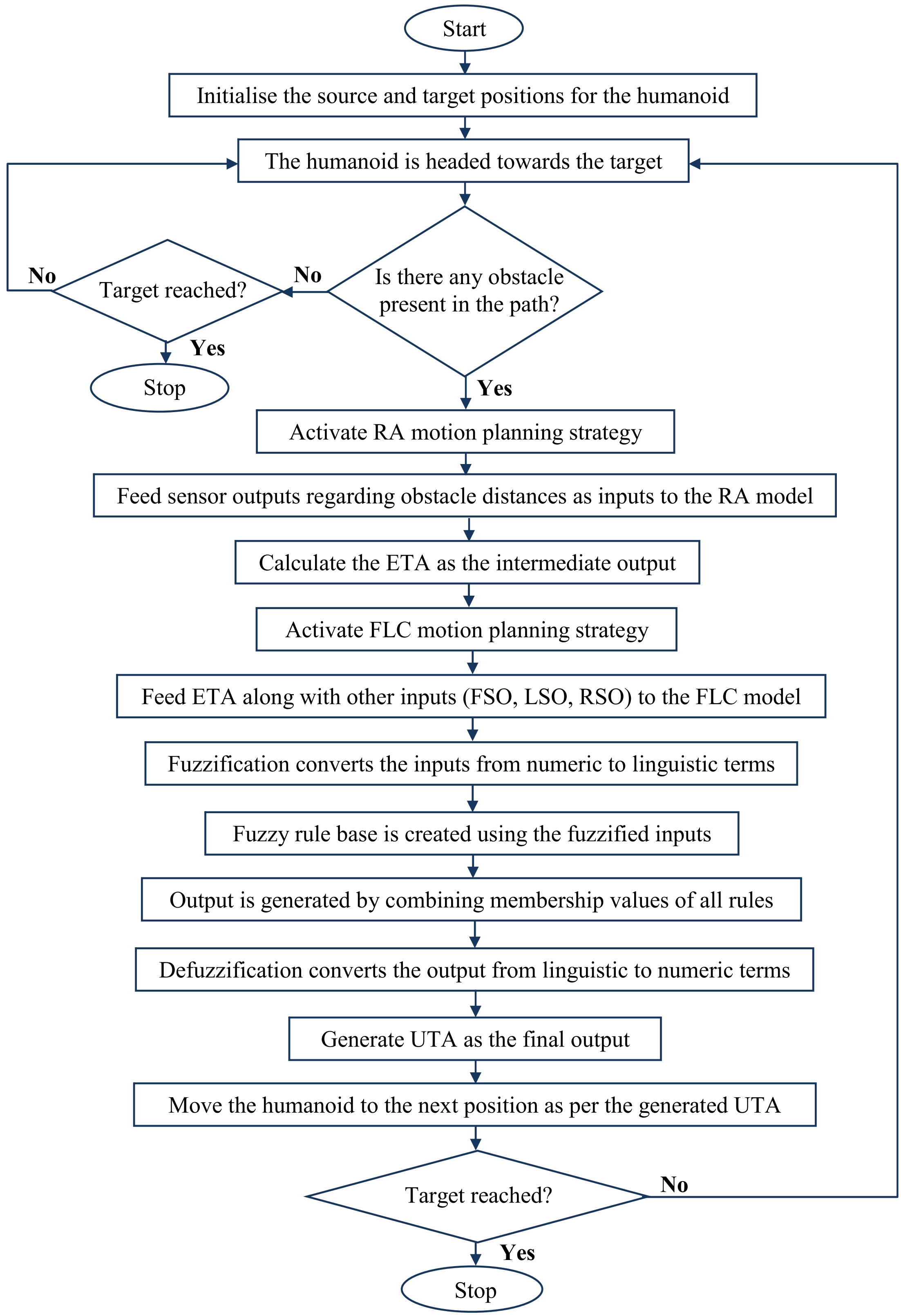


Fig. 9. Flowchart of RA-FLC hybrid model.

6.2. Navigation of multiple humanoids

Navigation of multiple humanoids differs from the navigation of a single humanoid in a way that the former one possesses dynamic obstacles and to negotiate dynamic obstacles, Petri-Net architecture is required. Here, the arena size was kept exactly similar to the navigation of single humanoid. Two humanoids and several obstacles are used for the navigational analysis, and definite source and target locations are designated for each humanoid. After supplying the logic of the developed hybrid model

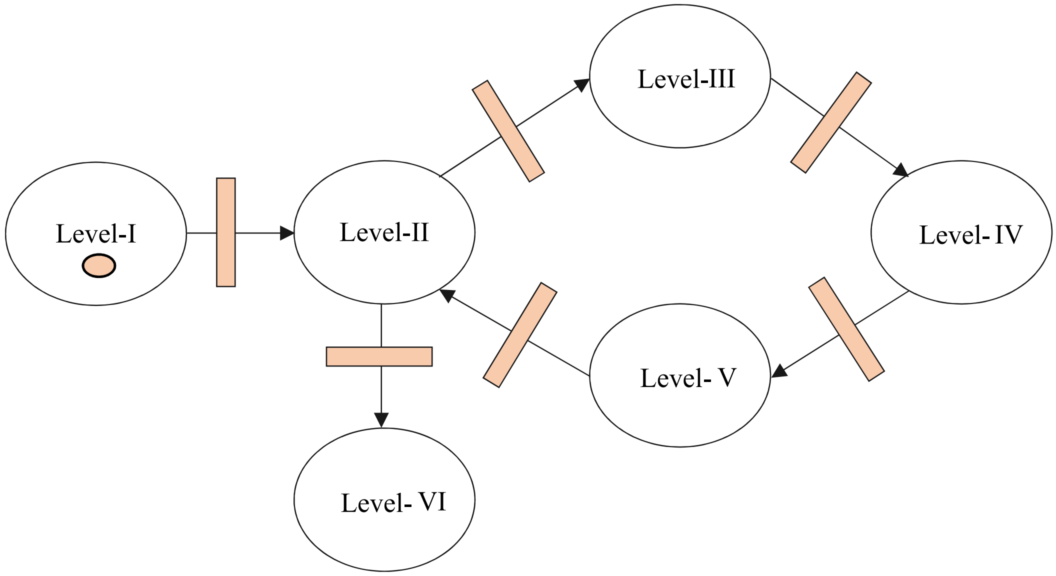


Fig. 10. Petri-Net control architecture.

Table 2
Assessment of navigation route length between simulation and real-time results for a single humanoid in scene 1.

Sl. no.	Navigation route length in simulation (cm)	Navigation route length in real-time (cm)	Deviation in %
1	340.57	360.5	5.53
2	340.92	360.8	5.51
3	339.68	359.7	5.57
4	341.2	361.4	5.59
5	340.15	361.2	5.83
Average	340.5	360.72	5.61

Table 3
Assessment of navigation route length between simulation and real-time results for a single humanoid in scene 2.

Sl. No.	Navigation route length in simulation (cm)	Navigation route length in real-time (cm)	Deviation in %
1	314.58	333.9	5.79
2	315.89	334.2	5.48
3	314.76	334.8	5.99
4	316.42	333.7	5.18
5	315.95	334.6	5.57
Average	315.52	334.24	5.6

Table 4
Assessment of navigation time consumed between simulation and real-time results for a single humanoid in scene 1.

Sl. No.	Navigation time consumed in simulation (s)	Navigation time consumed in real-time (s)	Deviation in %
1	45.95	48.59	5.43
2	45.98	48.73	5.64
3	46.27	49.17	5.9
4	46.02	48.9	5.89
5	45.9	48.84	6.02
Average	46.02	48.85	5.78

Table 5
Assessment of navigation time consumed between simulation and real-time results for a single humanoid scene 2.

Sl. No.	Navigation time consumed in simulation (s)	Navigation time consumed in real-time (s)	Deviation in %
1	42.56	45.18	5.8
2	42.81	45.31	5.52
3	42.67	45.32	5.85
4	42.97	45.38	5.31
5	42.55	45.29	6.05
Average	42.71	45.3	5.71

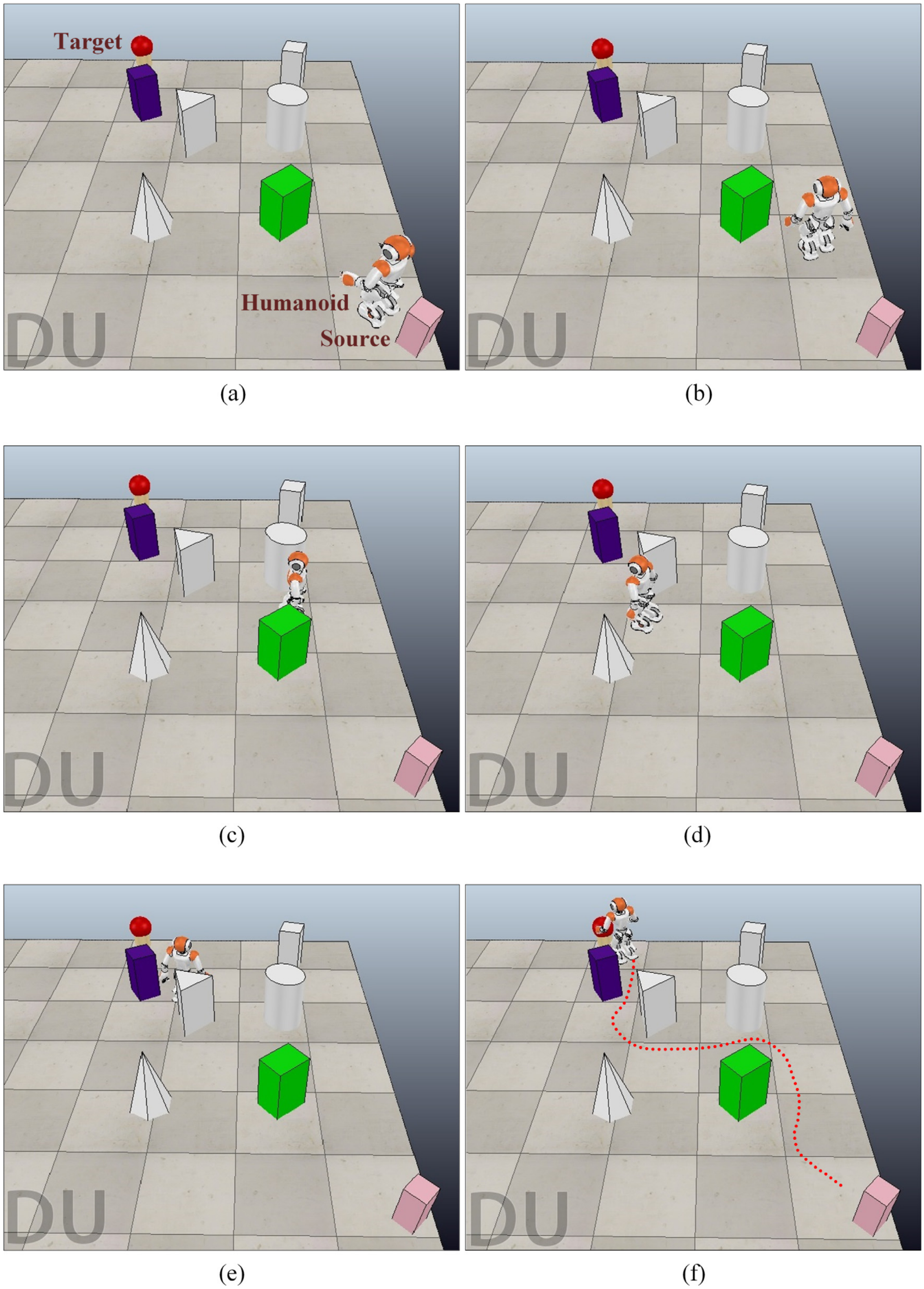


Fig. 11. Simulation results for navigation of a single humanoid in scene 1.

along with Petri-Net architecture, the humanoids are advanced towards their respective targets. Figs. 15 and 16 depict the simulation results obtained for the navigation of multiple humanoids in scene 1 and scene 2 respectively.

The navigational results obtained from the simulation environment are also validated in real-time platforms. Figs. 17 and 18 depict the real-time results obtained for the navigation of multiple humanoids in scene 1 and scene 2 respectively.

The simulation and real-time results are also assessed against each other and depicted in Table 6, Table 7, and Table 8, Table 9 for navigation route length and navigation time consumed in scene 1 and scene 2 respectively.

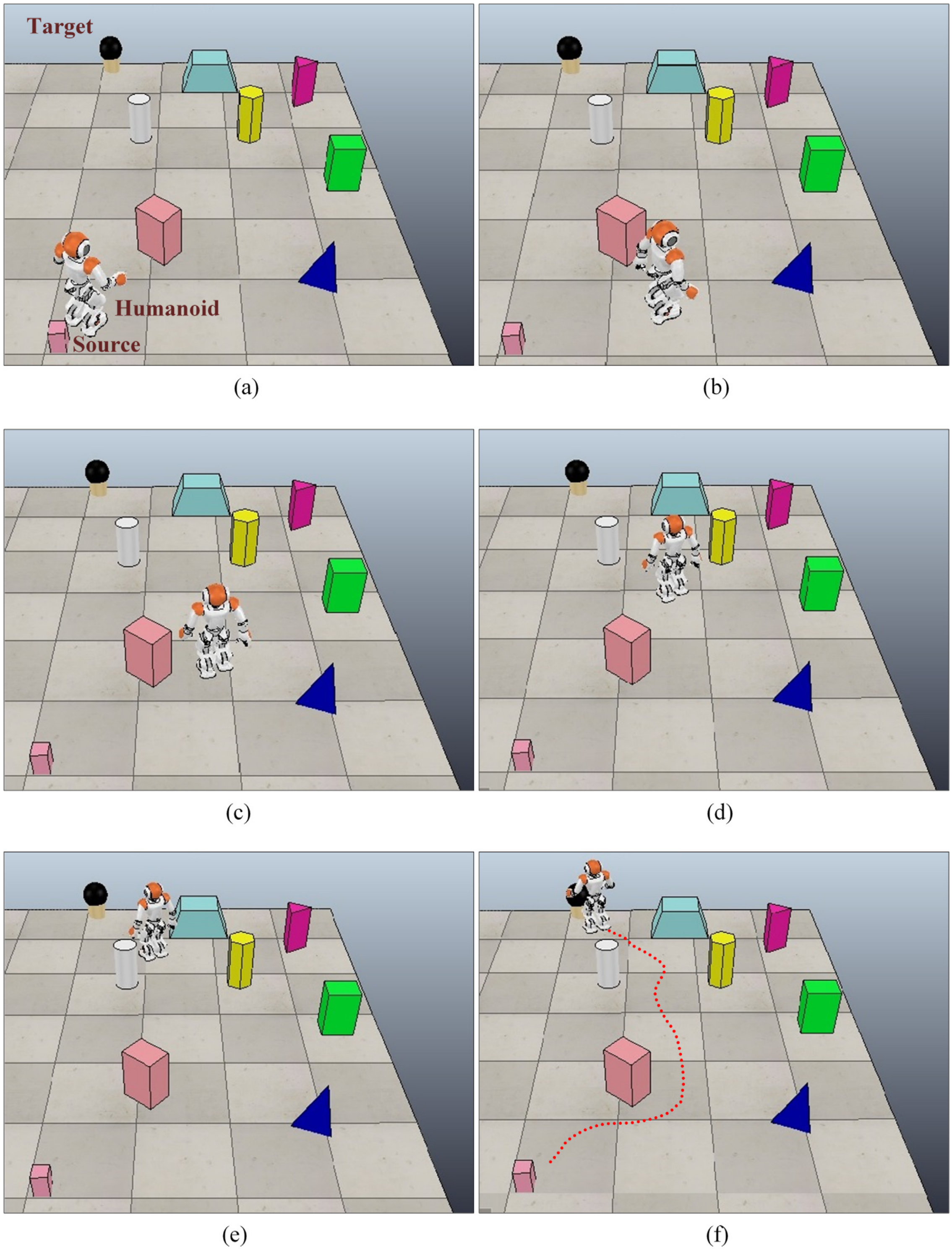


Fig. 12. Simulation results for navigation of a single humanoid in scene 2.

The assessment of results from both the environments in the navigation of multiple humanoids has also revealed satisfactory results which state that the developed hybrid control architecture has been successful in navigating single as well as multiple humanoids in complicated terrains with proper negotiation with both static and dynamic obstacles and reaching the respective target locations with ease. The observation of minimal error limits within the acceptable range also signifies effective working and proper execution of the developed RA-FLC based hybrid motion planning controller.

7. Evaluation of the developed RA-FLC hybrid control architecture against another existing technique

To efficiently prove the validity of the developed hybrid control architecture, it has been evaluated against an existing navigational model. Omrane et al. [11] have developed a fuzzy logic based navigational controller for navigation of autonomous robotic agents. Fig. 19 depicts the comparison of the trajectory followed between the fuzzy logic based approach [11] and the

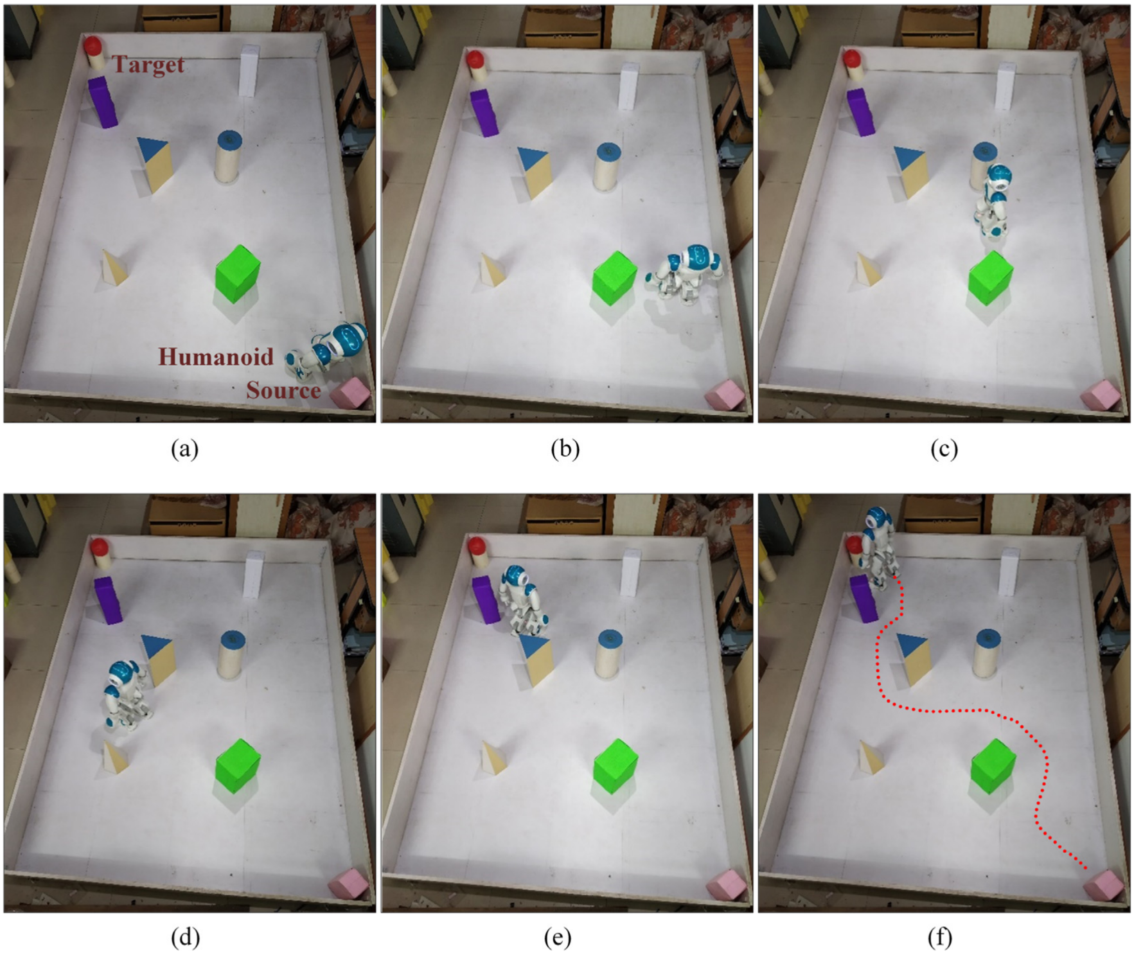


Fig. 13. Real-time results for navigation of a single humanoid in scene 1.

Table 6
Assessment of navigation route length between simulation and real-time results for multiple humanoids in scene 1.

Sl. No.	Simulation results		Real-time results		Deviation in %	
	Navigation route length (cm)					
	H_1	H_2	H_1	H_2	H_1	H_2
1	315.24	325.91	334.8	346.2	5.84	5.86
2	315.82	326.58	334.9	346.7	5.7	5.8
3	316.35	327.4	335.8	347.2	5.79	5.7
4	315.9	326.84	336	346.9	5.98	5.78
5	316.8	326.93	336.2	347.8	5.77	6
Average	316.02	326.73	335.54	346.96	5.82	5.83

Table 7
Assessment of navigation route length between simulation and real-time results for multiple humanoids in scene 2.

Sl. No.	Simulation results		Real-time results		Deviation in %	
	Navigation route length (cm)					
	H_1	H_2	H_1	H_2	H_1	H_2
1	322.53	331.78	341.9	352.4	5.67	5.85
2	322.78	331.95	342.5	352.8	5.76	5.91
3	323.59	332.46	343.1	351.9	5.69	5.52
4	323.62	331.53	342.9	352.6	5.62	5.98
5	322.91	332.42	343.8	352.8	6.08	5.78
Average	323.09	332.03	342.84	352.5	5.76	5.81

developed hybrid control architecture and Table 10 depicts the comparison of navigation route length.

The evaluation of the developed hybrid control scheme has produced better results than the existing navigational model which validates the enhanced efficiency of the same. Along with that, the developed controller executes navigation of single as well multiple humanoids in a common platform with obstacle detection and goal reachability in an optimal fashion that can be considered as the advantages of the developed model compared to other existing models.

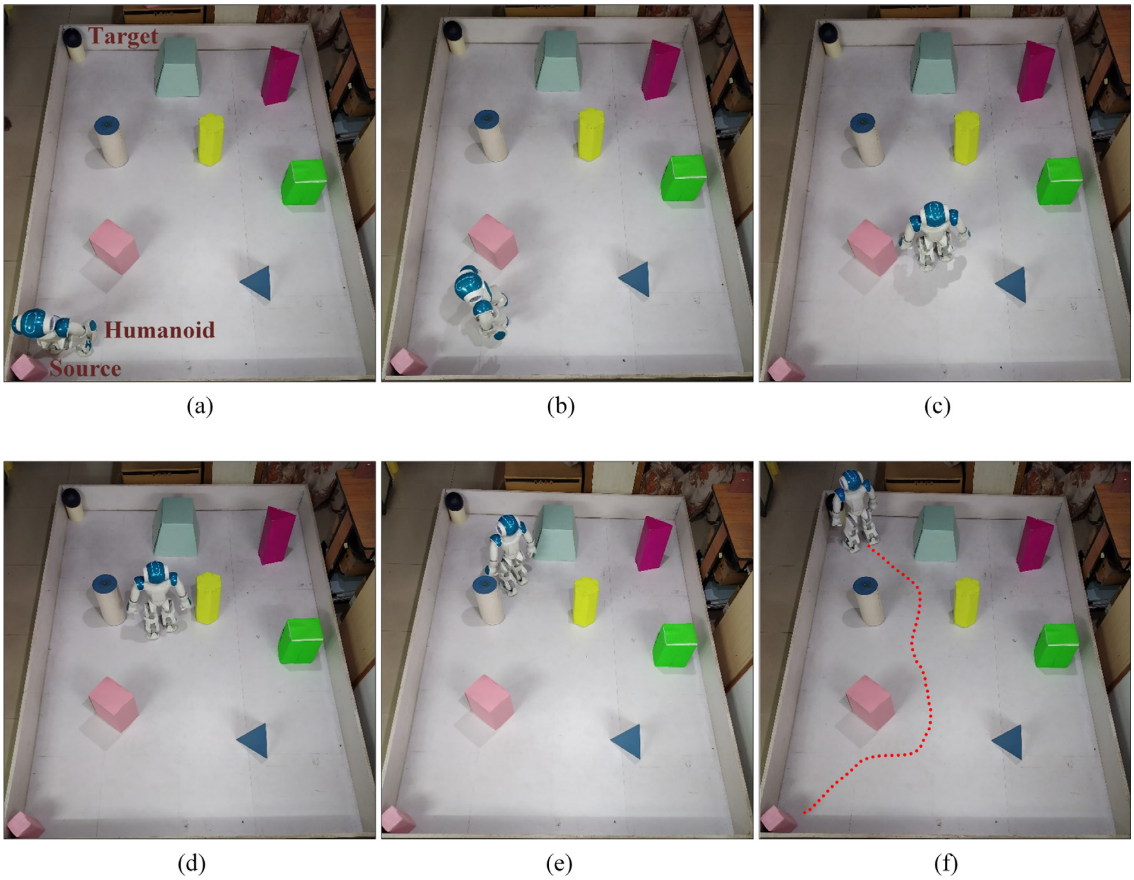


Fig. 14. Real-time results for navigation of a single humanoid in scene 2.

Table 8
Assessment of navigation time consumed between simulation and real-time results for multiple humanoids in scene 1.

Sl. No.	Simulation results		Real-time results		Deviation in %	
	Navigation time consumed (s)					
	H_1	H_2	H_1	H_2	H_1	H_2
1	42.75	44.24	45.37	47.24	5.77	6.35
2	42.89	44.62	45.49	47.48	5.72	6.02
3	43.27	44.9	45.86	47.35	5.65	5.17
4	43.4	45.27	46.23	47.84	6.12	5.37
5	42.96	45.02	45.8	48.25	6.2	6.69
Average	43.05	44.81	45.75	47.63	5.89	5.92

Table 9
Assessment of navigation time consumed between simulation and real-time results for multiple humanoids in scene 2.

Sl. No.	Simulation results		Real-time results		Deviation in %	
	Navigation time consumed (s)					
	H_1	H_2	H_1	H_2	H_1	H_2
1	43.96	45.29	46.69	47.91	5.85	5.47
2	44.11	45.22	46.75	48.15	5.65	6.09
3	44.08	45.65	46.91	48.47	6.03	5.82
4	43.92	45.18	46.61	48.25	5.77	6.36
5	44.28	45.44	46.84	48.31	5.47	5.94
Average	44.07	45.36	46.76	48.22	5.75	5.94

8. Conclusions

With an aim to strive for easing human efforts in tedious and repetitive tasks, navigation and path planning has become a brainstorming session for almost all robotic practitioners. In the current work, a novel hybrid navigational architecture has been developed and implemented for single as well as multiple humanoids in a common platform. The developed control architecture has been prepared by two-step hybridization of the

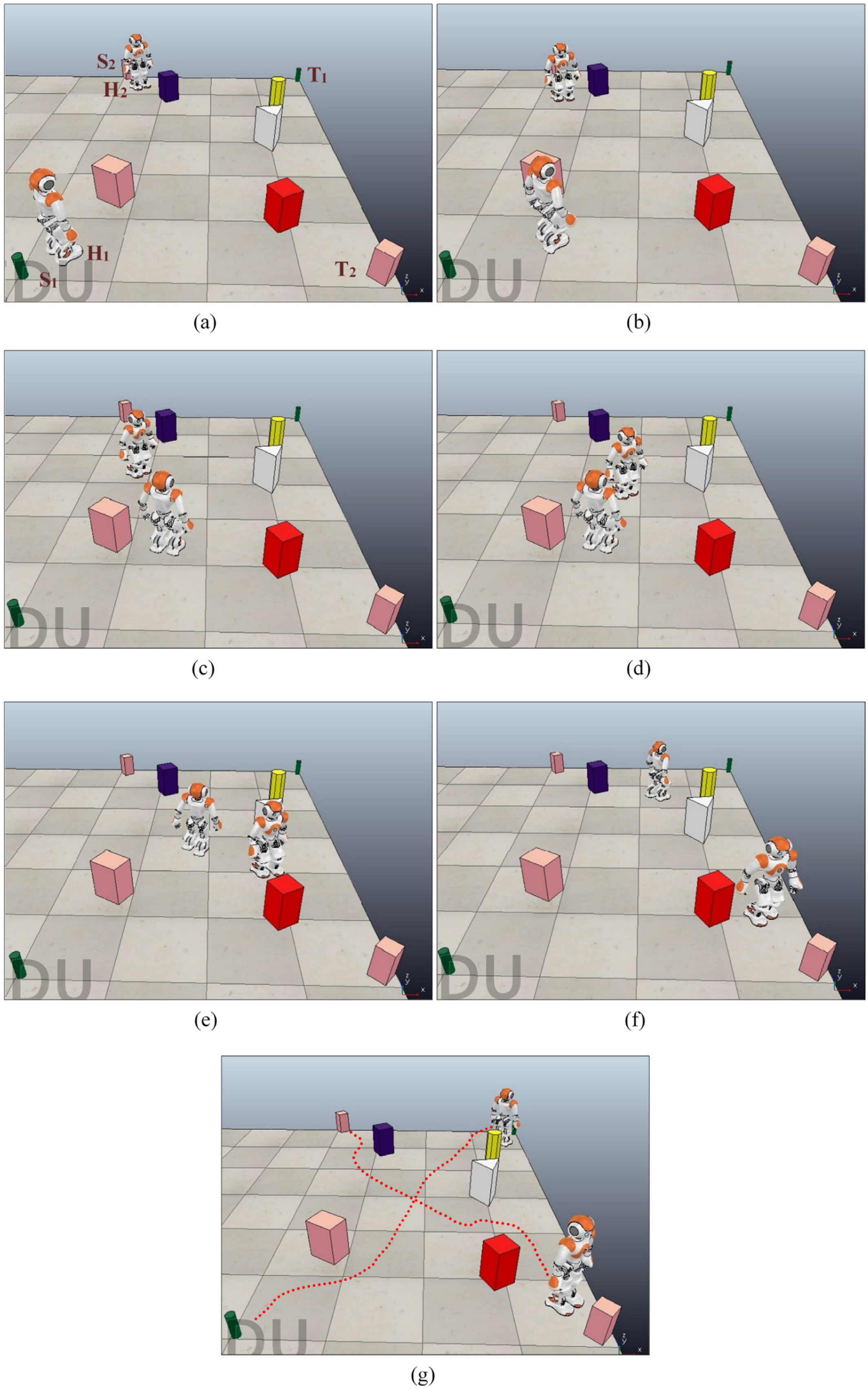


Fig. 15. Simulation results for navigation of multiple humanoids in scene 1.

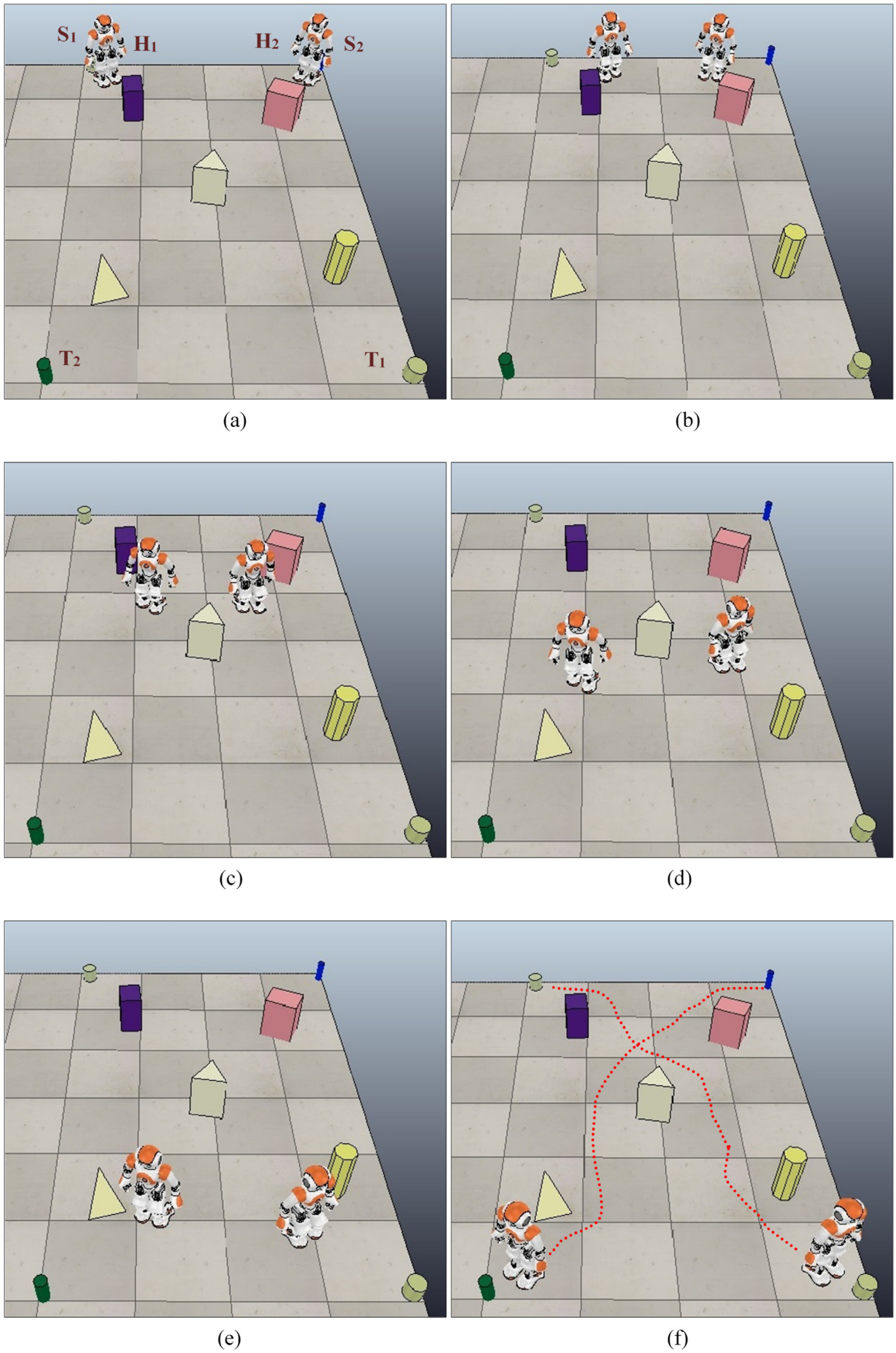


Fig. 16. Simulation results for navigation of multiple humanoids in scene 2.

regression model with a fuzzy architecture. In the proposed control scheme, sensory information regarding the obstacle distances are preliminarily supplied to the regression architecture, and an interim turning angle is generated as the primary output. The interim turning angle is again supplied to the fuzzy architecture along with other conventional inputs, and ultimate turning angle is generated as the final output of the hybrid architecture. The working of the hybrid control scheme is executed on a simulation environment, and the simulation results are validated through real-time replications of the simulation platforms. The results

Fig. 17. Real-time results for navigation of multiple humanoids in scene 1.

Table 10
Evaluation of navigation route length between fuzzy-based approach [11] and RA-FLC approach.

Technique used	Navigation route length in m	Deviation in %
Fuzzy-based approach [11] (Fig. 15(a))	1.84	6.52
RA-FLC approach (Fig. 15(b))	1.72	

from both the platforms are assessed against each other in terms of selected navigational parameters with a minimal percentage of deviations. To avoid possible inter-collisions in the navigation of multiple humanoids in a common platform, a Petri-Net control architecture has been proposed. Finally, the developed hybrid scheme is also evaluated against another existing navigational model, and enhancement of efficiency is observed. The proposed hybrid model can also be tested for other forms of robots, and different intelligent methods can also be combined along with the existing one which can be considered as a future endeavour of the current work.

Declaration of competing interest

No author associated with this paper has disclosed any potential or pertinent conflicts which may be perceived to have impending conflict with this work. For full disclosure statements refer to https://doi.org/10.1016/j.asoc.2020.106088.

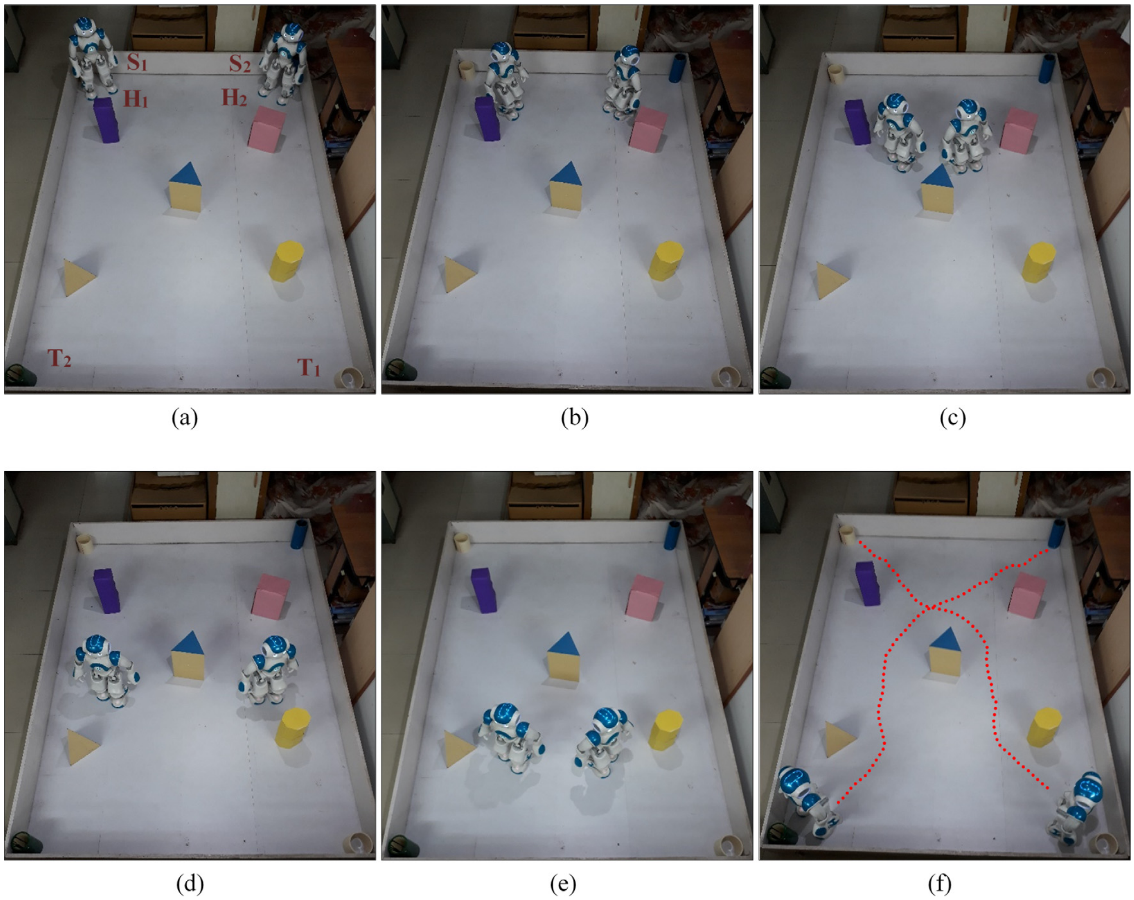


Fig. 18. Real-time results for navigation of multiple humanoids in scene 2.

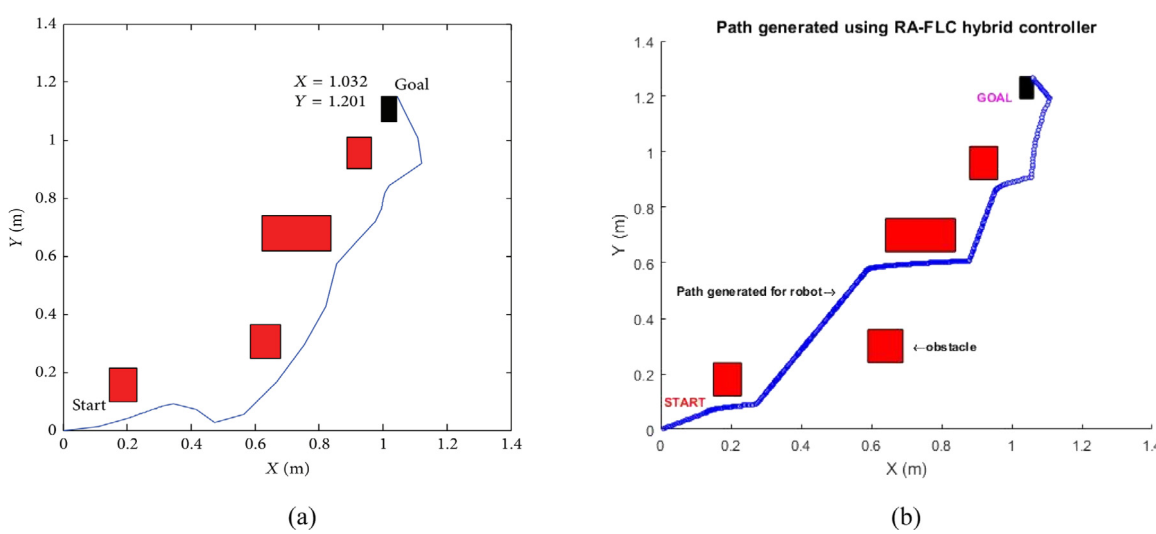


Fig. 19. (a) Path generated in fuzzy based approach [11] (b) Path generated in RA-FLC hybrid approach.

References

[1] J. Armstrong, Illusions in regression analysis, 2011.

[2] L. Benamati, C. Cosma, P. Fiorini, Path planning using flat potential field approach, in: Advanced Robotics, 2005. ICAR'05. Proceedings. 12th International Conference on, IEEE, 2005, pp. 103–108.

[3] Z. Hong, Y. Liu, G. Zhongguo, C. Yi, The dynamic path planning research for mobile robot based on artificial potential field, in: Consumer Electronics, Communications and Networks (CECNet), 2011 International Conference on, IEEE, 2011, pp. 2736–2739.

[4] G. Li, A. Yamashita, H. Asama, Y. Tamura, An efficient improved artificial potential field based regression search method for robot path planning, in: Mechatronics and Automation (ICMA), 2012 International Conference, IEEE, 2012, pp. 1227–1232.

[5] G. Li, Y. Tamura, A. Yamashita, H. Asama, Effective improved artificial potential field-based regression search method for autonomous mobile robot path planning, Int. J. Mech. Autom. 3 (3) (2013) 141–170.

[6] J.K. Ong, K. Bouazza-Marouf, D. Kerr, Fuzzy logic control for use in in-pipe mobile robotic system navigation, Proc. Inst. Mech. Eng. I 217 (5) (2003) 401–419.

[7] A. Meléndez, O. Castillo, F. Valdez, J. Soria, M. Garcia, Optimal design of the fuzzy navigation system for a mobile robot using evolutionary algorithms, Int. J. Adv. Robot. Syst. 10 (2) (2013) 139.
[8] M. Faisal, R. Hedjar, M. Al Sulaiman, K. Al-Mutib, Fuzzy logic navigation and obstacle avoidance by a mobile robot in an unknown dynamic environment, Int. J. Adv. Robot. Syst. 10 (1) (2013) 37.
[9] A. Al-Jumaily, C. Leung, Wavefront propagation and fuzzy based autonomous navigation, Int. J. Adv. Robot. Syst. 2 (2) (2005) 10.
[10] K. Al-Mutib, F. Abdessemed, Indoor mobile robot navigation in unknown environment using fuzzy logic based behaviors, Adv. Sci. Technol. Eng. Syst. J. 2 (3) 327-337.
[11] H. Omrane, M.S. Masmoudi, M. Masmoudi, Fuzzy logic based control for autonomous mobile robot navigation, Comput. Intell. Neurosci. (2016) http://dx.doi.org/10.1155/2016/9548482.
[12] N.H. Singh, K. Thongam, Mobile robot navigation using fuzzy logic in static environments, Procedia Comput. Sci. 125 (2018) 11–17.
[13] T. Fernando, H. Gammulle, C. Walgampaya, Fuzzy logic based framework for mobile robot navigation with target tracking, Int. J. Comput. Sci. Netw. 4 (5) 761-770.
[14] M. Amiri, Z. Abbasi, F.S. Tafreshi, Using fuzzy logic in robot navigation to find animals, Int. J. Comput. Technol. 12 (4) (2014) 3382–3392.
[15] T.T. Van Nguyen, M.D. Phung, Q.V. Tran, Behavior-based navigation of mobile robot in unknown environments using fuzzy logic and multi-objective optimization, 2017, arXiv preprint arXiv:1703.03161.
[16] H. Qin, X. Sun, L. Cong, Using fuzzy logic control for the robust carrier tracking loop in a global positioning system/inertial navigation system tightly integrated system, Trans. Inst. Meas. Control 36 (3) (2014) 354–366.
[17] S.M. Raguraman, D. Tamilselvi, N. Shivakumar, Mobile robot navigation using fuzzy logic controller, in: Control, Automation, Communication and Energy Conservation, 2009. INCACEC 2009. 2009 International Conference on, IEEE, 2009, pp. 1–5.
[18] D.T. Pham, M.H. Awadalla, Fuzzy-logic-based behaviour coordination in a multi-robot system, Proc. Inst. Mech. Eng. B 218 (6) (2004) 583–598.
[19] F. Rovira-Más, Q. Zhang, Fuzzy logic control of an electrohydraulic valve for auto-steering off-road vehicles, Proc. Inst. Mech. Eng. D 222 (6) (2008) 917–934.
[20] M.T. Ibrahim, D. Hanafi, R. Ghoni, Autonomous navigation for a dynamical hexapod robot using fuzzy logic controller, Procedia Eng. 38 (2012) 330–341.
[21] H.R. Beom, H.S. Cho, A sensor-based navigation for a mobile robot using fuzzy logic and reinforcement learning, IEEE Trans. Syst. Man Cybern. 25 (3) (1995) 464–477.
[22] A.S. Al Yahmedi, M.A. Fatmi, Fuzzy logic based navigation of mobile robots, in: Recent Advances in Mobile Robotics, 2011, InTech.
[23] H. Shi, X. Li, W. Pan, K.S. Hwang, Z. Li, A novel fuzzy three-dimensional grid navigation method for mobile robots, Int. J. Adv. Robot. Syst. 14 (3) (2017) 1729881417710444.
[24] J. Jaafar, E. McKenzie, Decision making method using fuzzy logic for autonomous agent navigation, Electron. J. Comput. Sci. Inf. Technol. 3 (1) (2011) 8–18.
[25] P. Nattharith, M.S. Güzel, Machine vision and fuzzy logic-based navigation control of a goal-oriented mobile robot, Adapt. Behav. 24 (3) (2016) 168–180.
[26] T. Wang, H. Zhang, G. Tang, Predictor–corrector guidance for entry vehicle based on fuzzy logic, Proc. Inst. Mech. Eng. G (2017) 0954410017737574.
[27] M. Mendon, I.R. Chrun, L.V.R. de Arruda, E.I. Papageorgiou, Autonomous navigation applying dynamic-fuzzy cognitive maps and fuzzy logic, in: IFIP International Conference on Artificial Intelligence Applications and Innovations, Springer, Berlin, Heidelberg., 2013, pp. 215–224.
[28] Dirik, M, Collision-free mobile robot navigation using fuzzy logic approach, Int. J. Comput. Appl. 179 (9) (2018) 33–39.
[29] K. Sun, S. Mou, J. Qiu, T. Wang, H. Gao, Adaptive fuzzy control for non-triangular structural stochastic switched nonlinear systems with full state constraints, IEEE Trans. Fuzzy Syst. (2018) http://dx.doi.org/10.1109/TFUZZ.2018.2883374.
[30] J. Qiu, K. Sun, T. Wang, H. Gao, Observer-based fuzzy adaptive event-triggered control for pure-feedback nonlinear systems with prescribed performance, IEEE Trans. Fuzzy Syst. (2019) http://dx.doi.org/10.1109/TFUZZ.2019.2895560.
[31] S. Keshmiri, S. Payandeh, Regression analysis of multi-rendezvous recharging route in multi-robot environment, Int. J. Soc. Robot. 4 (1) (2012) 15–27.
[32] S. Keshmiri, S. Payandeh, Multi-robots, multi-locations recharging paradigm: A regression route technique, in: Proceedings of the 14th IASTED International Conference, Robotics and Applications, Cambridge, MA, USA, pp. 160–165.
[33] S. Keshmiri, S. Payandeh, Robot navigation controller: A non-parametric regression approach, IFAC Proc. Vol. 43 (22) (2010) 22–27.
[34] W. Takano, Y. Nakamura, Real-time unsupervised segmentation of human whole-body motion and its application to humanoid robot acquisition of motion symbols, Robot. Auton. Syst. 75 (2016) 260–272.
[35] S. Oßwald, A. Görög, A. Hornung, M. Bennewitz, Autonomous climbing of spiral staircases with humanoids, in: Intelligent Robots and Systems (IROS), 2011 IEEE/RSJ International Conference on, IEEE, 2011, pp. 4844–4849.
[36] D. Maier, C. Lutz, M. Bennewitz, Integrated perception, mapping, and footstep planning for humanoid navigation among 3d obstacles, in: Intelligent Robots and Systems (IROS), 2013 IEEE/RSJ International Conference on, IEEE, 2013, pp. 2658–2664.
[37] D. Clever, M. Harant, H. Koch, K. Mombaur, D. Endres, A novel approach for the generation of complex humanoid walking sequences based on a combination of optimal control and learning of movement primitives, Robot. Auton. Syst. 83 (2016) 287–298.
[38] D. Clever, K.D. Mombaur, An inverse optimal control approach for the transfer of human walking motions in constrained environment to humanoid robots, Robot.: Sci. Syst. (2016).
[39] O. Castillo, H. Neyoy, J. Soria, M. García, F. Valdez, Dynamic fuzzy logic parameter tuning for ACO and its application in the fuzzy logic control of an autonomous mobile robot, Int. J. Adv. Robot. Syst. 10 (1) (2013) 51.
[40] P.B. Kumar, C. Sahu, D.R. Parhi, K.K. Pandey, A. Chhotray, Static and dynamic path planning of humanoids using an advanced regression controller, Sci. Iran. 26 (1) (2019) 375–393.
[41] P.B. Kumar, S. Mohapatra, D.R. Parhi, An intelligent navigation of humanoid NAO in the light of classical approach and computational intelligence, Comput. Animat. Virtual Worlds 30 (2) (2019) e1858.
[42] R. Choomuang, N. Afzulpurkar, Hybrid kalman filter/fuzzy logic based position control of autonomous mobile robot, Int. J. Adv. Robot. Syst. 2 (3) (2005) 20.
[43] A. Melingui, R. Merzouki, J.B. Mbede, T. Chettibi, A novel approach to integrate artificial potential field and fuzzy logic into a common framework for robots autonomous navigation, Proc. Inst. Mech. Eng. I 228 (10) (2014) 787–801.
[44] R. Zhao, D.H. Lee, H.K. Lee, Mobile robot navigation using optimized fuzzy controller by genetic algorithm, Int. J. Fuzzy Logic Intell. Syst. 15 (1) (2015) 12–19.
[45] F. Boufera, F. Debbat, L. Adouane, M.F. Khelfi, Mobile robot navigation using fuzzy limit-cycles in cluttered environment, Int. J. Intell. Syst. Appl. 6 (7) (2014) 12–21.
[46] O. Azouaoui, N. Ouadah, I. Mansour, A. Semani, Neural networks and fuzzy logic navigation approach for a bi-steerable mobile robot, in: Ubiquitous Robots and Ambient Intelligence (URAI), 2011 8th International Conference on, IEEE, 2011, pp. 44–49.
[47] M.R. Panda, S. Dutta, S. Pradhan, Hybridizing invasive weed optimization with firefly algorithm for multi-robot motion planning, Arab. J. Sci. Eng. (2017) 1–11.
[48] N. Kofinas, E. Orfanoudakis, M.G. Lagoudakis, Complete analytical forward and inverse kinematics for the NAO humanoid robot, J. Intell. Robot. Syst. 77 (2) (2015) 251–264.
[49] L.A. Zadeh, Information and control, Fuzzy sets 8 (3) (1965) 338–353.
[50] D.R. Parhi, Navigation of mobile robots using a fuzzy logic controller, J. Intell. Robot. Syst. 42 (3) (2005) 253–273.
[51] J.L. Peterson, Petri net theory and the modeling of systems, 1981.
[52] D.T. Pham, D.R. Parhi, Navigation of multiple mobile robots using a neural network and a Petri Net model, Robotica 21 (1) (2003) 79–93.