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Smart Navigation of Humanoid Robots Using DAYKUN-BIP Virtual Target Displacement and Petri-Net Strategy

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SUMMARY
With an ability to mimic the human behaviour and replace human efforts in proper platforms, humanoid robots have always acquired a special place among robotics practitioners. Being a complex method of analysis, navigation and path planning, humanoid robots still possess an interesting yet challenging area of investigation. In the current work, a novel navigational strategy has been proposed for smooth and hassle-free movement of single as well as multi-humanoid robots in complex environments. Here, the navigational plan is based on a virtual target displacement strategy which is activated when the robot is unable to find a safe path along the actual target line. After detection of a potential obstacle by the sensors of the robot, a number of virtual targets are generated around the actual target. Then, the most feasible path and point to move are calculated by assigning suitable weightage through several selected parameters to each target line and visualizing the safest path. The proposed approach is implemented on a V-REP simulation platform, and the simulation results are also validated against an experimental set-up prepared under test conditions. The validation of simulation results against experimental counterparts has revealed satisfactory agreement between them. To avoid possibility of any inter-collision during navigation of multi-humanoids under a common platform, a Petri-Net strategy has been integrated along with the proposed control strategy. Finally, the developed approach is also assessed against another existing navigational controller, and a significant performance improvement has been observed.

KEYWORDS: Humanoid NAO; Navigation; Virtual target displacement; Petri-Net; V-REP.

1. Introduction

The prime motive behind the development of several intelligent methodologies to guide autonomous robots is to attain complete autonomy without the need of any external regulation and operator control. To attain such autonomy, a robotic agent needs to first map the environment and stabilize its knowledge regarding the obstacle locations and its relative position in regard to the start and end positions. However, such a type of navigation is called as a model-based approach that, although seemingly easy to deal with, actually differs largely from the practical environmental conditions that the robot may face during its navigation. Therefore, based on the preliminary knowledge regarding environmental conditions supplied to a robotic agent, navigational approaches are classified as model-based and sensor-based approaches. While the model-based approaches are easy to tackle with, the sensor-based approaches closely resemble practical navigational path. In model-based approaches, the robot has initial information regarding the environmental conditions, while in sensor-based approaches, the robot has no such information. Similarly, the methods developed for

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navigational purposes are also categorized as classical and artificial intelligent (AI) methodologies based on the theoretical formulations of the techniques.[1,2] While most of the classical methods such as regression analysis (RA), voronoi diagram (VD), edge detection (ED) technique, so on are derived from the standard statistical procedures, AI methods such as artificial neural network (ANN), genetic algorithm (GA), fuzzy logic control (FLC) are derived mostly from nature inspired phenomena. On a broad range, each technique has been criticized with its own advantages and limitations. However, on a broad side, classical methods can produce more converged results within a limited problem space, and AI techniques can be more accurate than the classical ones although they might take some more time in converging. The last few decades of robotics research are mostly devoted towards navigational analysis of different forms of robots. Although navigational analysis of all the forms of robots are simultaneously important, humanoids have created their separate place in researcher's mind by virtue of their resemblance to human structure. Some of the prominent researches in the aspect of navigation for humanoids and other forms of robots can be summarized over here.

Pun-Cheng et al.[3] used an exact cell decomposition method to design an autonomous path planning approach for smooth navigation of mobile robots. Glavaski et al.[4] proposed two classical techniques based on exact cell decomposition and artificial potential field approaches to navigate mobile robots in simulation environments. Cai and Ferrari[5] used an approximate cell-decomposition-based approach to detect multiple fixed target points during navigation of a mobile robot through sensors employed on it. Bhattacharya and Gavrilova[6,7] used Voronoi-diagram-based approaches to define an optimal path between source and target locations in a robotic path planning problem. Chen et al.[8] improvised the basic VD-based algorithm and obtained improved results by applying the same in navigation of a mobile robot. Haihan and Li[9] used Voronoi Diagram and Dijkatra's algorithm in a robot navigation problem and verified the approach in a simulation platform. Nattharith and Güzel[10] proposed a vision-integrated fuzzy-based control strategy for navigation of a target-following mobile robot. Dirik[11] discussed a fuzzy-logic-based navigational approach for hassle-free movement of a mobile robotic agent in an indoor arena. Shi et al.[12] developed a grid navigation model based on fuzzy concepts and applied the same in simulation and experimental platforms. Al-Mutib and Abdessemed[13] incorporated fuzzy-based reactive patterns on a mobile robot navigating in an indoor arena. Van Nguyen et al.[14] applied fuzzy-based reactive behaviours on a robotic platform and tested it successfully in an unknown environment. Zhong et al.[15] used a self-organizing neural network-based approach for navigation of a mobile robot in a complex environment. Sierakowski and dos Santos Coelho[16] used a bacterial colony-based navigational technique in smooth movement of a mobile robot in simulation platforms. Jhankal and Adhyaru[17] compared bacterial foraging-based approaches with simulated annealing-based ones and reviewed regarding the advantages and limitations of both. Chen et al.[18] critically reviewed regarding the limitations of the basic bacterial foraging method and proposed some modifications to overcome these limitations. Sharma and Satav[19] used the computational intelligence associated with bacterial foraging methods to navigate mobile robots in cluttered environments. Patle et al.[20,21] used firefly algorithm (FA) as a potential navigation strategy for mobile robots in obstacle-prone environments. They have verified their approach through multiple simulations and experiments. Parhi et al.[22–27] designed several intelligent algorithms for navigational analysis of multiple mobile robots. Pal and Sharma[28] reviewed regarding different swarm intelligence methods and discussed regarding their potential use in several engineering optimization problems. Hidalgo-Paniagua et al.[29] proposed an FA-based approach for online monitoring of mobile robot navigation in complex environments. Liu et al.[30,31] modified the basic firefly-based approach and used it in navigation of an underwater robot. Brand and Yu[32] developed an FA-based navigational controller for a mobile robot and used it in a simulation environment. Lee et al.[33] separated a complete problem of humanoid navigation into a series of small multi-objective optimization problems and tried to solve each part by the introduction of evolutionary algorithms. Rath et al.[34–36] discussed regarding use of several nature-inspired algorithms in humanoid navigation. Ariffin et al.[37] added a mobile platform to a regular humanoid robot and proposed a sensor-based path finding strategy for the same. Kumar et al.[38–42] proposed various intelligent methodologies to plan smooth and hassle-free path for humanoid robots. Karkowski et al.[43] developed a footstep planning strategy for a humanoid model and combined it with A* algorithm and adaptive action sets for smooth movement in a rough terrain. Sahu et al.[44,45] developed humanoid motion planning schemes using swarm intelligence. Yoo and Kim[46] proposed a gaze-control-based navigational architecture for a humanoid model. Moulard et al.[47] developed a vision-based localization scheme for navigational analysis of humanoid robots.

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The review of existing works suggests that navigational analysis has been mostly applied on wheeled robotic forms and the use of the same in humanoid navigation is limited. Although some of the researchers have devoted their attention towards humanoid navigation, most of their approaches are focused on posture control, stability analysis and footstep planning. Online obstacle detection in complicated terrains and smooth avoidance of the detected obstacles is not yet fully explored in the existing works. Along with that, navigation of multiple humanoids on a common platform and verification of the simulation results in experimental platforms are yet to be completely defined in robotics world. Although some of the intelligent algorithms may navigate humanoids in a simple terrain, in complicated obstacle settings when there is possibility of arriving at a dead-end situation it is not taken care of in the existing schemes. Therefore, the current work is dedicated towards the design, development and implementation of a robust navigational strategy for humanoid robots capable of smooth navigation in any environment cluttered with obstacles. The controller is based on a virtual target displacement method named as DAYKUN-BIP Virtual Target Displacement (DVTD) strategy in which the robot is made to move along the direction of a virtual target if the path along the actual target is not collision-free. The selection of the virtual target line is governed by several factors nominated carefully based on the detailed control strategy of the algorithm. The scheme of moving the robot along a virtual target line helps in negotiating with a dead-end situation created by complicated obstacle settings. The proposed algorithm is verified in a simulation platform and validated in an experimental platform for navigational analysis of both single and multi-humanoid robots. To avoid any possibility of arriving at a conflict regarding avoidance of dynamic obstacles in navigation of multi-humanoids, a Petri-Net control strategy is integrated along with the proposed technique. The results obtained from both simulation and experimental platforms are compared against each other, and satisfactory agreement has been recorded. Finally, the developed navigational model is also validated against another existing navigational method, and a significant performance enhancement has been observed.

2. Control Architecture of DVTD Strategy

Mostly, classical methods are prone to continuous trapping at local minima; sometimes, AI techniques also face the same problem. It happens due to the fact that the robot has sensibility towards its immediate surrounding only and no prior knowledge regarding the global setting of the work environment. Along with that, the robot also doesn't remember the previous reactive behaviours it has undergone through. Due to high attraction from the target in a target-following behaviour, the robot sometimes gets trapped in a situation where it becomes very difficult to proceed further. To avoid these difficulties, virtual target shifting methods[48,49] were derived. Although there were discussions regarding the application of virtual target switching to mobile robots, the virtual target displacement method for navigation of humanoids was never taken into consideration. Humanoid navigation being the most discussed and challenging area of investigation of present-day robotics researchers requires an intelligent target displacement strategy with smooth obstacle avoidance, target-following behaviour along with avoiding being trapped at local minima.

2.1. Humanoid navigational model using DVTD strategy

The proposed control architecture of DVTD method can be discussed as follows. In the current work, NAO robots are used as the humanoid platform. NAO is a medium-sized programmable humanoid robot equipped with a large sensory network[50] consisting of SONARs, infrareds, tactile sensors, pressure sensors, force resistors, inertia board, cameras so on.

2.1.1. Analysis of obstacle intensity weight along target line. Figure 1 represents a typical arena condition with a robot at source location, multiple obstacles positioned at random locations and a predefined actual target. The initial heading angle of the robot is always directed towards the target location as the robot always obeys the target-following behaviour.

After the sensors detect an obstacle within the set threshold limit (30 cm for the current investigation), and no movement along the target direction is possible as it may result in a collision with the obstacles, the robot creates z number of virtual targets around the actual target along a curve of radius R_g from robot's current position, that is, the actual target is displaced to virtual target locations. R_g is the length of the actual target from the robot's current location.

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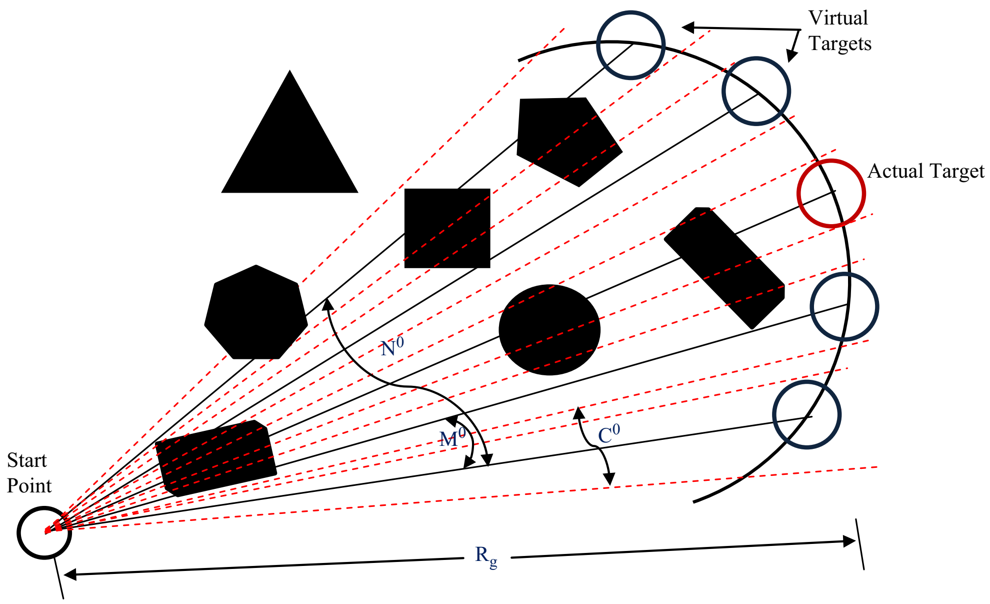

Fig. 1. Arena with actual and virtual targets.

T = Total possible direction of net feasible best position path (Total targets) = $z + 1$

The virtual targets are generated in a conical range of $N°$ and they are created at an equal interval of $M°$ around the actual target. Here, $N = 80^{\circ}$.

For an example purpose, four virtual targets are created here around the actual target which makes the total number of targets 5 (including actual target). The virtual targets are generated at an interval of $M = 20°$ around the actual target. The conical angle of visibility around each target is $C/2°$ in clockwise and $C/2°$ in anti-clockwise direction from the robot's current location to target position. $C°$ may vary from 0° to 60°. Here, it is taken as 30°. Now the robot calculates the total obstacle weightage along each target line by the following formulations.

Let front obstacle distance (FOD), left obstacle distance (LOD) and right obstacle distance (ROD) denote the nearest obstacle distances around front, left and right side respectively. Based on the specifications of the sensors used in the current work, a maximum and minimum detection range has been set as follows

Maximum obstacle distance (MAOD) = 250 cm, Minimum obstacle distance (MIOD) = 30 cm

The weightage of each obstacle (OW) at a distance 'OD' can be calculated by

$$\mathrm{OW} = \frac{\mathrm{OD} - \mathrm{MIOD}}{\mathrm{MAOD} - \mathrm{MIOD}}. \tag{1}$$

For an example, front obstacle weight (FOW) can be calculated as

$$\mathrm{FOW} = \frac{\mathrm{FOD} - \mathrm{MIOD}}{\mathrm{MAOD} - \mathrm{MIOD}}.$$

Now the total obstacle weight along a target line can be calculated as

$$W_{K1} = w_{\mathrm{t}}\,(0.6 \times \mathrm{FOW} + 0.2 \times \mathrm{LOW} + 0.2 \times \mathrm{ROW}), \tag{2}$$

where w_t is the target line weightage.

The actual target line is given a weightage of 1, and subsequently, there is a decrease of $\frac{0.5}{z/2}$ for each virtual target on either side. For example, if there are four virtual targets, where the first virtual target gets a weightage of 0.75, the second virtual target gets a weightage of 0.5 in either side of the actual target. It has to be noted that R_g has to lie within the MAOD set in the current problem; otherwise, the actual target is assumed to be shifted to the MAOD length along its own line, and the

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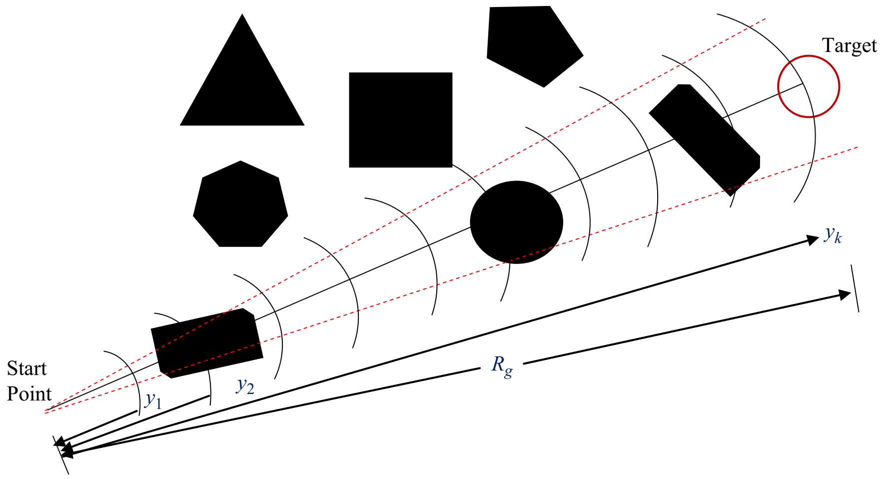

Fig. 2. A sample target line subdivided to equal intervals.

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The humanoid starts navigating towards the actual target
The sensors detect a potential obstacle within the set threshold limit:
DVTD strategy is activated
        z number of virtual targets are generated around the actual target at equal intervals
        Obstacle intensity weightage is calculated along each target line
        Obstacle availability weightage is calculated along each target line
        Step size weightage is calculated along each target line
        Calculate the total global weightage along each target line
                If (Total global weightage is zero for all target lines)
                        If (no-obstacle path available in front 180^0 of robot's current target line)
                                Robot moves in 90^0 on either side of robot's current target line
                        Else
                        Robot searches for a no-obstacle path in 180^0 in the back side
                Else
                The robot moves to the next step along the target line having maximum global weightage
                If (Actual target is reached)
                        Stop navigation mode
                Else if (Obstacle is detected)
                        Repeat the DVTD strategy to find next feasible step
                Else
                        Keep in navigation mode until an obstacle is detected or actual target is reached
```

Fig. 3. Pseudo code of DVTD strategy.

virtual targets are generated accordingly. Thus, the obstacle weight is calculated along each target line separately. It can be observed that a greater value of obstacle intensity weightage indicates a safer path to move.

2.1.2. Analysis of obstacle availability weight at various intervals of a target line. Figure 2 represents a single target line and the obstacles around it. The target length R_g is divided into k equal intervals at distances $y_1, y_2, y_3, \ldots, y_k$ from the robot's current location.

At each boundary of the set interval, the availability of obstacles (OA) is found out.

If obstacle is available, OA $= 1$, if obstacle is not available, OA $= 100$.

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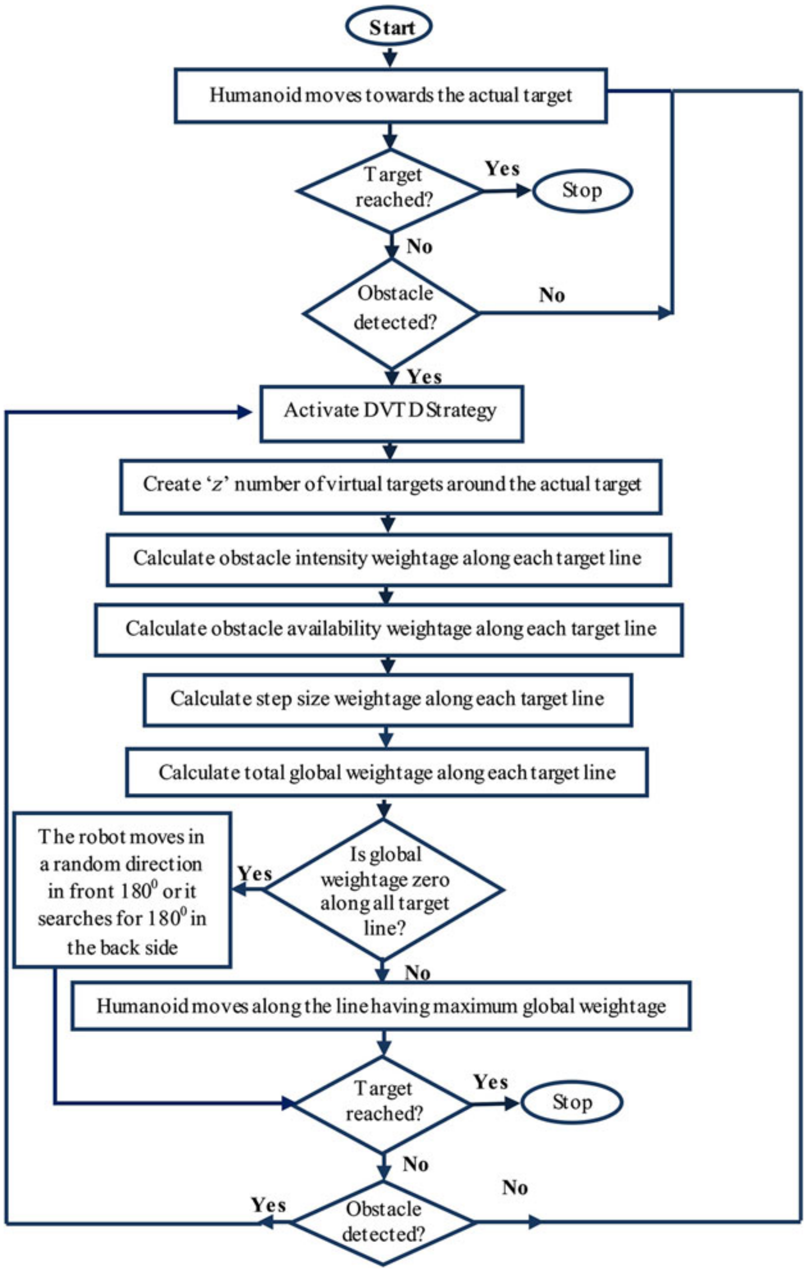

Fig. 4. Flowchart of DVTD strategy.

The total obstacle availability weightage along a target line is calculated as

$$W_{K2} = w_t \times \frac{\sum_{i=1}^{k} \frac{(k+1)-i}{k} \times \text{OA}}{k}, \tag{3}$$

where w_t carries the same meaning as explained in the previous section.

It can also be observed that a higher value of obstacle availability weightage indicates a safer path to move.

2.1.3. Analysis of step size weightage. While selecting the next feasible point to move, the step size carries an important role to play. If an obstacle is present within the next step size of movement, then the robot cannot move to that point, and that path becomes a non-feasible path.

Hence, if obstacle is present within the step size, then $W_{K3} = 0$, otherwise $W_{K3} = 1$.

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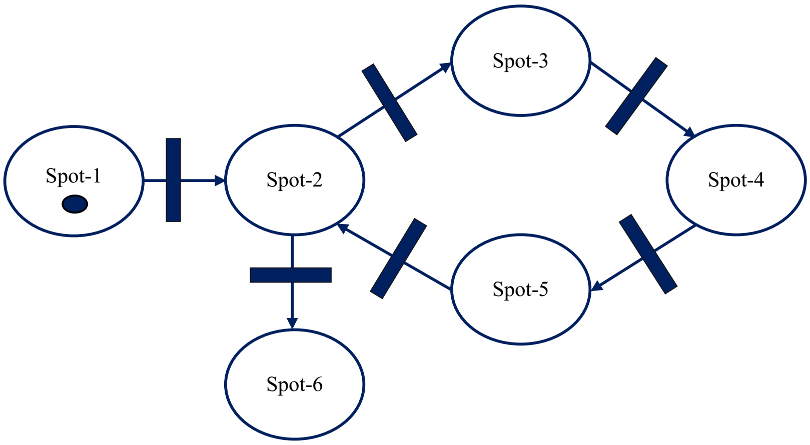

Fig. 5. Petri-Net control strategy.

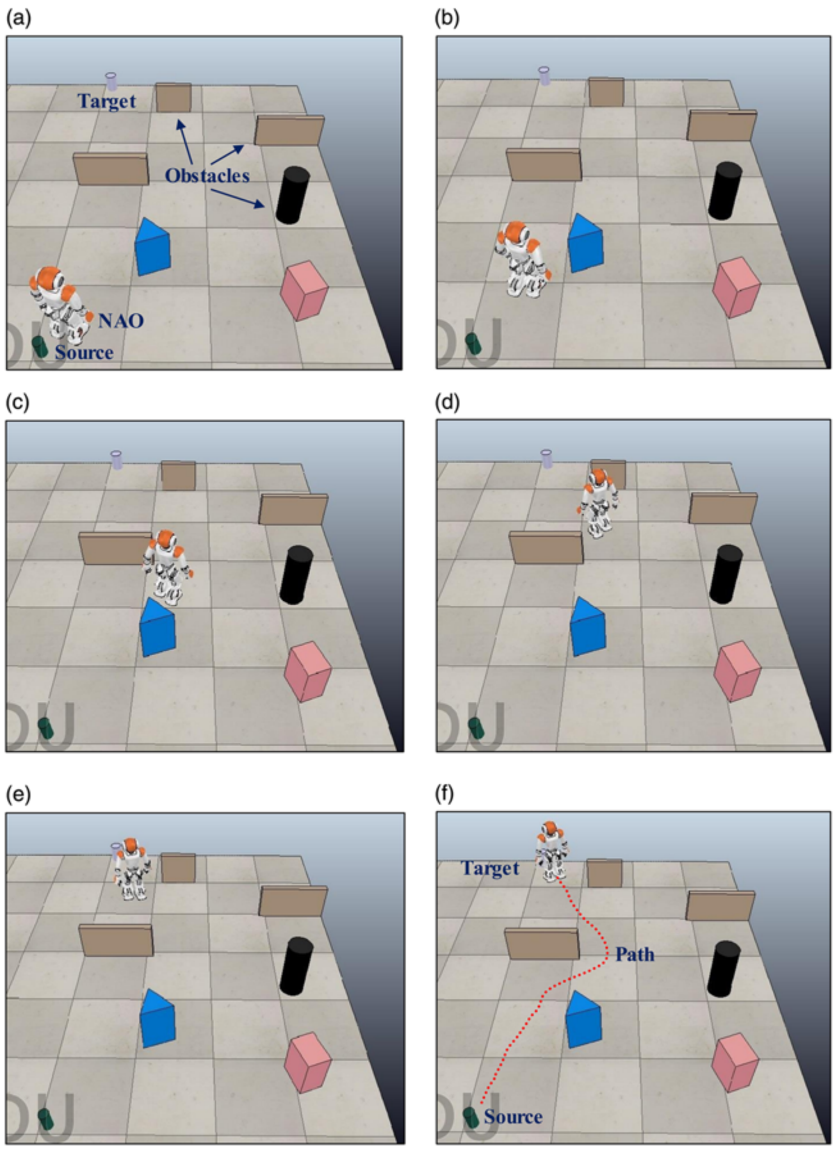

Fig. 6. Simulation results for navigation of a single humanoid using DVTD strategy.

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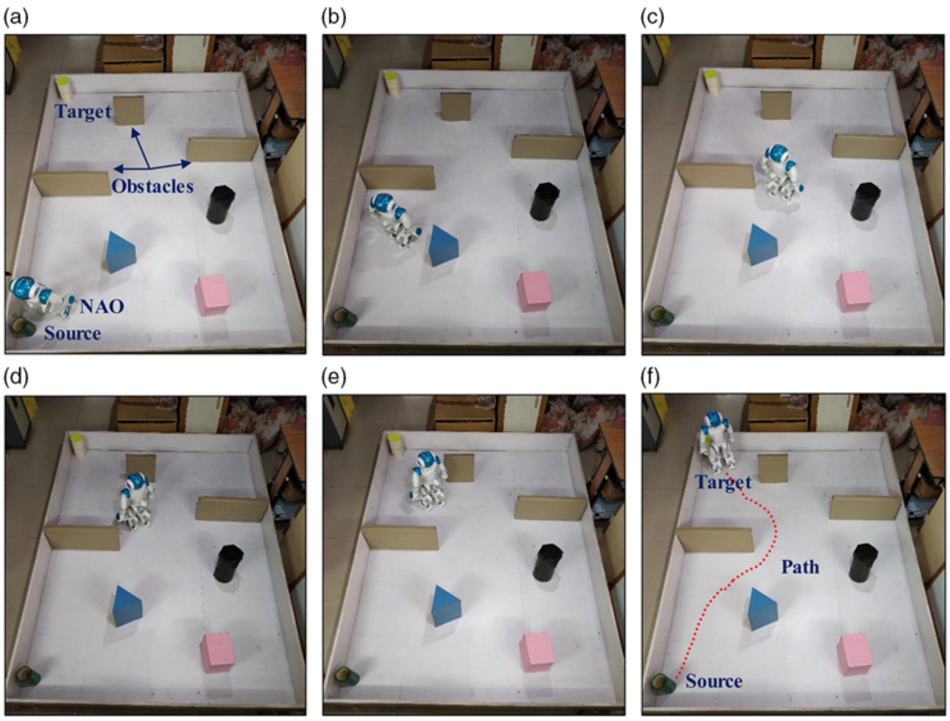

Fig. 7. Experimental results for navigation of a single humanoid using DVTD strategy.

2.1.4. Calculation of total global weightage along a target line. The total weightage along a target line is calculated as

$$W_{Kg} = W_{K1} \times W_{K2} \times W_{K3}. \tag{4}$$

As it is a maximization problem, the robot selects the target line having the maximum value of global weightage as the next feasible direction to move and proceeds for a specific step size in that direction and thus repeats the process unless reaches the actual target. There is a possibility that the value of W_{Kg} may be zero for all possible lines; in that case, the robot will choose a random direction in front 180° (90° on either side of robot's current target line in front side of the robot), and if no feasible path is available in front side of the robot, then it searches for 180° in the back side (90° on either side of robot's current target line in back side of the robot) where there is absence of obstacles and proceeds accordingly.

The entire process of navigational control using DVTD method is demonstrated as a pseudo code in Fig. 3 and as a flowchart in Fig. 4.

3. Petri-Net Control Strategy

The proposed control strategy has been applied to both single and multi-humanoid platforms. While navigating multi-humanoids on a common platform, the environment becomes a dynamic one. In a dynamic environment, there may be some conflicts in deciding the safe direction of turn while multi-humanoids come in the contact of a common obstacle. Therefore, a Petri-Net control strategy[51,52] is designed and integrated along with the proposed navigational model for smooth navigation of multi-humanoids. The working of a Petri-Net control strategy can be explained by the help of Fig. 5.

In Fig. 5, an oval mark denotes the present location of the robot, and the bar symbol denotes transition from one spot to another spot. The complete strategy is formulated using six spots, and each spot can be summarized as follows:

Spot-1: In this spot, all the robots are ready to navigate towards their respective target locations. Here, they are waiting for a start command, and the robots don't have any information regarding each other's current location.

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Table I. Validation of simulation results against experimental results for track span in navigation of a single humanoid.

Sl. No.	Track span in simulation (cm)	Track span in experiment (cm)	Inaccuracy in %
1	273.54	289.7	5.58
2	273.86	289.9	5.53
3	274.31	290.3	5.51
4	273.8	291	5.91
5	273.15	291.4	6.26
Average	273.73	290.46	5.76

Table II. Validation of simulation results against experimental results for interval lapsed in navigation of a single humanoid.

Sl. No.	Interval lapsed in simulation (s)	Interval lapsed in experiment (s)	Inaccuracy in %
1	37.24	39.58	5.91
2	37.47	39.74	5.71
3	38.1	40.41	5.72
4	37.65	40.27	6.51
5	37.96	40.05	5.22
Average	37.68	40.01	5.81

Spot-2: In this spot, start command is already initiated, and the robots proceed towards their target by the help of target-following behaviour. Here, the robots may encounter obstacles in their path.

Spot-3: It denotes the detection of a dynamic obstacle by a robot.

Spot-4: To resolve the conflict of a dynamic obstacle, the robot having less distance left towards its target is given a higher priority than the other robot, and it moves further while the other one waits as a static obstacle.

Spot-5: It denotes a regularity check if any further dynamic obstacles are present.

Spot-6: It denotes a special waiting condition in which a robot detects another set of robots already in a situation of conflict. In that case, the robot which has entered late to the system gets the lowest priority and waits as a static obstacle until the conflict between the first set of robots is resolved. After resolution of the conflict, the robot which was at a waiting condition commences its journey again stating from Spot-2.

The above discussed strategy can be used as a very effective way of handling multi-humanoid robots in a common platform.

4. Implementation of Proposed DVTD Strategy in Humanoid Navigation

As already stated, NAO humanoid robots are used as the platforms on which the proposed DVTD strategy has been implemented. The working of the control strategy is verified in both simulation and experimental platforms.

4.1. Navigation of a single humanoid using DVTD strategy

Here, Virtual Robot Experimental Platform (V-REP) has been selected as the suitable simulation platform for humanoid navigational analysis taking into consideration its advantageous properties like better collision detection and motion planning. Along with that, in V-REP, the humanoid is represented as a complete model which is not possible in MATLAB platform. An arena size of 240×160 units has been designated as the navigational space for humanoid movement. Six static obstacles are positioned at arbitrary locations of the arena, and the humanoid is fed with the logic of the developed control strategy in the form of a code formulated in LUA language. After defining

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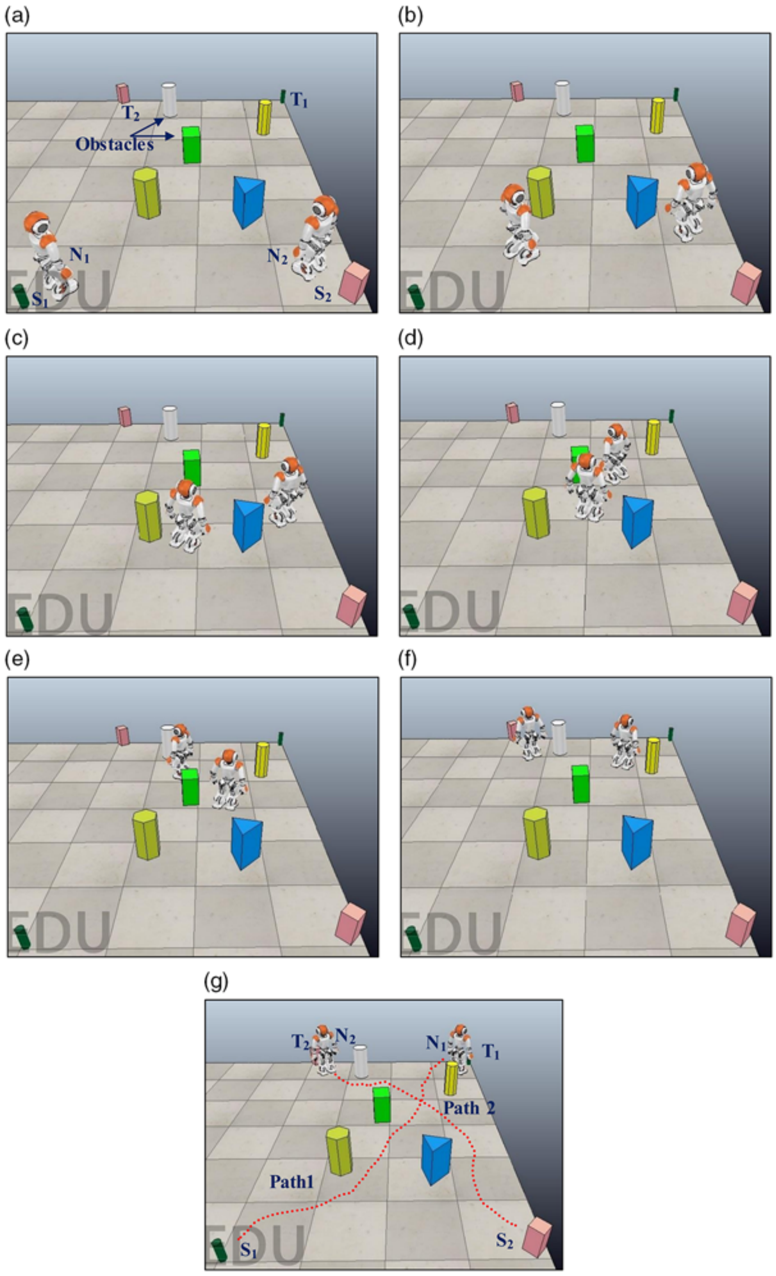

Fig. 8. Simulation results for navigation of multi-humanoids using DVTD strategy.

the specific source and target locations for the humanoid, it was set for motion towards its target. Figure 6 represents the simulation results obtained from the navigation of a single humanoid by the implementation of DVTD strategy.

The simulation results have revealed satisfactory results with the humanoid safely reaching the target location without any collision with the obstacles present in the arena.

To validate the simulation results, an experimental platform has been prepared under test conditions. The navigational space size is kept exactly same as 240 × 160 units, and the obstacles are also designed to the exact size of the simulation platform conditions. By placing the obstacles at their exact locations as that of the simulation, specific source and target locations are predefined for the humanoid. In the experimental platform, the logic of the developed control strategy is implemented on the humanoid by the help of python programming and the robot is operated on Wi-Fi mode. Figure 7 represents the experimental results obtained from the navigation of a single humanoid by the implementation of DVTD strategy.

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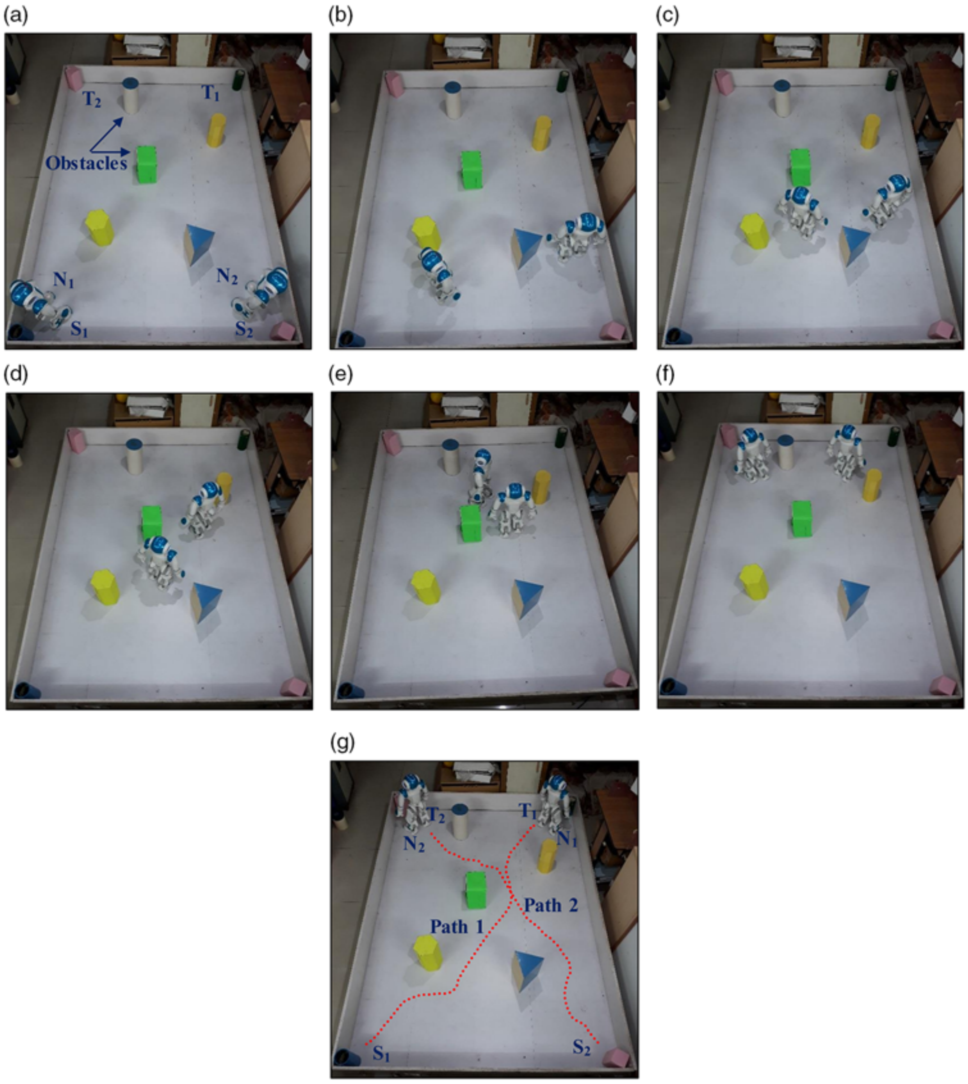

Fig. 9. Experimental results for navigation of multi-humanoids using DVTD strategy.

The experimental results have also revealed safe navigation of the humanoid from the source location to the target location. The validation of the simulation results against the experimental results has been performed through comparison of trajectory generated in navigation and suitable selected navigational parameters. Here, track span and interval lapsed in reaching the target location from the source location are selected as the two navigational parameters. These two parameters are directly recorded from the simulation window and are recorded by the help of a measuring tape and stopwatch, respectively, from the experimental platform. Tables I and II represent the validation of simulation results against experimental results for track span and interval lapsed, respectively.

The validation of simulation results against experimental counterparts earns minimal percentage of inaccuracy within the acceptable limit. It can be noticed that the values in experimental parts show a higher range than the simulation parts. The reason for the same is the presence of external hindrance factors like slippage effect, frictional reductions, data transmission losses, so on in the experimental platform which are ideal for the simulation platform.

4.2. Navigation of multi-humanoids using DVTD strategy

As discussed before, the Petri-Net control strategy is integrated along with the proposed navigational model for smooth movement along with possible conflict resolution for navigation of multi-humanoids. Here, the navigational space is kept constant as that of the previous section. Two

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Table III. Validation of simulation results against experimental results for track span in navigation of multi-humanoids.

	Simulation results		**Experimental results**			
	Track span (cm)				**Inaccuracy in %**	
Sl. No.	**H_1**	**H_2**	**H_1**	**H_2**	**H_1**	**H_2**
1	336.58	344.28	357.3	365.7	5.8	5.86
2	336.86	344.43	357.6	365.9	5.8	5.87
3	337.24	345.82	359.2	366.6	6.11	5.67
4	336.91	344.17	358.9	367.3	6.13	6.3
5	336.57	345.2	357.4	367.7	5.83	6.12
Average	336.83	344.78	358.08	366.64	5.93	5.96

Table IV. Validation of simulation results against experimental results for interval lapsed in navigation of multi-humanoids.

	Simulation results		**Experimental results**			
	Interval lapsed (s)				**Inaccuracy in %**	
Sl. No.	H_1	H_2	H_1	H_2	H_1	H_2
1	45.91	47.18	48.76	50.14	5.84	5.9
2	46.05	47.36	48.79	50.17	5.62	5.6
3	46.27	47.97	48.85	50.59	5.28	5.18
4	46.08	48.2	48.98	51.48	5.92	6.37
5	45.96	47.84	49.44	51.36	7.04	6.85
Average	46.05	47.71	48.96	50.75	5.94	5.98

humanoids and five static obstacles are used for the analysis. Specific predefined source and target locations are designated for each humanoid, and the logic of both DVTD and Petri-Net control strategy is supplied to the humanoids. Fig. 8 represents the simulation results, and Fig. 9 represents the experimental results obtained from the navigation of multi-humanoids by the implementation of DVTD strategy, respectively. Similarly, Tables III and IV represent the validation of simulation results against experimental results for track span and interval lapsed, respectively, for each humanoid.

The navigational pattern followed by the humanoids and validation of navigational results from both the platforms have also provided safe and convincing results which indicate the efficiency and accuracy of the developed control strategy.

5. Assessment of the Proposed DVTD Strategy against Another Existing Navigational Model

The proposed DVTD strategy has been assessed against an existing navigational model to prove performance enhancement of the control scheme. Al Yahmedi and Fatmi[53] have developed a fuzzy-logic-based navigational model for a robotic system and tested their approach in a simulation platform. They have designed a fuzzy-logic-based navigational model along with the integration of goal searching, obstacle avoidance, wall following and emergency situation behaviours with the fuzzy-logic-based model. The simulation platform developed by Al Yahmedi and Fatmi[53] has been replicated, and an assessment has been performed in terms of trajectory followed and track span. Fig. 10 represents the assessment in terms of trajectory followed and Table V represents the assessment in terms of path span.

It can be observed that there is an improvement about 14% by using the developed DVTD strategy compared to existing navigational model. Hence, the efficiency of the developed model is definitely

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Table V. Assessment of track span between fuzzy-based approach [38] and DVTD strategy.

Technique used	Track span in units	Enhancement in %
Fuzzy-based approach[53] (Fig. 10(a))	11.6	14.14
DVTD strategy (Fig. 10(b))	9.96	

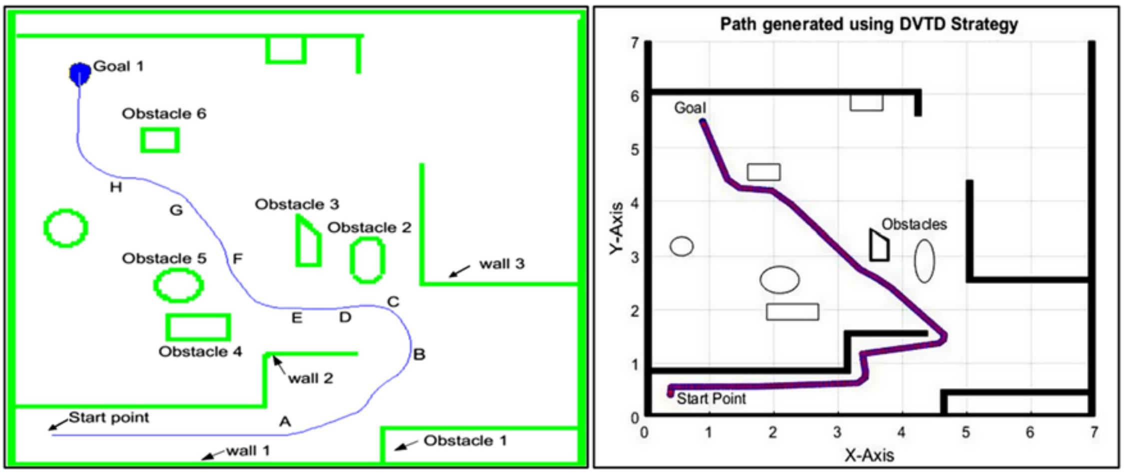

Fig. 10. (a) Path generated using fuzzy-based approach[53] and (b) path generated using DVTD strategy.

on an enhanced mode, and it can be used as a trusted navigational strategy for smooth and hassle-free movement of different forms of humanoid robots.

6. Conclusions

Being the most intelligent species on the entire globe, human beings always attempt to derive different intelligent plans to reduce human efforts in repetitive tasks. Navigation and path planning of humanoid models is one of the most prominent areas of research keeping in view of the growing demand towards industrial automation and smart manufacturing. In the current investigation, a novel DVTD-based navigational model has been proposed. In absence of an obstacle-free path along the actual target line, some virtual targets are generated around the actual target. Among all the target lines, the safest direction of motion is calculated by assigning suitable weightages to obstacle intensity, obstacle availability and step sizes. The proposed control strategy is implemented on a simulation platform and validated against an experimental platform using single as well as multi-humanoid robots. To avoid any possibility of inter-collision during navigation of multi-humanoids, a Petri-Net strategy is integrated with the developed model. Finally, the developed navigational model is also assessed against another existing navigational control scheme, and a significant improvement in the efficiency is observed.

References

1. D. R. Parhi and M. K. Singh, “Real-time navigational control of mobile robots using an artificial neural network,” *Proc. Inst. Mech. Eng. Part C* **223**(7), 1713–1725 (2009).
2. A. Pandey, R. K. Sonkar, K. K. Pandey and D. R. Parhi, “Path Planning Navigation of Mobile Robot with Obstacles Avoidance Using Fuzzy Logic Controller,” *IEEE 8th International Conference on Intelligent Systems and Control (ISCO)*, Coimbatore, India (2014) pp. 39–41.
3. L. S. C. Pun-Cheng, M. Y. F. Tang and I. K. L. Cheung, “Exact cell decomposition on base map features for optimal path finding,” *Int. J. Geogr. Inf. Sci.* **21**(2), 175–185 (2007).
4. D. Glavaski, M. Volf and M. Bonkovic, “Mobile robot path planning using exact cell decomposition and potential field methods,” *WSEAS Trans. Circuits Syst.* **8**(9), 789–800 (2009).
5. C. Cai and S. Ferrari, “Information-driven sensor path planning by approximate cell decomposition,” *IEEE Trans. Syst. Man Cybern. Part B (Cybernetics)* **39**(3), 672–689 (2009).

https://doi.org/10.1017/S0263574718001200 Published online by Cambridge University Press

6. P. Bhattacharya and M. L. Gavrilova, "Voronoi Diagram in Optimal Path Planning," *4th International Symposium on Voronoi Diagrams in Science and Engineering*, Glamorgan, UK (2007) pp. 38–47.
7. P. Bhattacharya and M. L. Gavrilova, "Roadmap-based path planning-using the voronoi diagram for a clearance-based shortest path," *IEEE Robot. Autom. Mag.* **15**(2), 58–66 (2008).
8. P. Chen, L. Xiaoqing, D. Jiyang and Y. Linfei, "Research of Path Planning Method Based on the Improved Voronoi Diagram," *25th Chinese Control and Decision Conference (CCDC)*, Guiyang, China (2013) pp. 2940–2944.
9. C. Haihan and S. Li, "Research on the Path Planning Based on Voronoi Diagram and Dijkatra's Algorithm," *IEEE Conference Anthology*, China (2013) pp. 1–4.
10. P. Nattharith and M. S. Güzel, "Machine vision and fuzzy logic-based navigation control of a goal-oriented mobile robot," *Adapt. Behav.* **24**(3), 168–180 (2016).
11. M. Dirik, "Collision-free mobile robot navigation using fuzzy logic approach," *Int. J. Comput. Appl.* **179**(9), 33–39 (2018).
12. H. Shi, X. Li, W. Pan, K. S. Hwang and Z. Li, "A novel fuzzy three-dimensional grid navigation method for mobile robots," *Int. J. Adv. Robot. Syst.* **14**(3), (2017). doi:10.1177/1729881417710444
13. K. Al-Mutib and F. Abdessemed, "Indoor mobile robot navigation in unknown environment using fuzzy logic based behaviors," *Adv. Sci. Technol. Eng. Syst. J.* **2**(3), 327–337 (2017).
14. T. T. Van Nguyen, M. D. Phung and Q. V. Tran (2017) "Behavior-based navigation of mobile robot in unknown environments using fuzzy logic and multi-objective optimization," preprint arXiv:1703.03161.
15. C. Zhong, S. Liu, Q. Lu and B. Zhang, "Continuous learning route map for robot navigation using a growing-on-demand self-organizing neural network," *Int. J. Adv. Robot. Syst.* **14**(6), (2017). doi:10.1177/1729881417743612
16. C. A. Sierakowski and L. dos Santos Coelho, "Path Planning Optimization for Mobile Robots Based on Bacteria Colony Approach," **In**: *Applied Soft Computing Technologies: The Challenge Of Complexity* (Springer, Berlin, Heidelberg, 2006) pp. 187–198.
17. N. K. Jhankal and D. Adhyaru, "Comparative analysis of bacterial foraging optimization algorithm with simulated annealing," *Int. J. Sci. Res. (IJSR)* **3**(3), 10–13 (2014).
18. H. Chen, Y. Zhu and K. Hu, "Adaptive bacterial foraging optimization," *Abstr. Appl. Anal.* **2011**, 1–27 (2011).
19. A. Sharma and S. Satav, "Path navigation using computational intelligence," *Int. J. Adv. Res. Comput. Sci. Softw. Eng.* **2**(7), 395–398 (2012).
20. B. K. Patle, D. Parhi, A. Jagadeesh and O. P. Sahu, "Real time navigation approach for mobile robot," *J. Chem. Phys.* **12**(2), 135–142 (2017).
21. B. K. Patle, D. R. Parhi, A. Jagadeesh and S. K. Kashyap, "On firefly algorithm: Optimization and application in mobile robot navigation," *World J. Eng.* **14**(1), 65–76 (2017).
22. D. R. Parhi and M. K. Singh, "Navigational strategies of mobile robots: A review," *Int. J. Autom. Control* **3**(2–3), 114–134 (2009).
23. P. K. Mohanty and D. R. Parhi, "A new hybrid optimization algorithm for multiple mobile robots navigation based on the CS-ANFIS approach," *Memetic Comput.* **7**(4), 255–273 (2015).
24. B. B. V. L. Deepak and D. R. Parhi, "Control of an automated mobile manipulator using artificial immune system," *J. Exp. Theor. Artif. Intell.* **28**(1–2), 417–439 (2016).
25. A. Pandey and D. R. Parhi, "Multiple mobile robots navigation and obstacle avoidance using minimum rule based ANFIS network controller in the cluttered environment," *Int. J. Adv. Robot. Autom.* **1**(1), 1–11 (2016).
26. P. K. Mohanty and D. R. Parhi, "A new intelligent motion planning for mobile robot navigation using multiple adaptive neuro-fuzzy inference system," *Appl. Math. Inf. Sci.* **8**(5), 2527 (2014).
27. J. K. Pothal and D. R. Parhi, "Navigation of multiple mobile robots in a highly clutter terrains using adaptive neuro-fuzzy inference system," *Robot. Auton. Syst.* **72**, 48–58 (2015).
28. N. S. Pal and S. Sharma, "Robot path planning using swarm intelligence: A survey," *Int. J. Comput. Appl.* **83**(12), 5–12 (2013).
29. A. Hidalgo-Paniagua, M. A. Vega-Rodríguez, J. Ferruz and N. Pavón, "Solving the multi-objective path planning problem in mobile robotics with a firefly-based approach," *Soft Comput.* **21**(4), 949–964 (2017).
30. C. Liu, Y. Zhao, F. Gao and L. Liu, "Three-dimensional path planning method for autonomous underwater vehicle based on modified firefly algorithm," *Math. Probl. Eng.* **2015**, 1–10 (2015).
31. C. Liu, Z. Gao and W. Zhao, "A New Path Planning Method Based on Firefly Algorithm," *Fifth International Joint Conference on Computational Sciences and Optimization (CSO)*, Harbin, China (2012) pp. 775–778.
32. M. Brand and X. H. Yu, "Autonomous Robot Path Optimization Using Firefly Algorithm," *International Conference on Machine Learning and Cybernetics (ICMLC)*, Tianjin, China, Vol. 3 (2013) pp. 1028–1032.
33. K. B. Lee, H. Myung and J. H. Kim, "Online multiobjective evolutionary approach for navigation of humanoid robots," *IEEE Trans. Ind. Electron.* **62**(9), 5586–5597 (2015).
34. A. K. Rath, H. C. Das, D. R. Parhi and P. B. Kumar, "Application of artificial neural network for control and navigation of humanoid robot," *J. Mech. Eng. Sci.* **12**(2), 3529–3538 (2018).
35. A. K. Rath, D. R. Parhi, H. C. Das, M. K. Muni and P. B. Kumar, "Analysis and use of fuzzy intelligent technique for navigation of humanoid robot in obstacle prone zone," *Defence Technol.* **14**(6), 677–682 (2018).

https://doi.org/10.1017/S0263574718001200 Published online by Cambridge University Press

36. A. K. Rath, D. R. Parhi, H. C. Das and P. B. Kumar, “Behaviour based navigational control of humanoid robot using genetic algorithm technique in cluttered environment,” *Modell. Measur. Control A* **91**(1), 32–36 (2018).
37. I. M. Ariffin, A. I. H. M. Rasidi, H. Yussof, Z. Mohamed, M. A. Miskam, A. T. M. Amin and A. R. Omar, “Sensor based mobile navigation using humanoid robot Nao,” *Procedia Comput. Sci.* **76**, 474–479 (2015).
38. A. Kumar, P. B. Kumar and D. R. Parhi, “Intelligent navigation of humanoids in cluttered environments using regression analysis and genetic algorithm,” *Arabian J. Sci. Eng.* **43**(12), 7655–7678 (2018).
39. P. B. Kumar, S. Mohapatra and D. R. Parhi, “An intelligent navigation of humanoid NAO in the light of classical approach and computational intelligence,” *Comput. Animat. Virtual Worlds*, e1858 (2018). doi:10.1002/cav.1858
40. P. B. Kumar, K. K. Pandey, C. Sahu, A. Chhotray and D. R. Parhi, “A Hybridized RA-APSO Approach for Humanoid Navigation,” *Nirma University International Conference on Engineering (NUiCONE)*, Ahmedabad, India (2017) pp. 1–6.
41. P. B. Kumar, C. Sahu and D. R. Parhi, “A hybridized regression-adaptive ant colony optimization approach for navigation of humanoids in a cluttered environment,” *Appl. Soft Comput.* **68**, 565–585 (2018).
42. P. B. Kumar, C. Sahu, D. R. Parhi, K. K. Pandey and A. Chhotray, “Static and dynamic path planning of humanoids using an advanced regression controller,” *Sci. Iranica* (2018). doi:10.24200/SCI.2018.5064.1071
43. P. Karkowski, S. Oßwald and M. Bennewitz, “Real-Time Footstep Planning in 3D Environments,” *IEEE-RAS 16th International Conference on Humanoid Robots (Humanoids)*, Cancun, Mexico (2016) pp. 69–74.
44. C. Sahu, P. B. Kumar and D. R. Parhi “An intelligent path planning approach for humanoid robots using adaptive particle swarm optimisation,” *Int. J. Artif. Intell. Tools* **27**(5), 1850015 (2018).
45. C. Sahu, D. R. Parhi and P. B. Kumar, “An approach to optimize the path of humanoids using adaptive ant colony optimization,” *J. Bionic Eng.* **15**(4), 623–635 (2018).
46. J. K. Yoo and J. H. Kim, “Gaze control-based navigation architecture with a situation-specific preference approach for humanoid robots,” *IEEE/ASME Trans. Mechatron.* **20**(5), 2425–2436 (2015).
47. T. Moulard, P. F. Alcantarilla, F. Lamiraux, O. Stasse and F. Dellaert, “Reliable indoor navigation on humanoid robots using vision-based localization,” Rapport LAAS Number 12549 (2012).
48. W. L. Xu, S. K. Tso and Y. H. Fung, “Fuzzy reactive control of a mobile robot incorporating a real/virtual target switching strategy,” *Robot. Auton. Syst.* **23**(3), 171–186 (1998).
49. W. L. Xu and S. K. Tso, “Sensor-based fuzzy reactive navigation of a mobile robot through local target switching,” *IEEE Trans. Syst. Man Cybern. Part C (Appl. Rev.)* **29**(3), 451–459 (1999).
50. N. Kofinas, E. Orfanoudakis and M. G. Lagoudakis, “Complete analytical forward and inverse kinematics for the NAO humanoid robot,” *J. Intell. Robot. Syst.* **77**(2), 251–264 (2015).
51. J. L. Peterson, *Petri Net Theory and the Modeling of Systems* (Prentice-Hall, Englewood Cliffs, NJ, 1981).
52. D. T. Pham and D. R. Parhi, “Navigation of multiple mobile robots using a neural network and a Petri Net model,” *Robotica* **21**(1), 79–93 (2003).
53. A. S. Al Yahmedi and M. A. Fatmi, “Fuzzy Logic Based Navigation of Mobile Robots,” In: *Recent Advances in Mobile Robotics* (InTech, London, UK, 2011).

https://doi.org/10.1017/S0263574718001200 Published online by Cambridge University Press