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Intelligent Hybridization of Regression Technique with Genetic Algorithm for Navigation of Humanoids in Complex Environments

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SUMMARY
In the current investigation, a novel navigational controller has been designed and implemented for humanoids in cluttered environments. Here, regression analysis is hybridized with genetic algorithm (GA) for designing the controller. The obstacle distances collected in the form of sensor outputs are initially fed to the regression controller; and based on the previous training pattern data, an intermediate advancing angle (AA) is obtained as the first output. The intermediate AA obtained from the regression controller along with other inputs is again fed to the GA controller, which generates the final AA as the desired final output to avoid the obstacles present in a complex environment and reach the destination successfully. The working of the controller is tested on a V-REP simulation platform. In the current work, navigation of both single as well as multiple humanoids has been attempted. To avoid inter-collision among multiple humanoids during their navigation in a common platform, a Petri-Net model has been proposed. The simulation results are validated through a real-time experimental platform developed under laboratory conditions. The results obtained from both the simulation and experimental platforms are compared against each other and are found to be in good agreement with acceptable percentage of errors. Finally, the proposed controller is also compared with other existing navigational controller and an improvement in performance has been observed.

KEYWORDS: Humanoid NAO; RA controller; GA controller; Petri-Net; Hybridization; V-REP.

1. Introduction

The ever-growing population diversity and the scarcity of available resources have forced researchers to develop intelligent techniques to increase production through industrial automation and smart manufacturing. As a result, the use of robotic agents has become popular in every sector of daily life. Humanoids are considered advantageous than their mobile robot counterparts with ability to assist and replace human efforts in complicated terrains. Therefore, navigation and path planning of humanoids has emerged as one of the most promising and challenging area of investigation among robotic researchers since last few decades. Path planning approaches are primarily categorized as global and local path planning based on the initial information available to the robot regarding the environmental conditions. Global path planning refers to having prior knowledge regarding the arena conditions and local path planning refers to being unaware regarding the same. Along with that, based on the approach to design the algorithm, navigational techniques are again categorized as classical approaches and computational or artificial intelligent (AI) approaches. Classical approaches

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are generally statistical approaches known for their high convergence rate within a limited time. AI approaches are known for their better accuracy than the classical ones. Over the last few years, several researchers have focussed on the development of different navigational techniques for robotic agents. Some of them can be summarized over here.

Atkinson[1] investigated some specific problems related to least square estimation and regression analysis (RA) and found out regression to be largely dependent upon the linear model that represents the problem. Frank *et al*.[2,3] used Gaussian regression as a potential path planning approach for manipulator robots with deformable objects. They tried to reduce the computational cost by the application of their approach. Qi *et al*.[4] modified the basic potential field-based approach as artificial potential field approach and used the same in mobile robot navigation. Lee and Bien[5] used parameters like stable gait trajectory, obstacle avoidance and goal seeking behaviour in designing the navigational controller for a quadruped robot by using an artificial thermal field. Kim *et al*.[6] have developed a kernel subspace learning algorithm for predicting pedestrian motion and subsequent control of an autonomous robot towards safe navigation. Dirik[7] has used fuzzy logic as a potential navigational technique for designing a safe navigational approach for mobile robots in indoor and outdoor environments. Keshmiri and Payandeh[8,9] designed a solution for multi-robot and multi-recharging station problem by enabling the robots to use their nearest recharging station rather than using a specific station and avoiding disturbance to other robots on the basis of regression technique. Li *et al*.[10,11] used an artificial potential field-based regression search technique for navigation of autonomous mobile robots in known and unknown environments. They have modified the algorithm to overcome the limitations like being trapped at local minima and avoiding oscillations. Lazaro *et al*.[12] collected sensory information regarding obstacles present in the environment and used it in a regression search for navigation of mobile robots. Dongre and Raikwal[13] used RA as a user web browsing prediction method based on previous training pattern. Kumar *et al*.[14–17] have discussed regarding the use of various nature inspired algorithms for navigational analysis of humanoid robots. Al *et al*.[18] used genetic algorithm (GA) to control the motion of a hybrid actuator by optimization of the parameters affecting the smooth movement. Wang *et al*.[19] modified basic GA with fitness scaling for solving the multiple depot vehicle routing problem in an efficient way. Nagib and Gharieb[20] designed a GA-based controller for path planning of a mobile robot in a static environment. Raouf and Pourtakdoust[21] optimized the reliability redundancy of a launch vehicle using GA combined with swarm optimization. Saraswathi *et al*.[22] have hybridized cuckoo search method with bat algorithm for navigation of a mobile robot in a simulation environment. Singh and Thongam[23] have used sonar data in a fuzzy logic-based system for generating a collision-free path for a mobile robot. Zhang *et al*.[24] used an improved GA(IGA)-based approach for navigation of a mobile robot in both static and dynamic environments. Tuncer and Yildirim[25] used a modified mutation operator in a GA-based dynamic path planning of a mobile robot. Allaire *et al*.[26] used GA for motion planning of an unmanned aerial vehicle (UAV) in a complex environment. Hu *et al*.[27] designed an effective vehicle navigation system using GA combined with an A*-based approach. Elshamli *et al*.[28] used a generic fitness function in designing a GA-based dynamic path planner of a mobile robot. Kwaśniewski and Gosiewski[29] have designed a GA-based technique to generate a smooth navigational pattern for a mobile robot. Lamini *et al*.[30] have proposed to modify the crossover operator in a standard GA approach to achieve performance enhancement. A GA-based path planner was designed by Bakdi *et al*.[31] for the navigation of a mobile robot using image processing techniques for collecting surrounding information and an adaptive fuzzy logic controller to keep track of its desired smooth path. Arantes *et al*.[32] proposed a safe emergency landing path re-planning for a UAV considering all unexpected environmental hazards. Meléndez *et al*.[33] used a fuzzy navigation system for a mobile robot using evolutionary algorithms for tuning of parameters. Hartjes and Visser[34] used GA-based approach for designing the safe departure trajectory of aircrafts. Sachin and Gaonkar[35] developed simulated model of a humanoid using 8051 microcontrollers and tested it for stability control and obstacle avoidance. Kim *et al*.[36] developed a control strategy for a bipedal walking on an uneven inclined floor. Hereid *et al*.[37] developed a fast and reliable method of stable gait synthesis for a walking humanoid model. Baskoro and Priyono[38] used zero moment point (ZMP) and inverse kinematics data for generating a stable walking pattern of a humanoid. Lin *et al*.[39] proposed a fuzzy logic controlled approach for dynamic balancing of a waist in an adult-sized humanoid robot. Inomata and Uchimura[40] developed a ZMP-based control strategy for a humanoid robot using three-dimensional contact points data along with ground reaction forces.

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It can be inferred from the extensive literature surveys that most of the classical and AI approaches are predominantly applied to mobile robots. The use of the same in humanoid platforms is limitedly reported. At the same time, the use of a hybrid method consisting of both classical and AI approach is very rare to find in case of humanoid navigation. Therefore, the current work is devoted towards the use of a hybrid methodology using RA and GA in humanoid navigation. A two-step hybridization model has been adopted in the current investigation where the initial output of the RA controller is again fed to the GA controller along with other inputs to find out the final output. Here, navigation of both single and multiple humanoids is attempted in complex platforms. NAO has been used as the humanoid platform, which has a large sensory network[41] consisting of SONARs, Infrareds, tactile sensors, cameras, *etc*. While the developed hybrid controller takes care of the navigation of a single humanoid; a Petri-Net model along with the proposed controller is required for navigation of multiple humanoids to avoid inter-collision. The working of the proposed hybrid scheme has been verified on a V-REP simulation platform and validated through an experimental platform.

2. RA Control Architecture

RA is popularly used as a statistical tool of data forecasting taking into consideration the trend of past data.

2.1. Basic overview

It is a simple method of relating dependent and independent variables with the help of some standard parameters. A basic mathematical expression of RA can be written as follows.

$$z_p = \hat{z}_p + \zeta_p \tag{1}$$

where

$\hat{z}_p = \mu_1 x_{p,1} + \mu_2 x_{p,2} + \ldots + \mu_p x_{p,n}$, $\mu = (\mu_1, \mu_2, \ldots, \mu_p)$ are taken as the parameters used in RA,

ζ_p = Error term.

In a similar way, humanoid navigation can be related to the logic of RA by careful consideration of navigational parameters.

2.2. Humanoid navigation using RA model

The prime motive of a navigational algorithm is to find a collision-free path and advance towards the destination by maintaining an optimized path. To do the same, a robot has to detect the obstacles present in the environment and reach the destination by avoiding the detected obstacles. The RA model considered in the current work has three input factors namely (i) Front Sonar Output (FSO), (ii) Left Sonar Output (LSO) and (iii) Right Sonar Output (RSO) and one output factor namely AA. The inputs are measured by the help of ultrasonic sensors present on the humanoid NAO. Figure 1 demonstrates the input and output parameters for RA model of humanoid navigation.

The regression model works in such a way that taking into consideration the three input parameters; the controller generates the output based on previous training pattern. Table I shows a sample training pattern data that has been used in the current investigation.

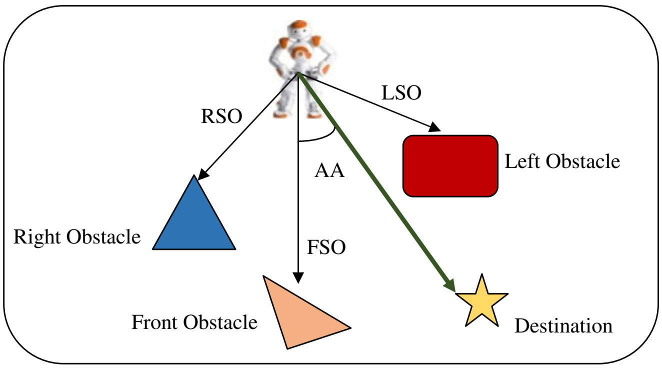

Fig. 1. Input and output parameters of RA model.

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

SN	FSO	LSO	RSO	AA	SN	FSO	LSO	RSO	AA	SN	FSO	LSO	RSO	AA
1	61	34	47	6	11	49	66	31	−13	21	39	38	47	11
2	40	45	60	10	12	61	32	46	3	22	65	46	60	2
3	35	70	40	−10	13	52	44	71	12	23	45	64	53	−17
4	30	50	35	−15	14	32	32	56	14	24	53	56	49	0
5	75	30	45	0	15	41	73	31	−18	25	40	52	66	10
6	30	40	40	−26	16	46	37	52	20	26	48	37	40	5
7	55	42	30	−27	17	51	52	41	−16	27	58	66	44	−13
8	41	64	43	−15	18	42	36	64	20	28	56	46	66	13
9	83	45	55	0	19	54	82	42	−23	29	34	50	66	−11
10	38	59	42	−10	20	46	38	59	14	30	60	43	53	14

While considering the AA towards the destination, basic sign convention has been followed. A turn towards left side is considered negative and a turn towards right side is considered positive. 800 data points are fed to the regression tool box of Minitab software and an equation is generated as follows.

$$Q_4 = -0.005869Q_1 - 0.2672Q_2 + 0.765592Q_3 - 24.0495 \tag{2}$$

where Q_1 is the FSO, Q_2 the LSO, Q_3 the RSO and Q_4 the AA.

With a definite source and destination position, the humanoid proceeds towards the destination. After detection of a potential obstacle within the set threshold range, the RA controller is activated and the required AA is calculated using the regression equation. Here, the threshold range is taken as 30 cm. To maintain an optimal path throughout the journey, some reactive behaviours such as destination following, obstacle avoidance and barrier following behaviours are implemented on the humanoid. By the help of destination following behaviour, the humanoid always maintains an AA towards the destination. In obstacle avoidance behaviour, the humanoid avoids a detected obstacle by taking a suitable AA. Barrier following is a complimentary behaviour by virtue of which it follows a long barrier without the activation of the controller to save energy and reach the destination.

3. GA Control Architecture

Inspired from natural genetics, GA has emerged as one of the most efficient method of solving engineering optimization problems.

3.1. Basic overview

GA works on a principle of transferring best genes to the next generation and discarding the weak ones. By selection of a particular set of chromosomes as parent set, an optimal solution is generated by following standard steps such as selection, crossover and mutation. Each chromosome represents a potential solution to the problem out of the initial set of chromosomes, which is considered as the parent set. The solutions are coded in binary where each bit represents a gene of the chromosome. Based on the calculated fitness value, the viability of a solution is represented. The continuous iteration that occurs throughout the process of GA aims to achieve a better solution in each step than its previous step up to the final optimality condition. The above-mentioned objective is achieved by selection of better parents with enhanced qualities, crossover among parents to generate offspring and mutation to introduce genes of diverse qualities to adopt the environmental changes.

3.2. Humanoid navigation using GA model

In the current investigation, the primary aim of the GA controller is to generate a safe position once the sensors detect a potential obstacle within the set threshold range. The current position of the humanoid is always taken into consideration while calculating the AA towards the destination. In the GA model, the inputs to the controller are (i) Nearest Sensor Output (NSO) and (ii) Destination Distance (DD). NSO represents the distance of the nearest obstacle to the humanoid and DD represents the distance of the destination point from the humanoid's current position. While NSO is

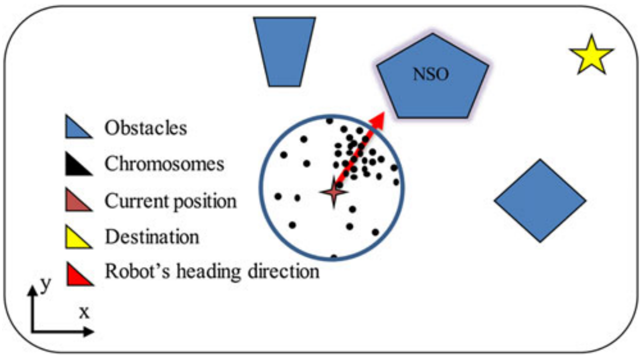

Fig. 2. Population generation by GA model.

obtained directly from the sensor output of the humanoid, DD is calculated by the following equation.

$$DD = \sqrt{(P_x - D_x)^2 + (P_y - D_y)^2} \tag{3}$$

where (P_x, P_y) and (D_x, D_y) represent the two-dimensional coordinates of humanoid's current position and destination point, respectively.

The steps of a standard GA model can be represented as follows.

3.2.1. Generation of initial population. The humanoid advances towards the destination from the source position as per the destination following behaviour. Once the sensors of the humanoid detect a potential obstacle within the set threshold range, GA controller is activated. The first step in the GA model is to generate possible next points for the humanoid movement. The next points are generated in a cluster around the obstacle. Figure 2 represents a typical population generation process by GA.

The points are generated as per the following set of rules.

(i) The next position should be inside a circular space having centre at the humanoid's current position and radius

$$r = \sqrt{(NSO_x - P_x)^2 + (NSO_y - P_y)^2} - T_h \tag{4}$$

where T_h is the set threshold range.

(ii) If $P_x \leq D_x$, 75% of points will have $P_x \leq Q_x$
Else 75% of points will have $P_x > Q_x$
where (Q_x, Q_y) is the two-dimensional coordinate of the next position.

(iii) If $P_y \leq D_y$, 75% of points will have $P_y \leq Q_y$
Else 75% of points will have $P_y > Q_y$

The number of solutions taken as the initial solution or parent is completely user defined. In the current work, 50 chromosomes are selected as the initial solution set. The two-dimensional coordinates for the parent solutions are generated by the following rule base.

(a) If $P_x \leq D_x$
  i. x-coordinates of 35 chromosomes are generated by

$$Q_x = P_x + K_1(0, 1) \times (NSO_x - P_x) \tag{5}$$

  ii. x-coordinates of 15 chromosomes are generated by

$$Q_x = P_x - K_1(0, 1) \times (NSO_x - P_x) \tag{6}$$

  iii. Else the above two rules are reversed with each other

(b) If $P_y \leq D_y$
  i. y-coordinates of 35 chromosomes are generated by

$$Q_y = P_y + K_2(0, 1) \times (NSO_y - P_y) \tag{7}$$

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ii. y-coordinates of 15 chromosomes are generated by

$$Q_y = P_y - K_2(0, 1) \times (NSO_y - P_y) \tag{8}$$

iii. Else the above two rules are reversed with each other

3.2.2. Generation of objective function. While designing the objective function of the humanoid navigation problem, criteria such as obstacle avoidance, path optimization and destination following are taken as the primary objectives. Therefore, the objective function is initially formulated for each part and individual parts are joined finally taking suitable weightage.

(i) Obstacle avoidance

The humanoid must maintain a maximum distance from the obstacles to avoid them safely. As the obstacle distance has to be maximized, the objective function has to be inversely proportional to the distance.

$$OF_1 \propto \frac{1}{\min(OA_D)} \tag{9}$$

where $OA_D = \sqrt{(Q_x - NSO_x)^2 + (Q_y - NSO_y)^2}$

(ii) Path optimization

The humanoid must follow the shortest possible path to reach the next position. As this distance is to be minimized, it can be considered a direct proportionality.

$$OF_2 \propto \min(PO_D) \tag{10}$$

where $PO_D = \sqrt{(Q_x - P_x)^2 + (Q_y - P_y)^2}$

(iii) Destination following

The destination following behaviour is designed in such a way that in absence of any obstacles in the environment, the humanoid always heads towards the destination. As the movement of the humanoid has to happen in the shortest path, it is considered as a direct proportionality.

$$OF_3 \propto \min(DF_D) \tag{11}$$

where $DF_D = \sqrt{(D_x - Q_x)^2 + (D_y - Q_y)^2}$

As already stated, the final objective function is generated by the weighted combination of the individual objective functions.

$$OF = \delta_1 \times OF_1 + \delta_2 \times OF_2 + \delta_3 \times OF_3 \tag{12}$$

where δ represents the weights assigned to individual parts of objective function.

In the current problem, the next point should lie close to the destination. So, the objective function with the least fitness value can be considered as the best solution. Hence, the current optimization problem is a minimization one. While deciding the fitness value of each individual solution, the weights assigned to the individual parts play a major role. Higher value of δ_1 would ensure that the humanoid is far away from the obstacles. By selecting a higher value of δ_2, the path length can be reduced as the next possible point would lie closer to the current position. Similarly, a higher value of δ_3 would reduce the path length by always advancing the humanoid towards the destination. As the primary motive is to avoid the obstacles present in the path, δ_1 value must be kept higher than δ_2 and δ_3. However, less value of scaling factors may lead to premature convergence in the GA model. Therefore, trial and error method has been adopted here to select the values of the weights assigned to the objective functions.

3.2.3. Selection of parent. Optimality check (to be discussed in further steps) has to be carried out before proceeding to selection of parent. If any of the optimality criteria is met, the algorithm is terminated and the parent with highest fitness (lowest objective function value) is selected as the best solution. If optimality criteria are not met, parent selection step is carried out. While selecting the parent, the good solutions are included and the bad ones are omitted. However, it has to be taken care of that a good parent with highest fitness value should not be included in the parent selection; otherwise, it may lead to premature convergence of the algorithm. Along with that, maintaining a diversified population would lead to successful solution generation in GA. In the current work,

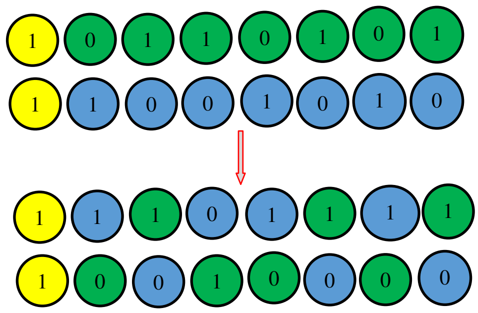

Fig. 3. Process of crossover.

fitness proportionate method has been used for parent selection. The probability of a certain parent to be selected can be written as:

$$P_{r_q} = 1 - \frac{OF_q}{\sum_{q=1}^{50} OF} \tag{13}$$

where P_{r_q} is the probability of a parent q to be selected and OF_q is the objective function of the parent q to be selected.

While performing parent selection, parents with less than 15% probability of getting selected are rejected and replaced by better ones.

3.2.4. Crossover. The parents selected for producing the next generation are ordered as per their fitness value. With an objective of producing better offspring, crossover operation is carried out. Here, 8-bit chromosome length is selected and to keep the generated solutions within a limited space, first gene of the chromosomes is kept un-altered, and rest of the genes are crossed by the help of uniform crossover method. The genes are exchanged with the other parent if the random number generated for it has a probability greater than equal to 50%. Figure 3 represents the process of crossover.

3.2.5. Mutation. Mutation is the process of adding new characteristics in a population keeping in view of the environmental changes. It introduces diversity in a population. To prevent GA from becoming a random search, mutation probability has been kept limited to 3% in the population. In the current problem, the initial population is generated around the obstacle itself. Although in most of the cases, it may provide the best solution, there may be cases where the best solution may lie far away from the obstacle locality. Therefore, if the random number generated for each parent has a probability of greater than equal to 98%, mutation is carried out.

3.2.6. Optimality check criteria. Although in each iteration GA produces better solutions than the previous step, there may be a time when the difference between the solutions generated from two consecutive steps becomes very minimal or the improvement becomes negligible. This is called as the saturation state of GA. In the current work, two termination criteria are set, and one of them will lead to termination of the algorithm.

(i) When the successive solution improvement is less than 2%.
(ii) When the number of iterations exceeds 100.

Unless until the algorithm meets its optimality criteria, it would repeat the steps as mentioned above. After generation of next best point, the AA to that point is calculated by the help of simple geometrical measures.

4. Proposed RA–GA Hybrid Controller

Classical methods are popular in converging within a limited sample space, and AI techniques are famous for their better accuracy. Humanoid navigation being a challenging area of investigation demands both accuracy and convergence within a limited time and space. Therefore, the

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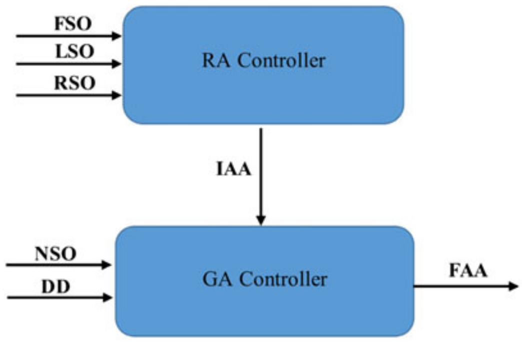

Fig. 4. RA–GA hybridization scheme.

hybridization of a classical method with an AI one is always interesting. Here, RA is hybridized with GA to avoid the limitations available in standalone methods. First, sensory information regarding obstacle distances (FSO, LSO and RSO) are fed as inputs to the RA controller. Based on the training pattern data provided to the RA controller, an intermediate IAA is generated from the controller. Then, the GA controller is fed with IAA along with other inputs (NSO and DD) to generate the final AA (FAA). Figure 4 demonstrates the scheme of hybridization that has been implemented in the current analysis.

The steps followed in the proposed RA–GA hybrid model for humanoid navigation can be summarized as follows.

(i) Define the source and destination points for the humanoid.
(ii) Advance towards the destination until the sensors detect any potential obstacle within the set threshold range.
(iii) Activate RA controller once the sensors detect an obstacle.
(iv) Feed FSO, LSO and RSO to the RA controller as inputs and obtain IAA as the first output.
(v) Feed GA controller with NSO, DD and IAA.
(vi) Generate the initial population, select the parents, perform crossover, introduce mutation and select the best solution as per the fitness value.
(vii) Check for optimality and terminate if the optimality criteria are met; otherwise, repeat the steps mentioned in (vi) until the optimality criteria are reached.
(viii) Generate the FAA.

Figure 5 represents the pseudo code of the RA–GA control scheme, and Fig. 6 represents the flowchart of the complete process.

5. Petri-Net Model for Navigation of Multiple Humanoids in a Common Platform

Petri-Net model[42,43] is used to design dynamic navigational systems. In the current work, navigation of multiple humanoids is also encountered along with single ones. In navigation of multiple humanoids, the system becomes a dynamic one as each humanoid acts as the dynamic obstacle for each other. The logic of the proposed RA–GA controller can avoid the obstacles and reach the destination; however, in deciding the priority when multiple humanoids come across same obstacle, it may not be self-sufficient. Therefore, along with the proposed hybridization scheme, a Petri-Net model is also designed to avoid the possible inter-collisions. Figure 7 represents the Petri-Net model used in the current work.

In the navigational mode, a circle represents the current position of a robot. A bar symbol denotes a phase transition. A black symbol represents the current phase of the robot. Here, six phases are shown in the model which can be described as follows.

Phase 1: Here, the robots are at random locations of the navigation environment being unaware regarding each other's position and ready to start the journey towards respective destinations.

Phase 2: By activation of destination following behaviour, the robots start their journey and track for obstacles in the environment.

Phase 3: It represents the detection of a dynamic obstacle.

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The humanoid heads towards the destination
When the sensors detect a potential obstacle within the set threshold limit:
RA controller is activated
        FSO, LSO and RSO are fed as inputs to the RA controller
        IAA is calculated as per the RA logic
GA controller is activated
        IAA, NSO and DD are fed as inputs to the GA controller
        Initial population of next positions is generated
        Fitness values of all the possible solutions are calculated
        Optimality is checked with the current fitness values
        If (Optimality is achieved)
                GA is stopped and FAA is calculated
                The humanoid moves to the calculated position with FAA
                If (Destination is reached)
                        Stop navigation
                Else if (Obstacle is detected)
                        Repeat the RA-GA controller to find next FAA
                Else
                        Keep navigating till an obstacle or destination is reached
        Else
                Select parents according to their fitness value
                Perform crossover and mutation to produce offspring
                Go back to the fitness value generation loop till optimality is achieved
```

Fig. 5. Pseudo code of RA–GA controller.

Phase 4: Phase 4 shows the negotiation stage where the robot having less distance towards the destination advances forward by getting higher priority.

Phase 5: Here, checking for any further conflicting situation occurs and in the absence of the same, the robot advances towards the destination.

Phase 6: Phase 6 shows a waiting condition. When a robot detects another set of robots already in phase 3, it will behave as a static obstacle. After conflict resolution, the robot moves further starting from phase 2.

By implementing the above logic, navigation of multiple humanoids can be approached in a common platform.

6. Implementation of RA–GA Controller in Humanoid Navigation

The RA–GA hybrid controller has been tested in both simulation and experimental environments taking humanoid NAO as the platform.

6.1. Navigation of a single NAO

Collision detection, minimum distance calculation and better motion planning are some of the advantageous properties of V-REP simulation software, which make it more suitable for the analysis of humanoid navigation than other counter parts. Here, V-REP has been selected as the simulation software with an arena size of 240 $\times$ 160 units. A code consisting of the logic of the proposed hybrid scheme has been written in LUA language and implemented on the humanoid in the simulation platform. Six obstacles are placed at arbitrary locations of the arena, specific source and destination positions are defined and the humanoid is advanced towards the destination. Figure 8 represents the simulation results obtained from the navigation of a single NAO. It can be observed that the humanoid is able to avoid the obstacles present in the arena and reach the destination smoothly. It is to be noted

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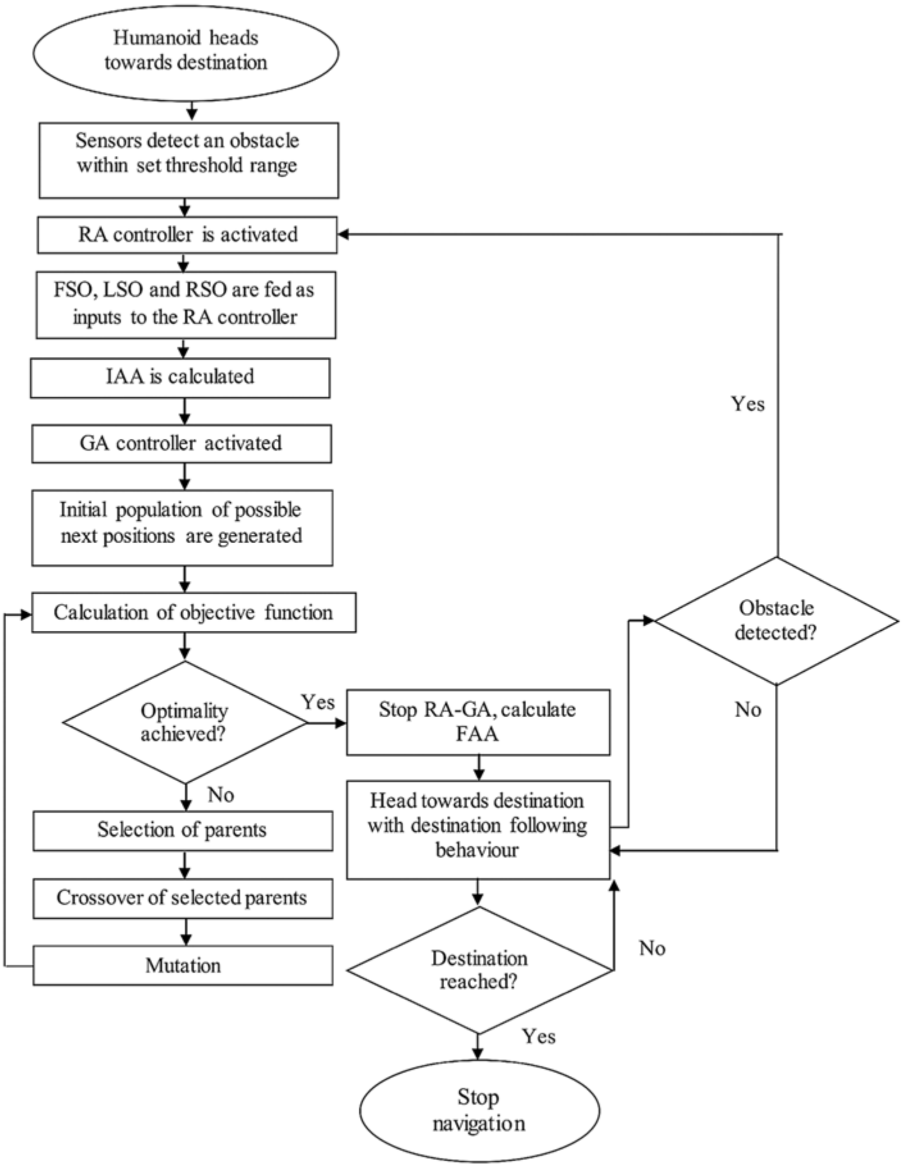

Fig. 6. Flowchart of RA–GA controller.

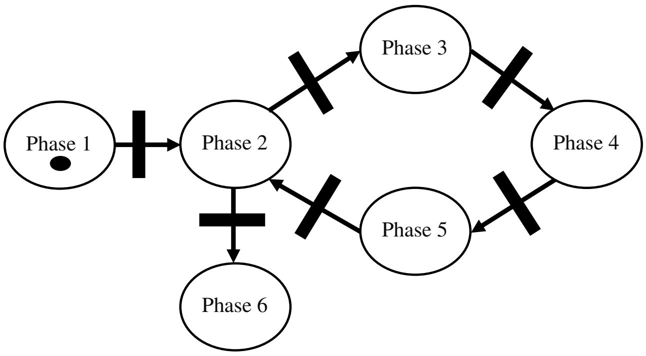

Fig. 7. Petri-Net model.

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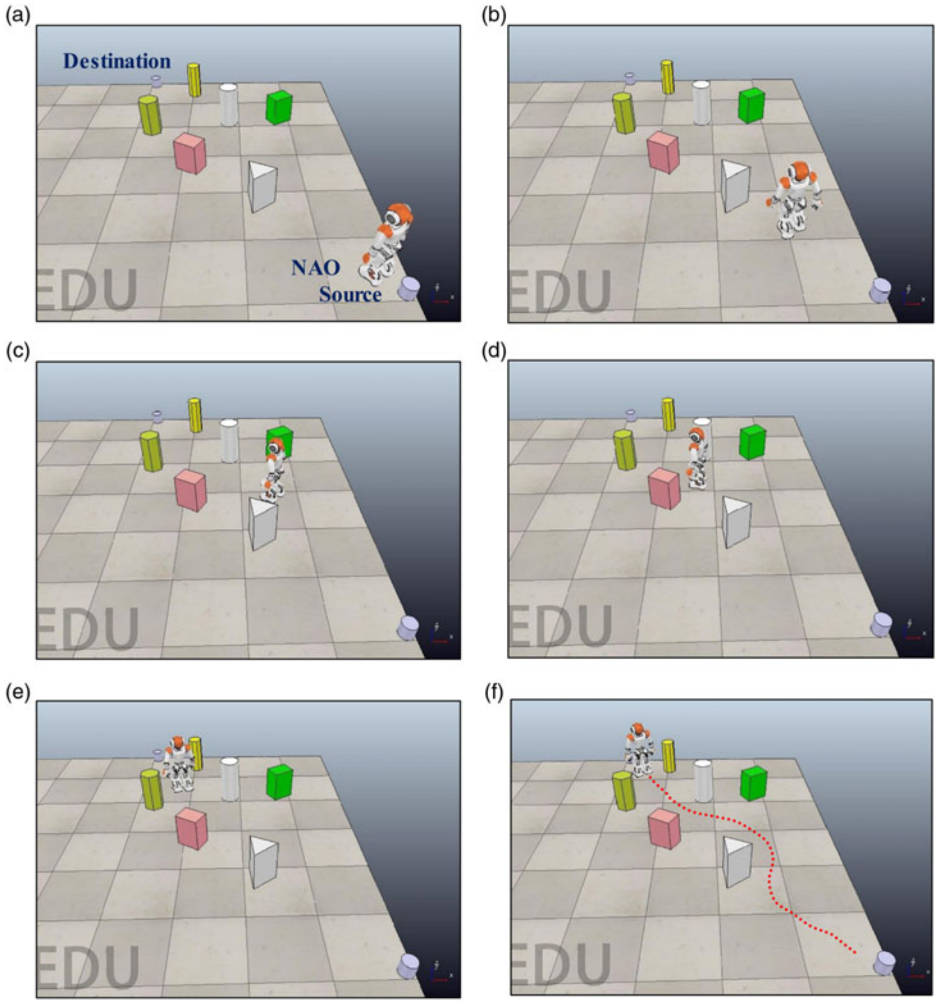

Fig. 8. Simulation results for navigation of a single NAO.

that simulation has been performed under several environmental conditions and only one case has been depicted pictorially.

To validate the simulation results, the navigational pattern is repeated in an experimental platform developed under laboratory conditions. Each scenario analyzed in the simulation platform is recreated in the experimental platform with similar arena conditions such as arena size, obstacle size, obstacle locations, source and destination positions. In the experimental platform, NAO is operated using Python programming with a Wi-Fi control. Figure 9 represents the experimental results obtained from the navigation of a single NAO. The experimental results have also revealed successful navigation of the NAO.

The validation of the simulation results with the experimental ones is not only done through the trajectory followed, but also through the comparison of some navigational parameters. In the current analysis, path to destination and time to destination are selected as the two navigational parameters for comparison purpose. These two are directly recorded from the simulation window of V-REP software and calculated by the help of a measuring tape and stopwatch from the experimental environment. Tables II and III demonstrate the comparison among simulation and experimental environments in terms of path to destination and time to destination, respectively.

The errors expressed in the above tables are limited to the acceptable bounds, which prove the smooth working of the proposed controller in humanoid navigation. It can be noticed that the experimental results possess higher values than the simulation counter parts in all the instances. This happens due to the presence of external factors like slippage, friction, data transmission loss, *etc*. in the experimental environment.

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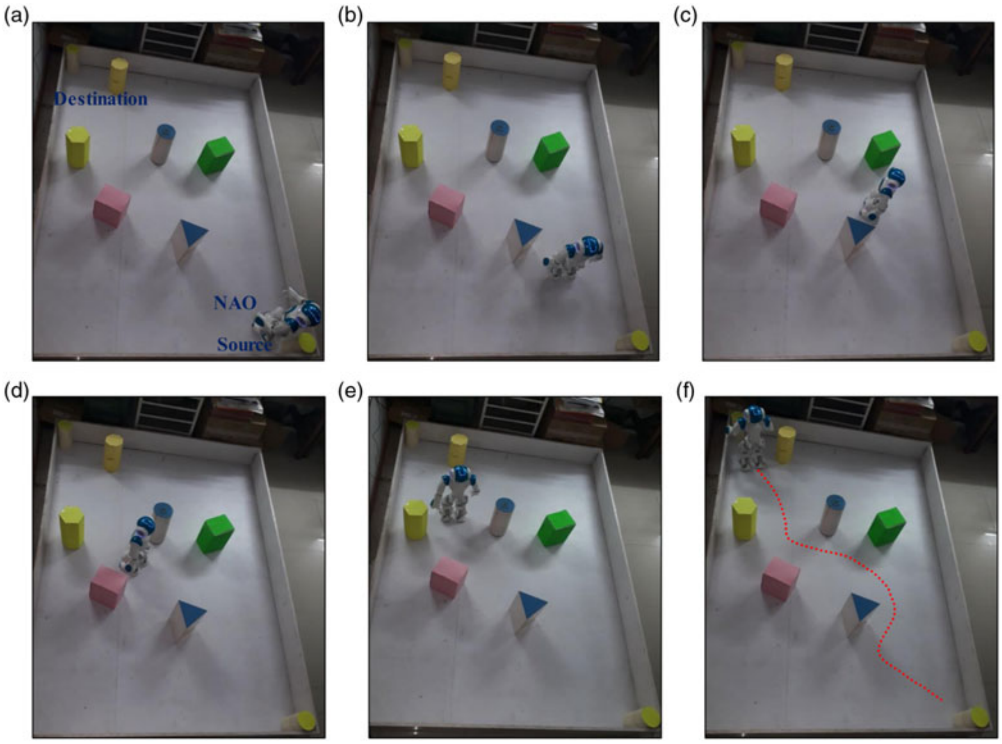

Fig. 9. Experimental results for navigation of a single NAO.

Table II. Comparison of path to destination between simulation and experimental results for navigation of a single NAO.

Sl. no.	Path to destination in simulation (cm)	Path to destination in experiment (cm)	% Error
1	345.28	363.5	5.01
2	346.7	365.7	5.2
3	345.96	366.4	5.58
4	346.2	367	5.67
5	346.54	365.8	5.27
Average	346.14	365.68	5.35

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

Sl. no.	Time to destination in simulation (s)	Time to destination in experiment (s)	% Error
1	46.53	49.47	5.94
2	46.82	49.62	5.64
3	47.31	50.24	5.83
4	46.9	49.8	5.82
5	47.14	50.1	5.91
Average	46.94	49.85	5.83

6.2. Navigation of multiple NAOs

As already stated, Petri-Net model is combined with the proposed RA–GA controller for navigation of multiple humanoids. V-REP platform with same arena size of 240 $\times$ 160 units is used for multiple humanoid navigation. Six obstacles of random size are placed at arbitrary locations of the arena. Here, two NAOs are fed with RA–GA controller along with Petri-Net model and advanced to their

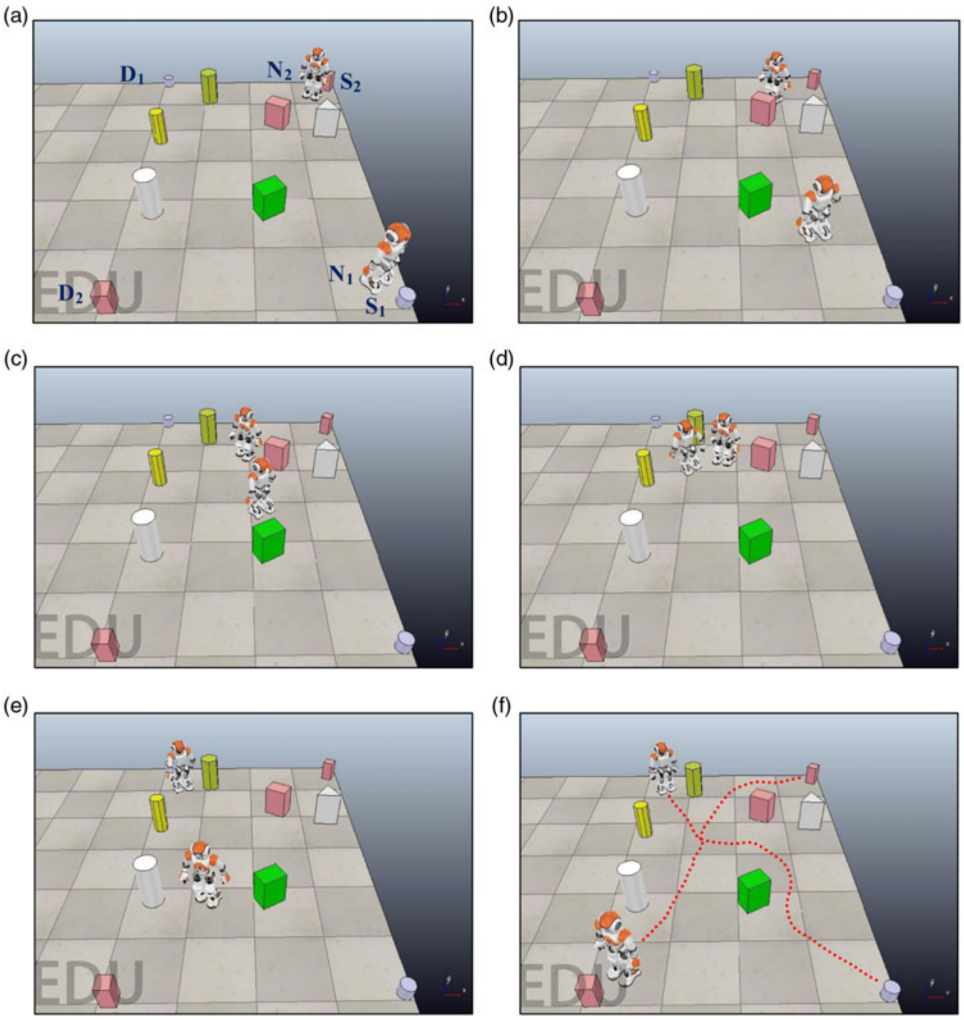

Fig. 10. Simulation results for navigation of multiple NAOs.

respective destinations. Figure 10 represents the simulation results obtained from the navigation of multiple humanoids in a common arena.

The simulation results are also verified through experimental observations. Keeping similar environmental conditions, two NAOs are tested for destination following and obstacle avoidance behaviour by controlling them through Wi-Fi module. Figure 11 represents the experimental results obtained from the navigation of multiple NAOs.

The results obtained from both the environments are compared in terms of path to destination and time to destination as was performed for the navigation of a single NAO and depicted in Tables IV and V, respectively.

The comparison of navigational parameters for multiple NAOs has also revealed satisfactory results with minimal error range. So, it can be inferred that the proposed RA–GA controller has worked well in smooth and collision-free navigation of single and multiple humanoids.

7. Comparison of the Proposed RA–GA Navigational Controller with Other Existing Techniques

The working of the proposed RA–GA controller has been successfully tested in both simulation and experimental environments. The humanoids have reached their destination points having a collision-free navigation by implementation of the proposed controller. However, to have a better insight into the efficiency of the controller, it has been compared against other existing navigational controller. Zhang *et al.*[24] have developed an IGA-based navigational controller for navigation of mobile robots in a complex arena. Figure 12 demonstrates a comparison of the proposed RA–GA controller

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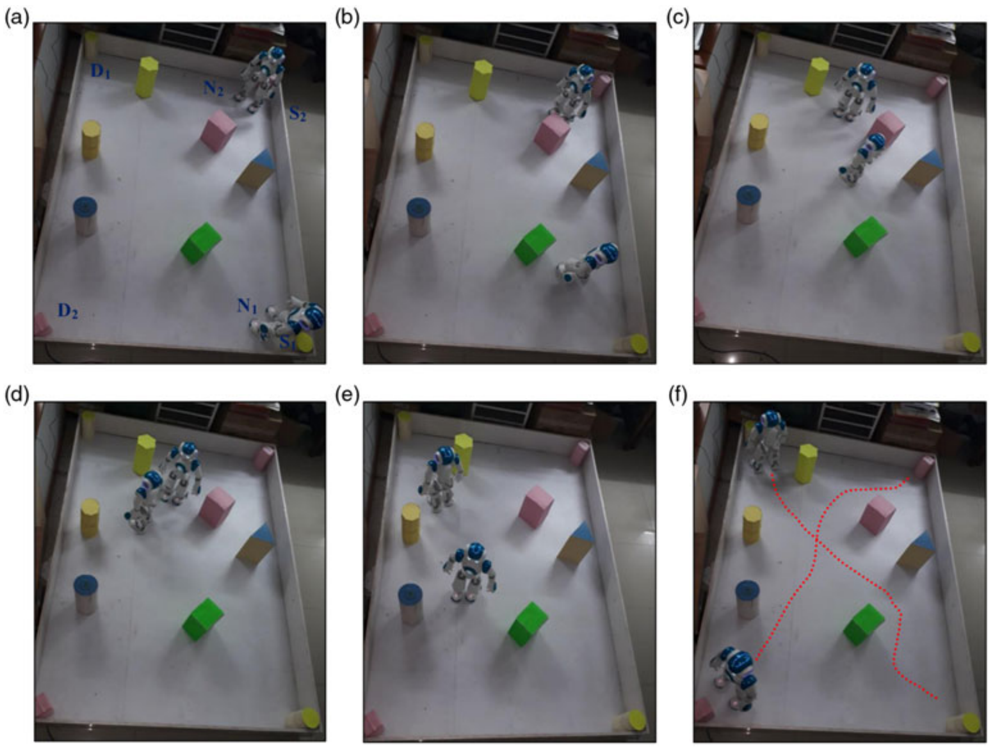

Fig. 11. Experimental results for navigation of multiple NAOs.

Table IV. Comparison of path to destination between simulation and experimental results for navigation of multiple NAOs.

	Simulation results		Experimental results			
	Path to destination (cm)				% Errors	
Sl. no	N_1	N_2	N_1	N_2	N_1	N_2
1	348.5	352.64	369.7	374.8	5.73	5.91
2	349.28	352.93	370.4	375.4	5.7	5.99
3	348.78	353.18	370	376.7	5.74	6.24
4	349.55	353.4	371.5	376	5.91	6.01
5	348.93	352.74	370.8	375.6	5.9	6.09
Average	349.01	352.98	370.48	375.7	5.8	6.05

Table V. Comparison of time to destination between simulation and experimental results for navigation of multiple NAOs.

	Simulation results		Experimental results			
	Time to destination (s)				% Errors	
Sl. no	N_1	N_2	N_1	N_2	N_1	N_2
1	45.24	49.61	48.55	53.25	6.82	6.84
2	45.68	49.82	48.76	53.67	6.32	7.17
3	46.29	50.94	49.18	54.27	5.88	6.14
4	45.91	50.43	48.93	53.8	6.17	6.26
5	46.48	49.68	49.5	53.82	6.1	7.69
Average	45.92	50.1	48.98	53.76	6.26	6.82

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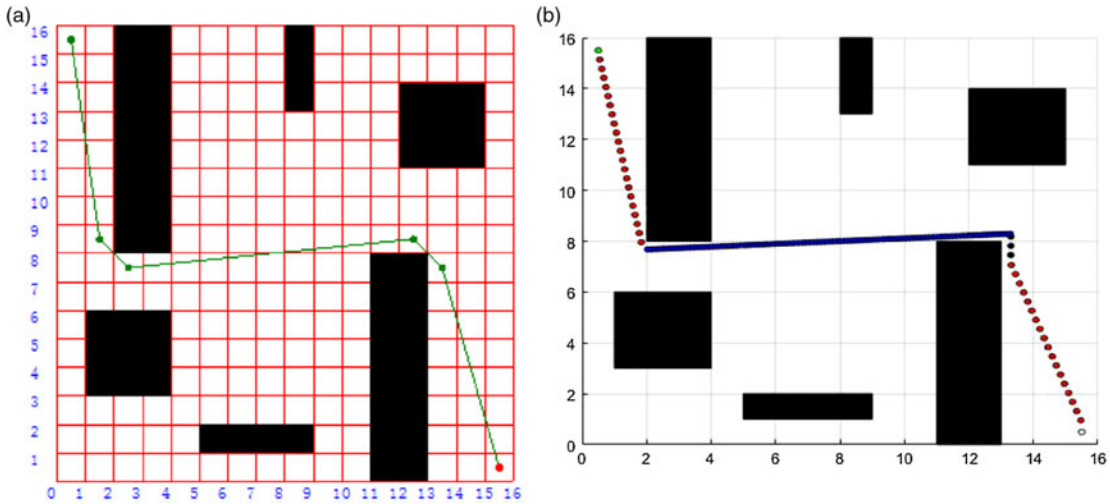

Fig. 12. (a) Path followed in IGA approach, (b) path followed in RA–GA approach.

Table VI. Comparison of path to destination between IGA approach[24] and RA–GA approach.

Technique used	**Path length (cm)**	**Deviation (%)**
IGA[24] (Fig. 12(a))	26.75	4.93
RA–GA (Fig. 12(b))	25.43	

with the IGA controller in terms of trajectory followed, and Table VI shows the path to destination comparison.

The proposed RA–GA controller has predicted better results than the existing navigational controller, which shows the enhancement in using the hybrid scheme.

8. Conclusions

Navigation and path planning of humanoids is the talk of the town among robotics practitioners. In the current work, a novel hybrid navigational controller has been proposed for smooth and collision-free movement of humanoids. Here, RA has been hybridized with GA for the performance improvement of standalone methods. The RA controller is initially fed with the obstacle distances in terms of sensor outputs, and an intermediate AA has been obtained as the first output. The IAA is again fed to the GA controller along with other inputs and the final AA has been obtained as the required angle to avoid obstacles present in the environment and reach the destination. The navigation of single and multiple humanoid NAOs has been attempted in the current study. To resolve the inter-collision conflict among multiple humanoids, a Petri-Net model has been proposed, which has been used in the navigation of multiple humanoids. The working of the controller has been verified in a V-REP simulation arena and validated through an experimental platform. The results obtained from both the arenas are compared against each other in terms of selected navigational parameters, and close agreement has been found with negligible error limit. Finally, the proposed hybrid scheme has been compared against an existing navigational model and performance improvement has been observed. By the use of the developed hybrid scheme, the navigation of other forms of robots can also be attempted which can be considered as a future endeavour of the current work.

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