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RESEARCH ARTICLE

Tailoring the motion planning of humanoids in complex arena: a regression-firefly-based approach

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Abstract
In the current investigation, a two-stage hybridization model has been used for the motion planning of humanoids in complex environmental conditions using regression analysis and the firefly algorithm. In the first step, sensory outputs are fed to the regression model, and an initial turning angle (ITA) is obtained. In the second step, the ITA is again fed as input to the firefly model along with other required inputs, and the final turning angle (FTA) is obtained. The FTA serves as the guiding parameter for the humanoids to reach their desired destinations. The developed motion planning scheme has been implemented on NAO humanoid robots in simulation and experimental platforms. A Petri-Net control strategy has been integrated along with the hybrid scheme while negotiating multiple humanoids in a common platform. The results obtained from the motion planning analysis in simulation and experimental arenas are compared against each other in terms of selected navigational parameters and observed satisfactory agreements. Finally, the proposed hybrid controller is also tested against another standard navigational model and substantial enhancement in the performance has been noticed.

1. Introduction
Industrial automation and the use of robotic agents in manufacturing have been the talk of the town since the last decade owing to the growing need of producing substantially within the stipulated time. Therefore, there has been tremendous use of different forms of robots in medical assistance, entertainment, manufacturing, and automation. However, humanoid robots have gained popularity due to their ability to imitate human behavior in cluttered environments without much need to alter the platform conditions. The human effort should ideally be replaced by robot-looking humans. Therefore, the humanoid robot NAO V4 H 25 is considered for the motion planning technique in this study. A humanoid robot resembles a human in most ways, including how it moves, walks, and goes from point A to point B.

To deal with all the work, a humanoid may competently perform, motion planning has been the most discussed and challenging analysis that requires intelligence to tackle unforeseen environmental conditions. A humanoid integrated with artificial intelligence (AI) can be able to handle obstacles that may be encounter while attempting a planned or unplanned journey. Based on the type of planned or unplanned motion synthesis, navigational approaches are classified as global and local path planning. Global path planning can be considered as a planned journey as the arena conditions are priory known to the robot. However, local path planning can be considered as an unplanned journey as the robot is only aware of the source and target locations. In the last few decades, there have been enormous discussions on the motion planning and navigational analysis of different forms of robots using both classical and AI techniques. Generally, classical approaches are popular for their quick convergence and AI techniques are popular for their accuracy.

Frank et al. [1] designed a Gaussian process regression-based control architecture for the navigational analysis of a mobile manipulator. They have considered deformable objects in their analysis along with discussions on deformation cost. Kim et al. [2] have proposed a kernel subspace learning approach toward autonomous robot navigation in a dynamic environment using Gaussian regression. Keshmiri and Payandeh [3] have attempted to solve a multi-robot recharging problem by utilizing the nearest recharging station for respective robots. Rouxel et al. [4] have designed a weighted projection regression-based model for visualizing the odometry of a small-scale humanoid robot without utilizing any vision assistance tool. Plagemann et al. [5] have proposed a learning probabilistic model of terrain surfaces using Bayesian regression to navigate a legged robot over a rough terrain. To design navigational models for mobile sensor networks, Xu et al. [6] have used a Gaussian process regression-based approach with truncated observations. Fentanes et al. [7] have used a testing framework in a large-scale robotics project in order to test the approach in simulation as well as experimental platforms. Belter et al. [8] have designed a navigational controller that uses the on-board sensors for perceiving the environmental map first and then use a predictive model to navigate a legged robot smoothly within the arena. Kumar et al. [9, 10] designed regression analysis (RA)-based humanoid navigational schemes for smooth and collision-free navigation within complex arena conditions.

To detect multiple sources in a mobile robotic platform, Krishnanand et al. [11] designed a navigational controller using firefly algorithm and tested the performance against other nature inspired algorithms. Patle et al. [12] have proposed a navigational model for smooth motion planning through obstacles based on firefly algorithm (FA). Their developed controller was tested on mobile robots in simulation as well as experimental arena and obtained satisfactory results. Wang et al. [13] experimented with combat air vehicles by using a firefly-based navigation approach and obtained enhanced results by modification of the standardized parameters of the algorithm. Hidalgo-Paniagua et al. [14] have considered safety, smoothness, and minimal path length for a navigational path while designing a controller for a mobile robot using a firefly-based approach. Fister et al. [15] have comprehensively reviewed firefly-based approaches in several engineering optimization problems and discussed the importance of tuning to standard parameters of the algorithm. Ali et al. [16] have discussed a critical review regarding the use of the firefly algorithm in navigational and other similar problems. They have also discussed the potential of the firefly algorithm in solving multidimensional problems. Liu et al. [17] have introduced new operators to the standard firefly algorithm while designing a navigational controller for the motion planning of an autonomous underwater vehicle. To reduce redundancies available in the environment, Christensen et al. [18] have used a firefly-based approach to navigate a swarm of robots with collision avoidance and smooth navigation. A demonstration of mobile robot navigation in a simulation environment was shown by Brand and Yu [19]. They proposed a firefly-based navigational scheme and attempted the navigational model in dynamic environments. Farahani et al. [20] have used a Gaussian distribution model to modify standard firefly operators and obtained enhanced results. A 3-D locomotion model for navigational control of a humanoid biped has been proposed by Saputra et al. [21]. They have used a biologically inspired recurrent neural network method to design the proposed motion planning model and verified it in a simulation platform considering a 12-DOF robot. He et al. [22] have developed an approach to design and analyze the Denavit–Hartenberg (DH) model of a humanoid robot's upper limb. To model all the motions of the limb, a recursive Newton–Euler formulation has been used, and the trajectory of each point has been obtained by use of a Particle Swarm Optimization approach. An inverse optimal control scheme to efficiently transfer motion control parameters from humans to humanoids has been proposed by Clever and Mombaur [23]. They have considered parameters like phase duration, mass trajectory, and orientation of the upper body and foot trajectories for designing the above control scheme. To enhance the performance of human–robot correlation, Ryu et al. [24] have proposed a navigational scheme using a time index and waypoints. A time index has been used to obtain a path in relation to human's way of selecting the most natural path, and a waypoint-based approach has been used to accurately track a robot's motion even in complex dynamic arenas. Kumar et al. [25] perform navigational analysis using their developed intelligent motion planner on a humanoid robot. Muni et al. [26–31] introduced and successfully implemented various artificial intelligence algorithms toward motion planning analysis of legged robots in obstacle-prone environments.

The extensive study of literature can be used to infer that RA and firefly algorithm as navigational controllers primarily find application in the field motion planning of mobile robots. However, finding them applied in the field of humanoid navigation is quite rare. Along with that, works on analyzing the navigation behavior of humanoids in a common environment are rare as well. The use of hybrid controllers in humanoid navigation is also rare to find. Therefore, the objective of this paper is geared toward the complete development of a hybrid regression-firefly-based motion planner for single to multiple humanoid navigations and its implementation in an environment with randomly placed obstacles.

Here, the research aims to design and develop a hybrid regression-firefly-based motion planner for motion planning of single and multiple humanoids for static and dynamic environments cluttered with complex obstacles.

The authors of the paper believed that the controller, designed and developed by implementing the two techniques (regression and firefly technique) provides an optimized path for the global path planning of humanoid robots in a cluttered environment with dynamic obstacles.

The outline of the research work is as follows:

- In Section 1, the introduction to the research is explained.
- Section 2 is focused on the regression model.
- Section 3 is focused on the firefly model.
- Section 4 describes the hybridization of the regression model with the firefly model.
- The Petri-Net Control Strategy has been described in Section 5 for the multiple humanoid robots.
- The simulation and experimental analysis have been depicted in Section 6.
- In Section 7, an evaluation of the proposed regression-firefly model against another navigational model has been described.
- The research work has been concluded in Section 8.

2. Regression model

Regression is a classic data forecasting tool that considers previous data trends to prepare an approximation for the future.

2.1. Technical basics

Regression relates dependent parameters with independent ones using standard functions. A primary regression-based mathematical equation can be expressed as follows:

$$u_p = \hat{u}_p + x_p \tag{1}$$

where

$u_p = \eta_1 y_{p,1} + \eta_2 y_{p,2} + \cdots + \eta_p y_{p,n}, \eta = (\eta_1, \eta_2, \ldots, \eta_p)$ are taken as the standard functions used in regression and x_p represents the error term.

A humanoid navigational model can also be formulated using the basic principles of regression which have been discussed in the following section.

2.2. Regression-based humanoid navigational model

Here, the major objective of the regression-based humanoid navigational model has been set as the generation of a collision-free trajectory toward the preset target with optimization of both path length and

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Table I. *Sample data trend used for regression-based humanoid navigational model.*

Sl. no.	FSY	LSY	RSY	ITA	Sl. no.	FSY	LSY	RSY	ITA
1	59	33	46	7	11	51	63	33	−15
2	41	44	61	11	12	62	30	44	4
3	36	71	41	−11	13	51	42	73	13
4	31	52	37	−16	14	34	34	58	15
5	73	32	44	0	15	40	72	32	−17
6	31	42	43	−27	16	44	38	51	19
7	56	41	32	−26	17	53	51	42	−15
8	40	62	45	−17	18	40	34	62	18
9	85	48	59	0	19	55	84	44	−25
10	40	56	44	−12	20	45	37	62	16

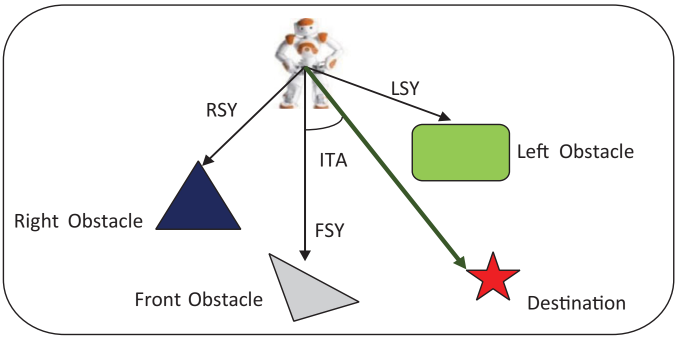

Figure 1. *Representation of input and output parameters for the regression-based humanoid navigational model.*

navigational time. The regression model takes three input parameters, namely front sensor yield (FSY), left sensor yield (LSY), and right sensor yield (RSY) and outputs the initial turning angle (ITA). Figure 1 represents the scheme in which the input and output parameters are presented for a regression-based navigational model [32].

As already stated, regression considers previous data trends to generate a futuristic prediction model. Table I represents a sample data trend used for the regression navigational model. The negative signs in Table I enforce the convention that a left turn by the humanoid is taken as negative while a right turn is taken as positive. Zero value in ITA represents no turn which means the humanoid proceeds in the previous angle of turn as it was moving. Around 750 training pattern data have been fed to a Minitab regression toolbox and an equation used for navigation has been obtained as follows:

$$E_4 = 0.005859E_1 - 0.2668E_2 + 0.764872E_3 - 23.9458 \quad (2)$$

where $E_1 = \mathrm{FSY}$, $E_2 = \mathrm{LSY}$, $E_3 = \mathrm{RSY}$, and $E_4 = \mathrm{ITA}$

With a preset start and goal location, the humanoid advances toward the goal with the help of a regression-based navigational model. The regression-based scheme comes into effect upon encountering a potential obstacle within the inception range of the humanoid. Here, the inception range has been considered as 25 cm from the robot's location. Various responsive behaviors such as hurdle avoidance, destination trailing, and wall guiding have been added to the navigation model to obtain an optimal toward the goal location. Hurdle avoidance behavior keeps a safe distance from the obstacles, destination trailing behavior maintains a straight path toward the destination when obstacles are absent, and wall guiding behavior follows a long obstacle to avoid excess consumption of energy when a long-sized obstacle is encountered by the robot [33].

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3. Firefly model

The Firefly algorithm is a nature-inspired intelligent approach derived from the flashing behavior of fireflies. It is based on the special manner in which fireflies move in their colony.

3.1. Firefly-based humanoid navigational model

Some assumptions mentioned below are considered as prerequisites for designing a humanoid navigational model:

i. Being considered to be unisexual in nature, all fireflies are attracted toward each other.
ii. The amount of attractiveness a firefly exhibits is considered directly proportional to its brightness. Hence, a firefly is attracted toward all the fireflies having more brightness. With an increase in the distance, the brightness diminishes. The brightest firefly in the entire colony does not have any other to be attracted, so it has the freedom of random movement.
iii. The brightness of a firefly is largely dependent on the fitness function considered for optimization.

In every iteration of the algorithm, the firefly is always attracted to a surrounding firefly that is brighter than itself. This probabilistic movement is represented in mathematical form as follows.

Let the probability of attraction of the pth firefly toward qth firefly be represented by λ_{pq} and given by:

$$\lambda_{p,q} = \frac{\mu_q}{\sum_{r \in S_p} \mu_r} \tag{3}$$

where $\mu_p < \mu_q$; μ_p, μ_q, and μ_r represent the light intensities of pth, qth, and rth fireflies, respectively.

Let all fireflies in the inception range having more brightness than the pth firefly be denoted by a set S_p and given as:

$$S_p = \left\{d\,(p, r) < I_{th}, \mu_p < \mu_r\right\} \tag{4}$$

The Euclidean distance between pth and rth firefly is denoted by $d(p, r)$. The equation is valid only when this distance is lesser than the inception range (25 cm for the current investigation).

As already stated, brightness follows a decreasing trend with distance, so it can be given as:

$$\mu\,(d) = \mu_0 e^{-\vartheta d} \tag{5}$$

where μ_0, ϑ, and d represent the initial brightness, the light absorption coefficient, and the distance, respectively.

Equation (5) can be simplified in terms of inverse proportionality as:

$$\mu\,(d) = \frac{\mu_0}{1 + \vartheta d} \tag{6}$$

As per the basic principle of the firefly algorithm, in each iteration, pth firefly approaches qth firefly as per the probabilistic equation and the new position of the firefly can be represented as follows:

$$x_p\,(n+1) = x_p\,(n) + \sigma \frac{x_q\,(n) - x_p\,(n)}{\left\| x_q\,(n) - x_p \right\|}$$

$$y_p\,(n+1) = y_p\,(n) + \sigma \frac{y_q\,(n) - y_p\,(n)}{\left\| y_q\,(n) - y_p \right\|} \tag{7}$$

where n denotes the iteration count, σ denotes the step size in each movement, and ||.|| denotes the distance vector.

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In each iteration, there is a possibility of a gradual decrease in the brightness of the fireflies. So, the brightness is updated in each iteration to enhance the possibility of the fireflies reaching the goal. This is given by the equation:

$$\mu_p (n + 1) = (1 - \theta_1)\, \mu_p (n) + \theta_2 f \left(x_p (n)\right) \tag{8}$$

where θ_1 and θ_2 are the balancing coefficients and $f(x_p)$ is the objective function of the pth firefly.

In the current investigation, NAO robots have been used as humanoid platforms. NAO [34] is a medium-sized intelligent humanoid capable of performing several handy operations with the help of its vast sensory network consisting of SONARs, Infrareds, tactile, and force resistors.

Here, SONARs are used for obstacle detection purpose.

3.2. Fitness function for humanoid navigational model (DD)

Fitness function plays a crucial role while designing humanoid motion planning as it reflects the effect of several navigational parameters. Here, three parameters, namely hurdle avoidance, destination trailing and drift minimization, are selected as the parts for formulating the overall fitness function [35].

3.2.1 Hurdle avoidance

In the firefly algorithm, the destination is considered to be the brightest firefly; as a result, all the surrounding fireflies are attracted toward it. The fireflies form a colony around the obstacle when one is detected within the range of inception. The Nearest Sensor Yield (NSY) is considered as one of the inputs to the firefly-based model. The destination being the brightest firefly attracts all other fireflies toward it. A maximum distance from the surrounding static obstacles should be maintained by the brightest firefly. This accounts for a specific set of movements to prevent a collision. The objective function has been considered as a minimization problem here. Hence, hurdle avoidance pattern can be considered as an inverse proportionality for the fitness function as:

$$\mathrm{FF_{HA}} \propto \frac{1}{\min\left(\mathrm{HA}_d\right)} \tag{9}$$

where $\mathrm{HA}_d = \sqrt{(\mathrm{UP}_x - \mathrm{NSY}_x)^2 + (\mathrm{UP}_y - \mathrm{NSY}_y)^2}$

$(\mathrm{UP}_x, \mathrm{UP}_y)$ denote the coordinates for the upcoming position of the firefly and $(\mathrm{NSY}_x, \mathrm{NSY}_y)$ denote the nearest sensor yield.

3.2.2 Destination trailing

In the absence of any obstacle in the path, the brightest firefly in the colony should always head toward the destination. Hence, the upcoming position of the firefly should always maintain a minimum distance from the destination. Here, the destination trailing pattern is a direct relationship:

$$\mathrm{FF_{DT}} \propto \min\left(\mathrm{DT}_d\right) \tag{10}$$

where $\mathrm{DT}_d = \sqrt{(\mathrm{DT}_x - \mathrm{UP}_x)^2 + (\mathrm{DT}_y - \mathrm{UP}_y)^2}$

And $(\mathrm{DT}_x, \mathrm{DT}_y)$ denote the coordinates for the robot's destination position.

3.2.3 Drift minimization

While selecting the upcoming position to move, a firefly must follow an optimal fashion which is mathematically given as follows:

$$\mathrm{FF_{DM}} \propto \min\left(\mathrm{DM}_d\right) \tag{11}$$

where $\mathrm{DM}_d = \sqrt{(\mathrm{UP}_x - \mathrm{CP}_x)^2 + (\mathrm{UP}_y - \mathrm{CP}_y)^2}$

$(\mathrm{CP}_x, \mathrm{CP}_y)$ denotes the current position of the robot.

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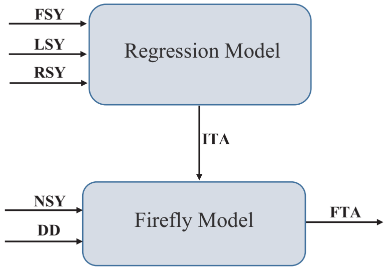

Figure 2. *Scheme of hybridization adopted in the current investigation.*

A linear combination of the individual parts with the help of suitable weightages is used to generate the final fitness function:

$$FF_f = \gamma_1 \times FF_{HA} + \gamma_2 \times FF_{DT} + \gamma_3 \times FF_{DM} \tag{12}$$

The individual parts of the final fitness function have weightages associated with them and denoted by γ.

Due to this being a minimization problem, the optimal solution is the one with the minimal value of the fitness function. Here, a hit and trail approach has been adopted to decide the values of the weightages assigned to the individual parts of the final fitness function. After finding out the best position to move, the required ITA can be calculated by simple geometrical considerations.

4. Hybridization of regression model with firefly model

As already discussed, regression model is a classical method of analysis and firefly is an artificial intelligent approach. While classical methods are combined with AI methods, both accurate and converged solutions can be generated. In the first step of hybridization, sensory data such as FSY, LSY, and RSY are fed as inputs to the regression model and ITA is generated as the initial output. In the second step of hybridization, NSY and Fitness Function for Humanoid Navigational Model (DD) along with ITA are fed as inputs to the firefly model, and final turning angle (FTA) is generated as the final output. Figure 2 represents the scheme of hybridization adopted in the current investigation [36, 37].

Figure 3 represents the pseudocode for the regression-firefly hybrid model, and Fig. 4 represent the flowchart for the same.

5. Petri-Net control strategy

As already discussed, in the current investigation, along with navigation of a single humanoid in a complex arena, navigation of multiple humanoids is also attempted. While multiple humanoids navigate in a common platform, there is a possibility of potential conflict in the path upon the encounter of a common obstacle. Hence, along with the proposed regression-firefly-based model, the integration of a Petri-Net control strategy [38, 39] is done for smooth and hassle-free navigation. Figure 5 demonstrates a standard Petri-Net control strategy.

In Fig. 5, the black circle represents current position and the bar symbol represents a stage transition. Here, six stages of the control strategy are operated as follows.

Stage 1: This is the initial stage where the robot has information about the source and destination locations only and is unaware of the position of fellow robots.

Stage 2: In this stage, the robots mark their journey toward their respective destinations while avoiding any static obstacles that are detected around them.

```
The robot starts heading towards the destination with destination trailing pattern
If (Destination is reached)
        Stop navigation
Else if a potential obstacle is detected within the set inception range
        Regression model is activated
        Sensor outputs FSY, LSY and RSY are fed as inputs to the regression model
        ITA is generated as the first output
        Firefly model is activated
        ITA is fed to the firefly model along with other inputs (NSY, DD)
        Colony of fireflies is generated
        Fireflies are arranged by the value of their brightness
        Formulation of the fitness function
        Upcoming optimal position of movement is generated
        FTA is calculated
        The generated FTA guides the robot to the upcoming position
        If (Destination is reached)
                Stop navigation
        Else if (Obstacle is detected)
                Repeat the regression-firefly model to find the upcoming position
        Else
                Keep navigating till an obstacle detection or reaching the goal
```

Figure 3. *Pseudocode for regression-firefly model.*

Stage 3: Stage 3 denotes the detection of a dynamic obstacle. This arises when multiple humanoids encounter a common obstacle.

Stage 4: Stage 4 is the negotiation stage where the robot closest to the destination is given preference to move first while the other robot waits as a static obstacle.

Stage 5: After the prioritized robot of stage 4 leaves the conflict, the other one checks for any further conflicts and marks its journey again.

Stage 6: Stage 6 is a special waiting state. If a robot encounters another set of robots already in stage 3, it waits as a static obstacle and after the resolution of conflict among the first set of robots, it again marks its journey starting from stage 2.

By integration of the above-discussed Petri-Net control strategy, the navigation of multiple humanoids in a common platform can be achieved.

6. Execution of proposed regression-firefly hybrid model

The proposed regression-firefly hybrid model has been executed for the navigation of both single and multiple humanoid robots. NAO has been taken as the humanoid platform for the stated purpose in this research.

6.1. Motion planning of a single NAO

Here, motion planning in both simulation and experimental platforms has been attempted using the proposed hybrid model. In order to represent the humanoid as a whole-body model, the selection of V-REP as an appropriate simulation platform is done. In the simulation platform, an area of size

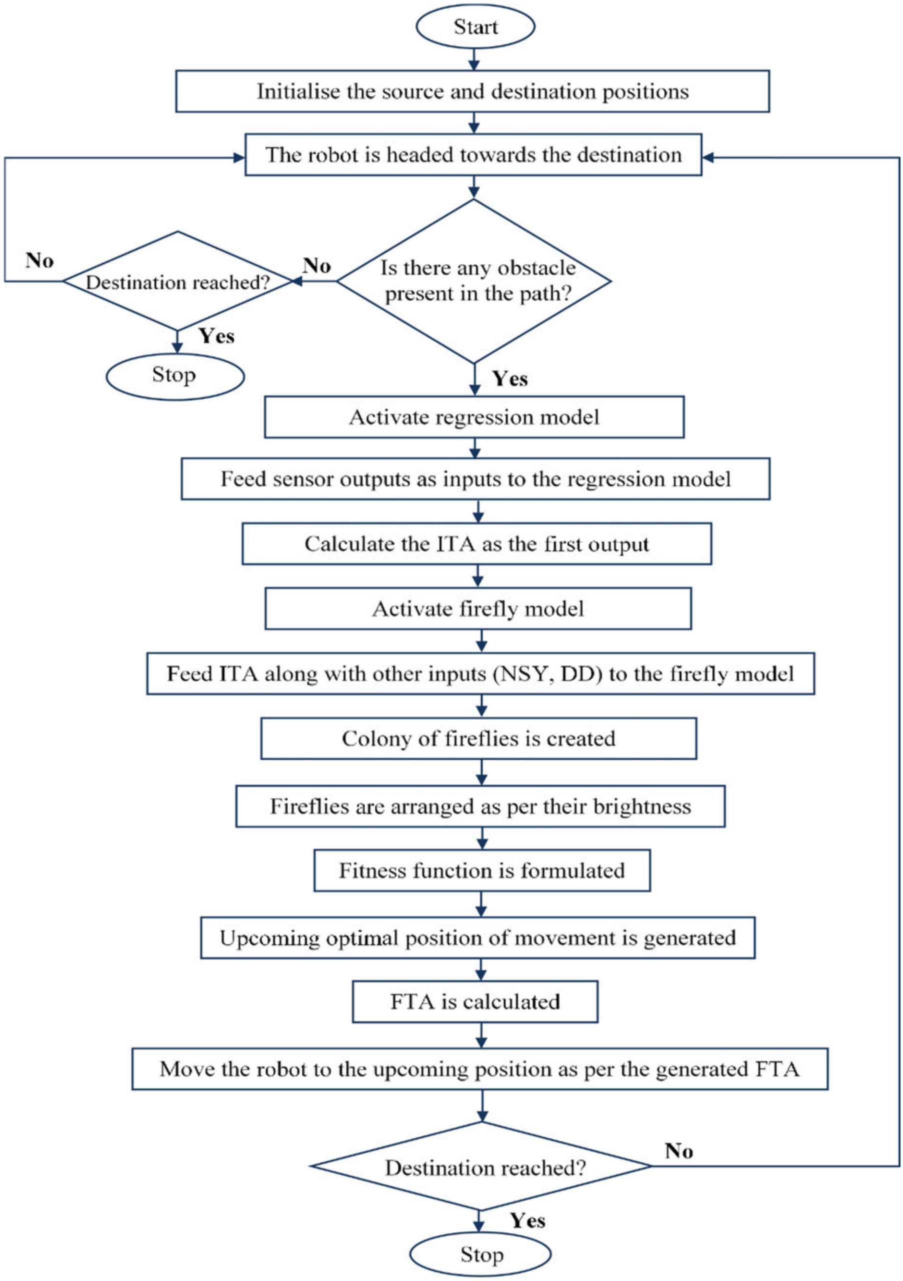

Figure 4. *Flowchart for regression-firefly model.*

240 × 160 units has been designated as the working size, and definite source and destination regions are defined. Seven hurdles of arbitrary shapes and sizes are spawned randomly in the arena. The humanoid communicates with the hybrid model through an LUA script to receive commands. Figure 6 represents the simulation arena results obtained in the current study. It can be observed that the humanoid has successfully reached the destination without colliding against any of the obstacles present in the arena.

To evaluate the results obtained from the simulation arena, an experimental platform having the same working size has been prepared under laboratory testing conditions. To keep coherence with the simulation platform, the position of source and destination, size, shape, and position of obstacles have been

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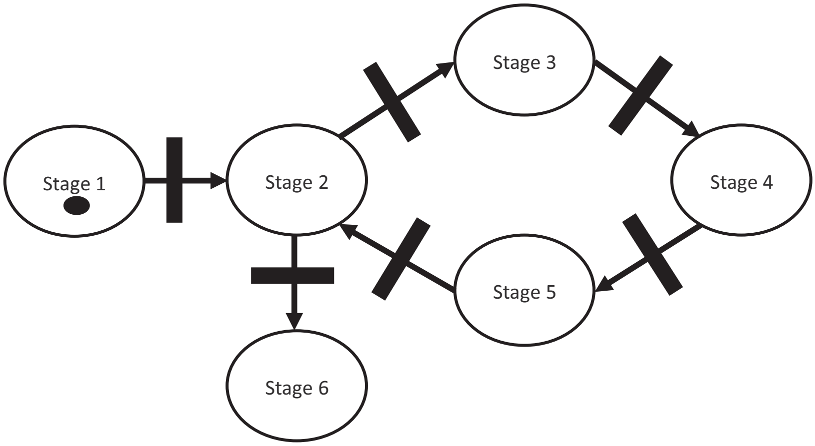

Figure 5. *Petri-Net control strategy.*

kept exactly alike. The connection to the humanoid is established through Wi-Fi and a Python script containing the hybrid model communicates with this humanoid. Figure 7 represents the experimental results obtained in the current study.

As seen from Figs. 6 and 7, the humanoid has followed an optimal trajectory while reaching the destination from the source location.

The Petri-Net control strategy, as explained above, can be found in Fig. 8(d) and (e), and Fig. 9(d) and (e), where N_2 acts as a static obstacle to N_1 and N_1 moves forward toward the target as it is very nearer to the goal location.

To have concrete evidence against the effectiveness of the proposed hybrid model, navigational parameters such as route length and time interval from source to destination are selected for comparison purposes. The values of these parameters can be directly obtained in simulation. In the case of real-world setup, their value is recorded by conducting measurements using a measuring tape and stopwatch. Tables II and III represent the comparison of the selected navigational parameters between the simulation and experimental results.

It can be observed from Tables II and III that the simulation and experimental results are well in agreement with each other with minimal error limits. Here, the experimental results always show higher values compared to the simulation counterparts. The reason for the same can be justified by the presence of external factors like the slippage effect, data transmission loss, and frictional losses in the experimental platform which are ideal for the simulation arena.

6.2. Motion planning of multiple NAOs

While navigating multiple humanoids in a common platform, the Petri-Net control strategy is integrated with the proposed hybrid model. Here, the arena size has been kept the same as used for the navigation of a single NAO. Five obstacles of random shape and size are placed at arbitrary locations in the arena, and two NAOs fed with the logic of the proposed hybrid model along with the Petri-Net control strategy are used for the navigation purpose. Figure 8 represents the simulation results.

The simulation results obtained from the motion planning of multiple NAOs are also verified in the experimental platform. Figure 9 represents the experimental results.

Tables IV and V demonstrate the comparison of simulation and experimental results in terms of route length and time interval, respectively.

It has been observed that the proposed regression-firefly hybrid model has worked efficiently for the navigation of both single and multiple humanoid robots.

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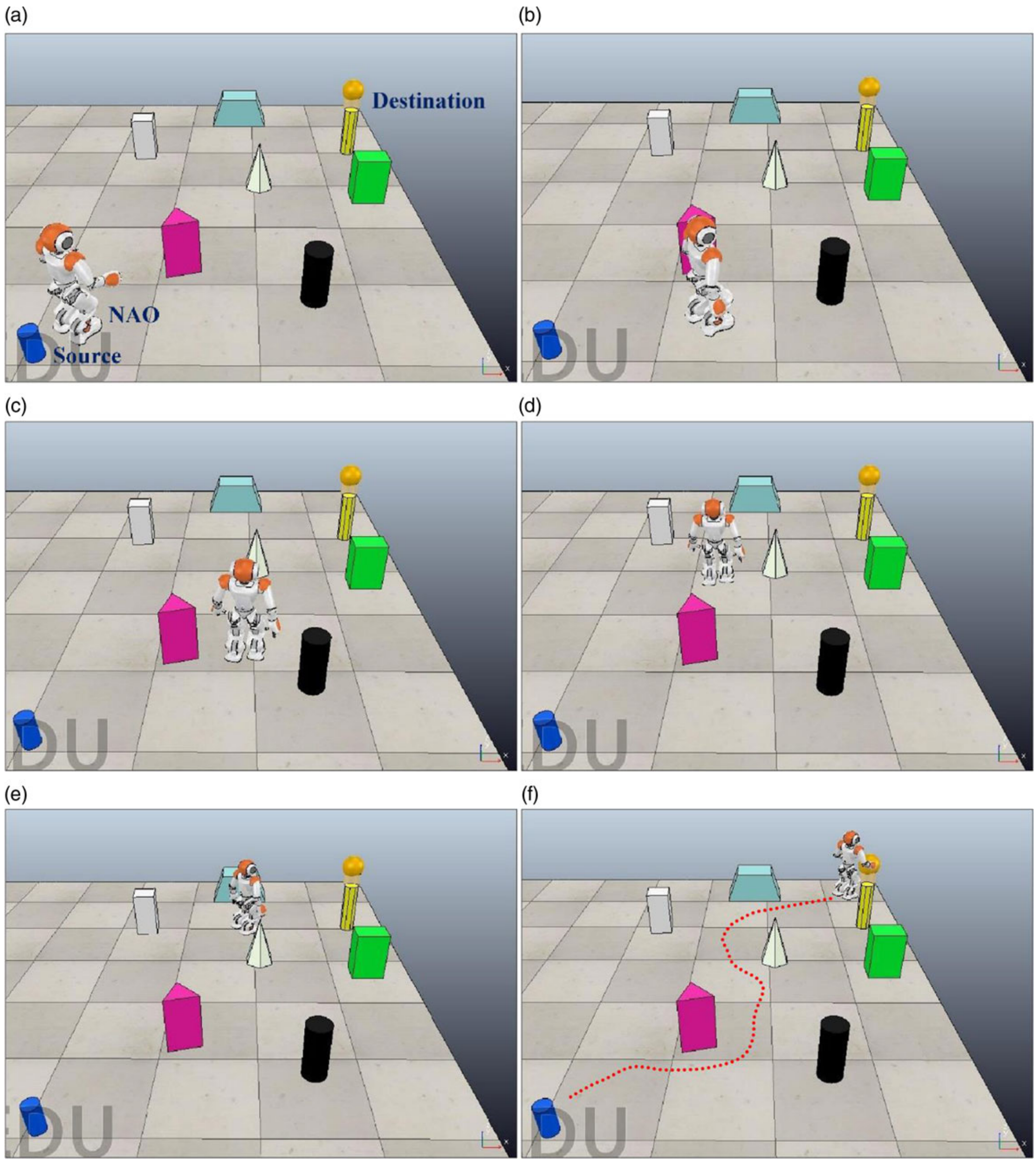

Figure 6. *Simulation results for motion planning of a single NAO.*

7. Evaluation of the proposed regression-firefly hybrid model against another navigational model

The developed regression-firefly hybrid model has been evaluated against another existing navigational model developed by Chen and Richardson [40] based on a neuro-fuzzy approach. Figure 10 represents a comparison of trajectory generated between both the navigational models and Table VI demonstrates the comparison of route length.

The proposed regression-firefly hybrid model has been proven to be more efficient than the existing path planning models.

Table II. Comparison of route length between simulation and experimental results for navigation of a single NAO.

Sl. No.	Route length in simulation (in cm)	Route length in experiment (in cm)	% of error
1	351.46	371.9	5.5
2	352.82	372.8	5.36
3	351.96	375.8	6.34
4	353.94	374.4	5.46
5	352.11	375.9	6.33
Average	352.46	374.16	5.8

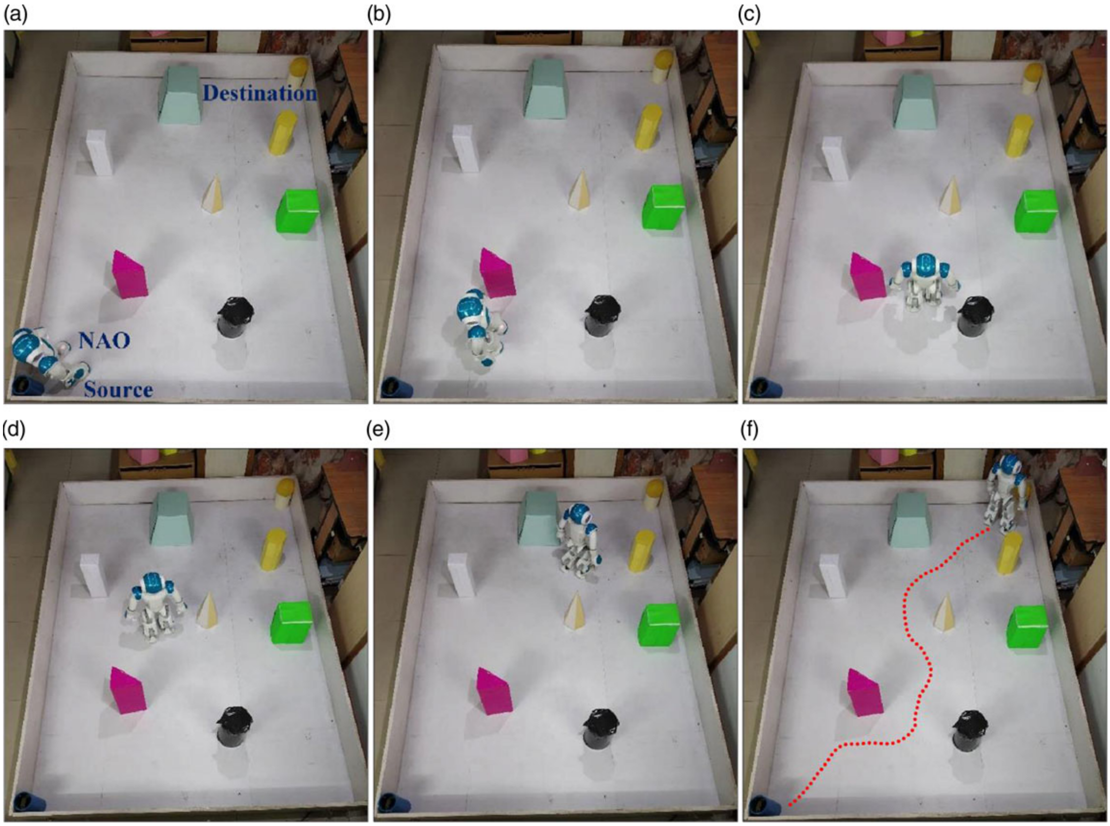

Figure 7. *Experimental results for motion planning of a single NAO.*

8. Conclusions

In the current investigation, a regression-firefly-based hybrid model has been designed and tested on single and multiple humanoids for smooth and efficient navigation in a complex arena. In the regression model, sensory information regarding the hurdles present in the arena is fed as inputs to calculate the ITA. In the second step of hybridization, along with the ITA generated in the first step, the nearest sensor range and destination distance are fed as inputs to the firefly model, and the FTA is generated as the ultimate guiding angle to move the humanoids toward the respective destinations. The proposed hybrid model has been implemented in simulation and experimental platforms for both single and multiple humanoids. The results obtained from both platforms are compared in terms of trajectory generated, route length, and time interval, and satisfactory results have been observed with a minimal percentage

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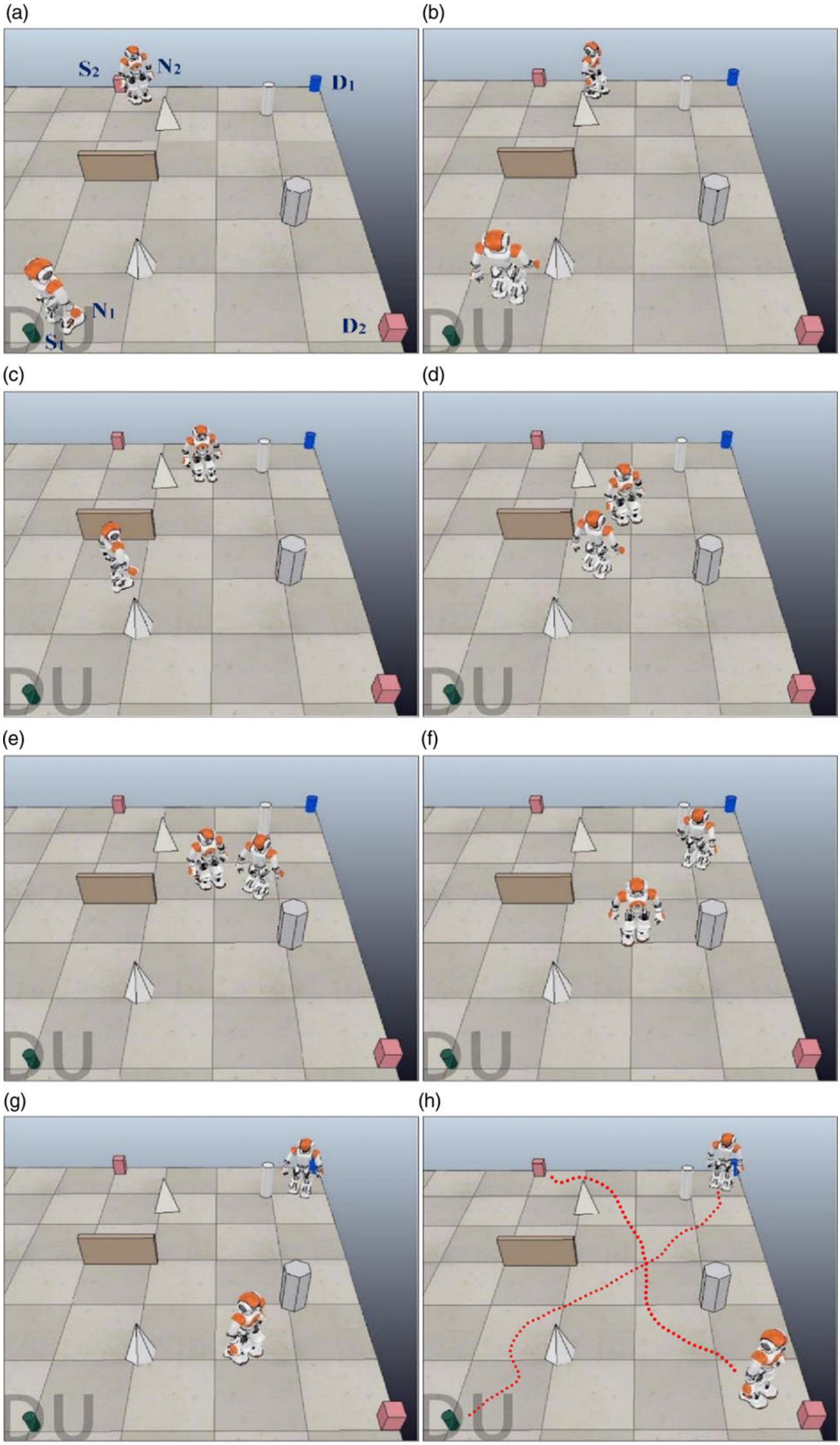

Figure 8. *Simulation results for motion planning of multiple NAOs.*

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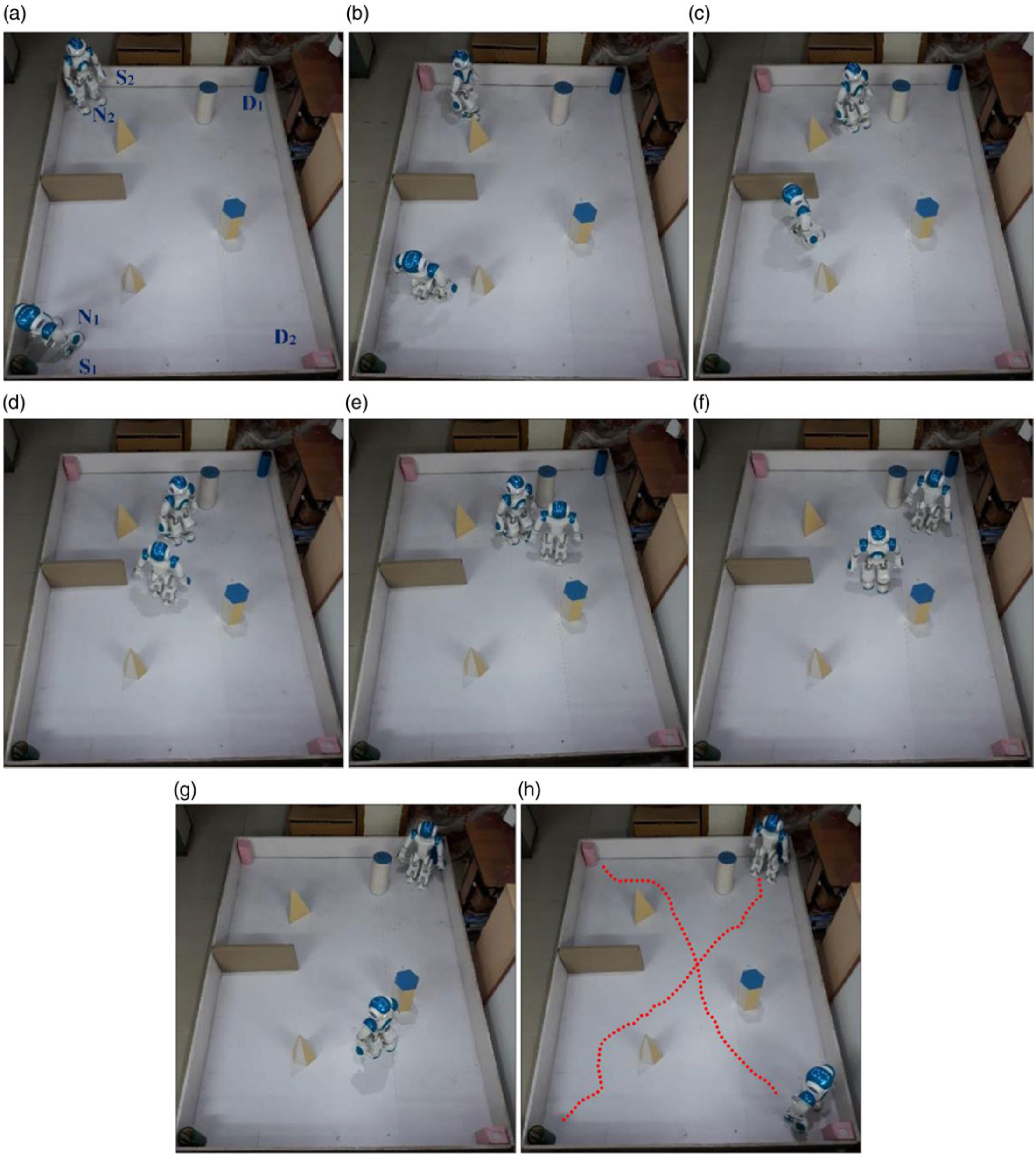

Figure 9. Experimental observations for motion planning of multiple humanoid NAOs.

of errors. Finally, the proposed hybrid model has been compared against another existing navigational model and significant performance enhancements have been recorded.

9. Future work

Motion planning analysis of humanoid robots in different environments has been successfully studied using the regression-firefly-based method. The developed novel technique is compared against existing methodology [40], and significant improvements of 8.33% in navigational parameters like route length have been observed. Though the motion planning analysis has been studied successfully, improvements

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Table III. *Comparison of time interval between simulation and experimental results for navigation of a single NAO.*

Sl. No.	Time interval in simulation (in s)	Time interval in experiment (in s)	% of error
1	48.23	51.24	5.87
2	48.49	51.37	5.61
3	48.75	51.82	5.92
4	48.36	51.94	6.89
5	48.91	51.8	5.58
Average	48.55	51.63	5.97

Table IV. *Comparison of route length between simulation and experimental results for navigation of multiple NAOs.*

	Simulation results		Experimental results			
	Route length (in cm)				% errors	
Sl. no	N_1	N_2	N_1	N_2	N_1	N_2
1	354.25	361.54	375.7	384.2	5.71	5.9
2	354.78	361.87	376.2	383.5	5.69	5.64
3	354.12	362.42	377	384.2	6.07	5.67
4	355.96	361.18	376.8	385.4	5.53	6.28
5	354.83	362.27	378.2	385.9	6.18	6.12
Average	354.79	361.86	376.78	384.64	5.84	5.92

Table V. *Comparison of time interval between simulation and experimental results for navigation of multiple NAOs.*

	Simulation results		Experimental results			
	Time interval (in s)				% errors	
Sl. No	N_1	N_2	N_1	N_2	N_1	N_2
1	49.35	51.74	52.41	54.95	5.84	5.84
2	49.46	51.82	52.56	55.12	5.9	5.99
3	49.85	52.65	52.81	56.28	5.6	6.45
4	50.24	51.97	53.61	55.84	6.29	6.93
5	49.97	52.22	53.33	55.41	6.3	5.76
Average	49.77	52.08	52.94	55.52	5.99	6.19

Table VI. *Comparison of route length between neuro-fuzzy approach [40] and regression-firefly model.*

Technique used	Route length in units	Improvement in %
Neuro-fuzzy approach [40] (Fig. 10(a))	15.6	8.33
Regression-firefly model (Fig. 10(b))	14.4	

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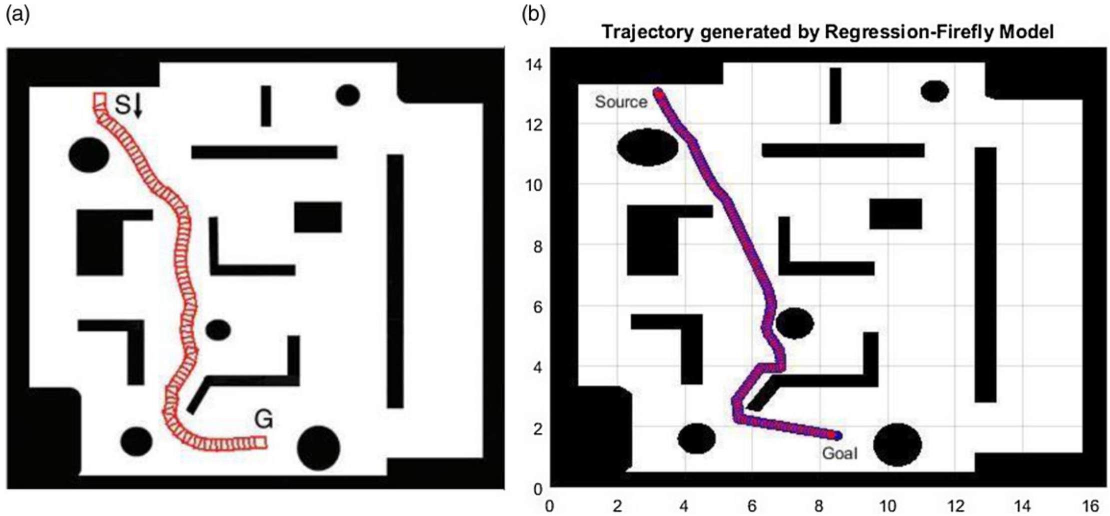

Figure 10. *(a) Trajectory generated by neuro-fuzzy approach [40]. (b) Trajectory generated by the regression-firefly model.*

toward dynamic stabilization, gait pattern analysis, analysis related to robustness and resilience [41], as well as hybridization methods to design and optimize autonomous mechatronics systems [42, 43] are still to be carried out.

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Manoj Kumar Muni: Validation, Formal analysis, Investigation, Writing – Review and Editing.

Saurabh Sameer Kamat: Formal analysis Investigation, Software, Data Curation, Writing – Review and Editing.

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