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Dynamic Strategy Planning of Humanoid Robots Using Glowworm-Based Optimization

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SUMMARY
In this paper, a novel dynamic navigational planning strategy is proposed for single as well as multiple humanoids in intricate environments on a glowworm-based optimization method. The sensory information regarding the obstacle distances and target information are supplied as inputs to the navigational model. The essential turning angle is generated as the output of the controller to avoid obstacles present in the environment and reach the target location with ease. The proposed model is certified in a V-REP simulation software, and the simulation results are authenticated in a real-time setup arranged under testing conditions.

KEYWORDS: Glowworm optimization; Humanoid; Dynamic planning; Petri-Net; V-REP.

1. Introduction

Human beings have always believed in a simple principle that the best way to avoid a problem is to create a feasible solution for it. To assist in tiresome and repetitive tasks of industrial automation and intelligent manufacturing, the use of robots has popularly increased. Humanoids have become the topic of major discussion since last few decades owing to their ability to replace human efforts in the above-mentioned areas. To do so, navigational analysis and motion planning bear a major importance. Hence, most of the researches in robotics sector have been devoted toward navigational analysis of enormous forms of robotic agents. Humanoid navigation being the most thought provoking area of investigation among robotics researchers demands careful attention toward selection of navigational parameters. The navigational techniques developed since the introduction of intelligent motion planning can be categorized broadly as model-based motion planning and sensor-based motion planning. While model-based motion planning takes into account the detailed information regarding the environmental conditions from the very beginning of planning step itself, sensor-based motion planning is a real-time obstacle detection and immediate planning strategy. Although

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model-based motion planning may seem easy to deal with, sensor-based motion planning can be most effective in real-life scenarios of robotics use. A critical insight into the intelligent navigational approaches justifies that each algorithm has got its own superiority and limitations over other. Some of the distinguished investigations toward robot navigations can be taken into consideration over here.

Glowworm optimization (GO) or Firefly Algorithm (FA) has gained approval from researchers in terms of ease in engineering problem-solving. Yang[1] introduced FA as an optimization algorithm for engineering problems and demonstrated the use of the same in a pressure vessel design problem. Krishnanand et al.[2,3] proposed a glowworm-based multiple source detection methodology in a robot navigation problem. Christenson et al.[4] used a glowworm-based self-reparatory system to assign incomplete tasks by a non-functional robot to a fully functional one along with creation of repairing mechanism by the swarm of robots. Hidalgo-Paniagua et al.[5] developed an FA-based navigational system to solve the multi-objective problem of robot path planning in a complicated obstacle setting. Ahmadi et al.[6] discussed the potential of both classical and evolutionary approaches toward generating a smooth motion planning model for unmanned aerial vehicles within constrained space. Patle et al.[7,8] used FA as a motion planning strategy for single as well as multiple mobile robots. Sathyan and Ma[9] used a genetic fuzzy-based approach for solving navigational analysis of multiple mobile robots in a common platform. Brand and Yu[10] developed a FA-based navigational strategy for humanoid robots and used it in a simulation arena. Liu et al.[11] proposed a firefly-based robot navigation model in a complex arena with obstacle avoidance behavior. Zhang et al.[12] used a combined model of FA with evolutionary techniques to solve a global optimization problem and obtained satisfactory results. Liu et al.[13] modified the basic version of a firefly-based algorithm and used it in navigational planning of an underwater robotic model. Horng and Jiang[14] used a firefly-based approach in multi-level image thresholding operation. Wang et al.[15] proposed a firefly-based approach in guiding a combat air vehicle in challenging terrains. Fister et al.[16] proposed a comparative review regarding the potential uses of FA in engineering optimization and other related applications. It can be observed that most of the uses of glowworm-based methods are focused on navigational motion planning for wheeled robotic forms. The use of the same in humanoid navigation is infrequently reported.

Some of the focused investigations on humanoid navigation can also be considered over here. Ariffin et al.[17] used a humanoid robot in a mobile robotic platform and performed sensor-based navigation of the system. Wei-guo and Yue-yang[18] analyzed the rapid walking behavior of a biped model using surface table cart scheme. Scianca et al.[19] proposed model predictive control schemes for stability and feasibility study of a humanoid gait pattern. Yussof et al.[20] developed a 21-degree of freedom humanoid model and designed its walking pattern synthesis. Pino et al.[21] used a humanoid NAO in memory program analysis which is helpful for elderly people having mild cognitive impairment. Nava et al.[22] proposed momentum-based controllers for humanoid navigation and formulated an approach for the stability analysis. Clever and Mombaur[23] developed a motion transfer scheme from humans to humanoids using a 3D template model. Kumar et al.[24–26] developed various humanoid motion planning models using computational intelligent techniques. Baskoro and Priyono[27] used zero moment point and inverse kinematics information for stability analysis of a humanoid model. Göngör and Tutsoy[28] proposed analysis of a facial character algorithm for a humanoid robot.

It can be inferred that although some of the works report regarding the humanoid analysis, yet most of them are focused on stability analysis, posture control and humanoid model synthesis. Online obstacle detection and motion planning approaches are yet to be fully explored for humanoid robots. GO being established as an effective method of solving mobile robot navigation problem has not been explored much for the analysis of humanoid motion planning. Therefore, keeping in view of the limitations available in the above literature citations, the objective of the current research is set as design and implementation of a novel dynamic motion planning strategy for humanoid robots in complicated terrains irrespective of the environmental conditions. Here, the motion planning strategy is based on GO algorithm. The sensory information regarding obstacle distances and target location are fed as inputs to the navigational model, and essential turning angle (ETA) is obtained as the output of the controller. The proposed navigational scheme is certified in a V-REP simulation platform, and the simulation results are authenticated in a real-time setup. The simulation and real-time results are evaluated against each other, and a proper agreement is found between them. To avoid the possibility of inter-collision in the navigation of multiple humanoids in a common platform, a Petri-Net control

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strategy is integrated along with the GO controller. Finally, the developed motion planning strategy is verified against another recognized navigational model, and a significant performance improvement has been recorded.

2. Humanoid Motion Planning Strategy Using Glowworm Optimization

GO is one of the well-recognized nature-inspired algorithms derived from the flashing behavior of fireflies.[1–3] GO acts as a signal generating mechanism by which each glowworm is attracted toward other glowworms following certain patterns of movement. There are certain assumptions in the working of a GO system which can be summarized as follows.

(i) Regardless of sex, all glowworms are attracted toward each other as they are considered to be unisexual in the algorithm.
(ii) The glowworms are drifted toward each other in proportion to their brightness. The less bright one always moves toward brighter one. Along with that, as the distance between two glowworms decreases, the brightness also increases, and *vice versa*.
(iii) The brightest glowworm in the population gets the highest priority of movement, and it is free to move in any direction in the selected workspace. The measure of the brightness is always determined by the type of objective function selected for the population.

2.1. Control architecture for humanoid navigation

The working of the proposed glowworm system can be summarized by the following mathematical formulations.

The brightness of a glowworm determines its attractiveness. Let I_f denote the brightness of a glowworm at a particular location l_x. As per a general convention,

$$I_f(x) \propto l_x \tag{1}$$

However, as distance between two glowworms increases, the brightness also decreases. Let p and q are two positions and the glowworms present at these two locations are taken into consideration. Let glowworm at p is less bright and glowworm at q is brighter; then, glowworm p would move toward glowworm q. Here, glowworm p can be considered as the source, and glowworm q can be considered as the target. In such a situation, light intensity can be defined as:

$$I_f(p) = \frac{I_{st}}{d^2} \tag{2}$$

where I_{st} denotes the standard or original light intensity and d represents the distance between two glowworms.

Let δ denote the standard light absorption coefficient, the variation of light intensity with respect to distance can be written as:

$$I_f = I_{st} e^{-\delta d} \tag{3}$$

To avoid a null value at zero distance, Eq. (3) can be reframed as:

$$I_f = I_{st} e^{-\delta d^2} \tag{4}$$

Let α denote the attractiveness of a glowworm toward other glowworms. As attractiveness of a glowworm has direct relationship with light intensity, it can be mathematically defined as:

$$\alpha = \alpha_z e^{-\delta d^2} \tag{5}$$

For simplicity purpose, the above exponential relation can be reframed as:

$$\alpha = \frac{\alpha_z}{1 + \delta d^2} \tag{6}$$

In the above Eqs. (5) and (6), a characteristics length where the attractiveness takes a shift from α_z to $\alpha_z e^{-1}$ or $\alpha_z/2$ can be defined as: $\Omega = 1/\sqrt{\delta}$.

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The distance between two glowworms at point p and q can be defined as:

$$d_{pq} = \sqrt{(p_y - q_y)^2 + (p_x - q_x)^2} \tag{7}$$

Hence, the drifting of one glowworm toward other glowworm in each step can be defined as:

$$\begin{aligned} p_{x+1} &= p_x + \alpha_z e^{-\delta d^2} \{p_x - q_x\} + \gamma\theta_p \\ p_{y+1} &= p_y + \alpha_z e^{-\delta d^2} \{p_y - q_y\} + \gamma\theta_p \end{aligned} \tag{8}$$

where $\gamma\theta_p$ accounts for the randomization present in the algorithm.

In the movement of the glowworms inside the work environment, there is a periodic drop of brightness observed. To balance it, the brightness of all the glowworms needs to be updated in each iteration as per the following rule:

$$I_f(n+1) = (1 - \sigma_1) I_f(n) + \sigma_2 . FF\{p_x(n)\} \tag{9}$$

where σ_1 and σ_2 are the coefficients used for balancing the periodic drop of brightness and $FF\{p_x(n)\}$ is the fitness function which relates to the glowworm p.

Here, humanoid NAO is considered as the humanoid platform on which the motion planning strategy is implemented. NAO is a smart humanoid robot armed with a variety of sensors[29] such as SONARs, infrareds, tactile sensors, inertial board, force resistors, etc. In the current work, the SONARs of NAO are considered to detect and process obstacles present in the arena.

2.2. *Formulation of fitness function*

To optimize the humanoid motion planning toward the set target, fitness function plays a vital role as it contains effect of selected navigational parameters. In the current work, obstacle evasion pattern, target seeking pattern and drifting minimization pattern are selected as the key parameters to be considered while formulating the fitness function.

2.2.1. Obstacle evasion pattern. The glowworm-based algorithm works in such a way that the motion of the agent is determined by the brightest firefly. The target is always considered as the brightest glowworm, and all other glowworms are drifted toward the target. When the sensors of the humanoid detect a potential obstacle within the minimum sensing range, a swarm of glowworms is created around the obstacle. The sensor output regarding the nearest obstacle from the humanoid is termed nearest obstacle range (NOR). In the swarm, the glowworms move systematically toward their brightest glowworm. However, the brightest glowworm in the swarm eventually moves toward the target as it experiences a strong attraction from it. In the population, the brightest glowworm should move in such a way that it maintains a maximum distance from the obstacle. Here, the global fitness function which is the combination of individual parts is considered as a minimization problem. So, the fitness function for obstacle evasion pattern has to be minimized and inversely proportional to the obstacle distance.

$$FF_{OIP} \propto \frac{1}{\min(OIP_d)} \tag{10}$$

where $OIP_d = \sqrt{(NP_x - NOR_x)^2 + (NP_y - NOR_y)^2}$

(NP_x, NP_y), (NOR_x, NOR_y) denote the coordinates of next position of glowworm's movement and NOR, respectively.

2.2.2. Target seeking pattern. In target seeking pattern, the brightest glowworm along with other glowworms should always head toward the target in the absence of obstacles present in the environment. Hence, the next point of movement should be selected in such a way that it keeps minimum distance from the target. Hence, it shows a direct relationship.

$$FF_{TSP} \propto \min(TSP_d) \tag{11}$$

where $TSP_d = \sqrt{(HT_x - NP_x)^2 + (HT_y - NP_y)^2}$

(HT_x, HT_y) denotes the coordinates of humanoid's target point.

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```
Start
        The humanoid heads towards the target
        If no obstacle is sensed
                If target is reached
                        Stop navigation
                Else
                        Keep heading towards target
        Else
                GO controller is provoked
                Swarm of virtual glowworms is created
                Glowworms are sorted as per their brightness
                Fitness function is formulated
                Global best position is designated
                Essential turning angle is calculated
                Humanoid moves to the next position as per ETA
                If target is reached
                        Stop navigation
                Else
                        Repeat the GO controller
End
```

Fig. 1. Pseudocode of GO-based navigational strategy.

2.2.3. Drifting minimization pattern. A glowworm should follow the shortest route while drifting toward the other glowworms to select the next position of movement. Hence, it can be considered as a direct relationship.

$$FF_{DMP} \propto \min(DMP_d) \tag{12}$$

where $DMP_d = \sqrt{(NP_x - CP_x)^2 + (NP_y - CP_y)^2}$

(CP_x, CP_y) denotes the coordinates of humanoid's current position.

The global fitness function can be obtained by suitable combination of the individual parts assigning certain weightage to each part as:

$$FF_{gl} = \mu_1 \times FF_{OIP} + \mu_2 \times FF_{TSP} + \mu_3 \times FF_{DMP} \tag{13}$$

where μ represents the weightages assigned to each part of the global fitness function.

As the global fitness function is considered as a minimization problem, the solution containing the least value of fitness function is considered as the most feasible one. Selection of the global fitness function is completely user-specific. Each artificial intelligent technique tends to optimize a mathematical function through a series of iterations, and it can either maximize or minimize the function. The user needs to design the function as per the problem requirement such that it satisfies the objective. As in the current humanoid navigation problem, it is required to generate minimal path for the humanoid to reach the target, the global fitness function has been considered as a minimization problem. The next step of humanoid's movement is greatly influenced by the weightages assigned to each part of the global fitness function. A trial and error method is adopted to select these values. After finding out the most feasible point to move, the ETA is calculated by simple geometrical measures and the humanoid moves to the next position as per the calculated ETA.

The proposed glowworm-based motion planning strategy is represented as a pseudocode in Fig. 1 and as a flow chart in Fig. 2.

3. Execution of the GO-Based Motion Planning Strategy

The developed navigational strategy has been executed in a V-REP simulation platform, and the simulation results are authenticated in a real-time setup arranged under testing conditions. Here, testing conditions refer to the laboratory conditions where an experimental setup is created similar to a real-life scenario.

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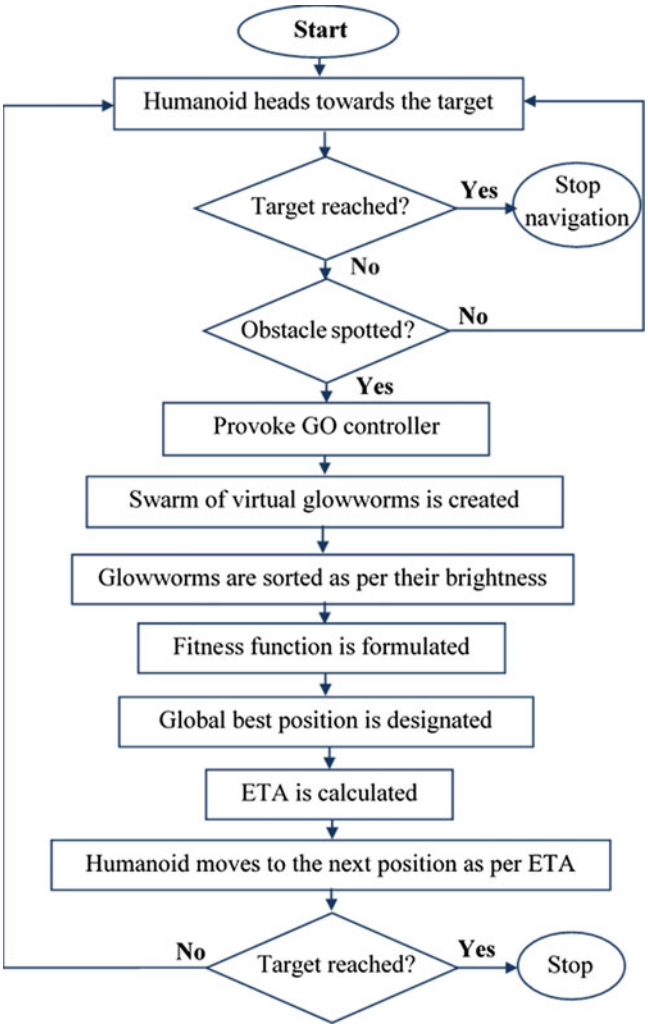


Fig. 2. Flow chart of GO-based navigational strategy.

3.1. Motion planning for a single humanoid

V-REP simulation software has gained popularity over other packages owing to its better motion planning and obstacle detection and processing criteria. In the current work, an arena of size 240×160 units is considered as the navigation space in the V-REP simulation window. Six obstacles of variable shape and size are placed randomly in the navigation space. Specific source and target positions are designated for the humanoid. The logic of the proposed navigational strategy has been fed in the form of a code to the humanoid, and it was set for heading toward the target. The simulation results are represented in Fig. 3.

To authenticate the simulation results, a real-time platform of same navigational space size has been arranged under test conditions. The obstacle sizes and locations are kept same as that of the simulation, and similar source and target locations are designated. Here, the humanoid was operated through a Wi-Fi mode, and the navigational strategy was fed as a Python software package. The real-time results are represented in Fig. 4.

The simulation and real-time results show promising outcomes in terms of ease in navigation and maintenance of optimal path. To evaluate the simulation results with real-time results, trajectory produced, track stretch and period lapsed are considered as the navigational parameters. From Figs. 3 and 4, it can be noticed that in both simulation and real-time arena, the humanoid has followed a similar trajectory. Track stretch and period lapsed are recorded directly from the V-REP simulation

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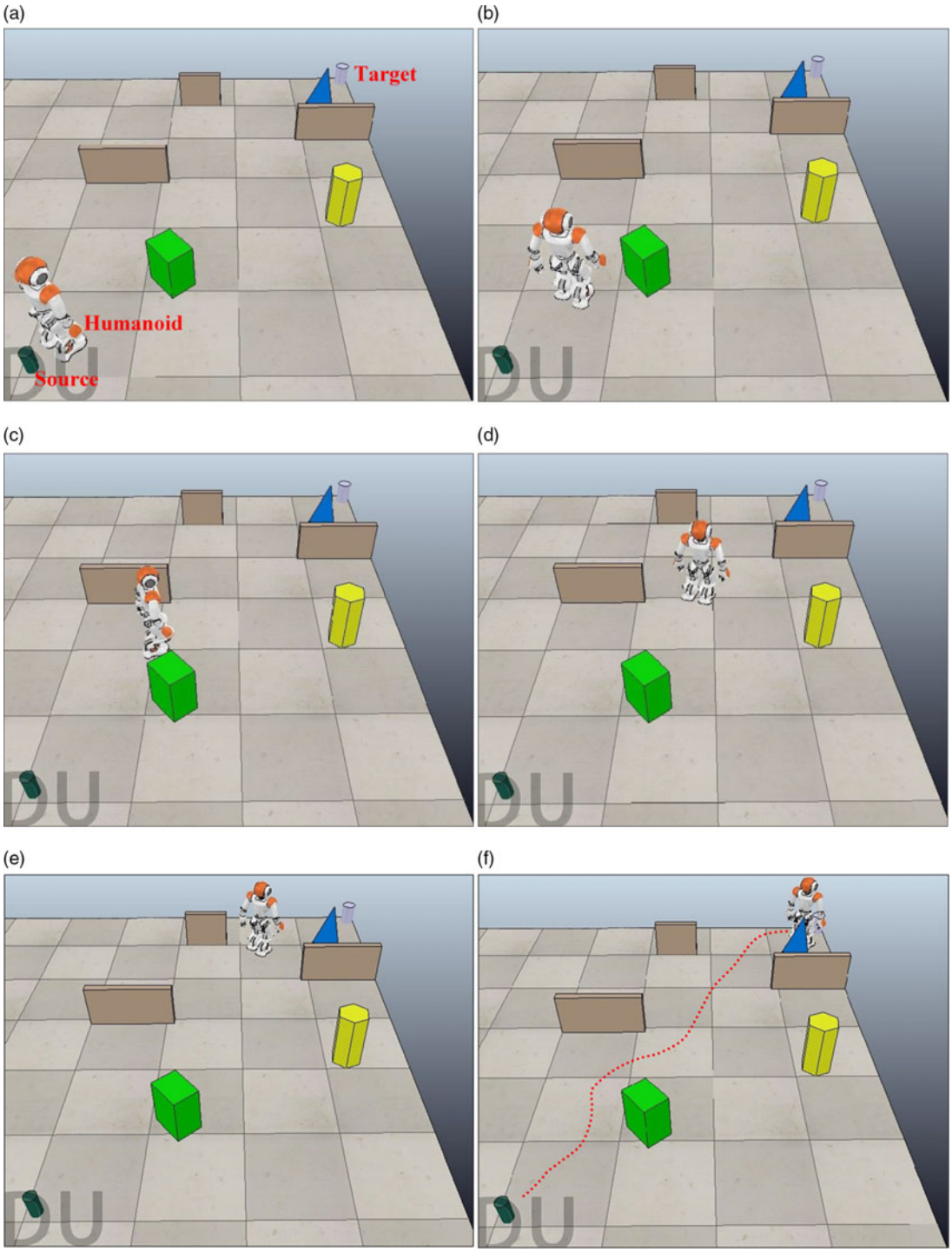


Fig. 3. Simulation results for a single humanoid.

window, and a measuring tape and stopwatch are used to record these two in the real-time setup. The evaluation of track stretch and period lapsed is represented in Tables I and II, respectively.

A proper agreement has been observed between the simulation and real-time results in execution of the proposed navigational strategy for a single humanoid. The real-time results can be noticed to generate higher values of the navigational parameters. Slippage loss, frictional loss and data transmission loss in the real-time arena account for the reason of the same.

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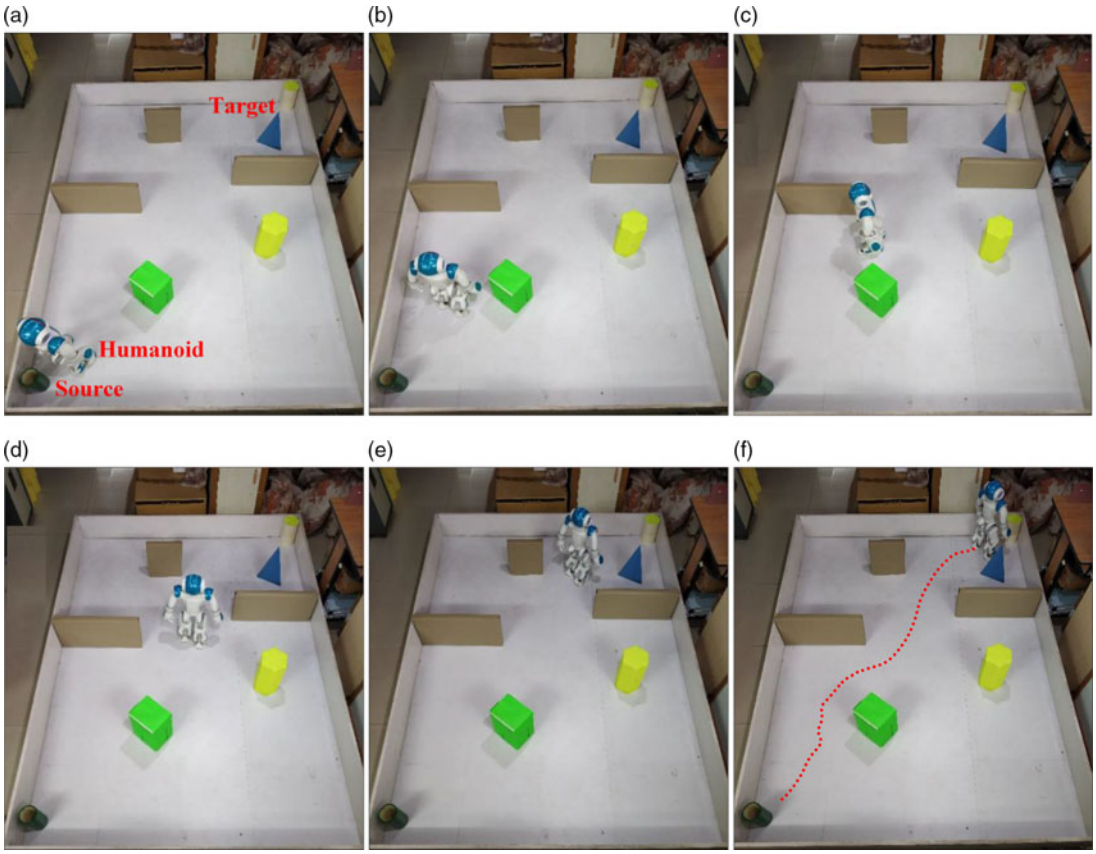


Fig. 4. Real-time results for a single humanoid.

Table I. Evaluation of simulation arena against real-time arena in terms of track stretch for a single humanoid.

Sl. No.	Track stretch in simulation (cm)	Track stretch in real-time (cm)	% Error
1	312.51	329.8	5.24
2	312.92	330.2	5.23
3	313.68	331.7	5.43
4	313.4	331.9	5.57
5	313.14	330.4	5.22
Average	313.13	330.8	5.34

Table II. Evaluation of simulation arena against real-time arena in terms of period lapsed for a single humanoid.

Sl. No.	Period lapsed in simulation (s)	Period lapsed in real-time (s)	% Error
1	42.78	45.15	5.25
2	42.93	45.36	5.36
3	43.47	45.92	5.34
4	43.32	46.04	5.91
5	42.95	45.62	5.85
Average	43.09	45.62	5.54

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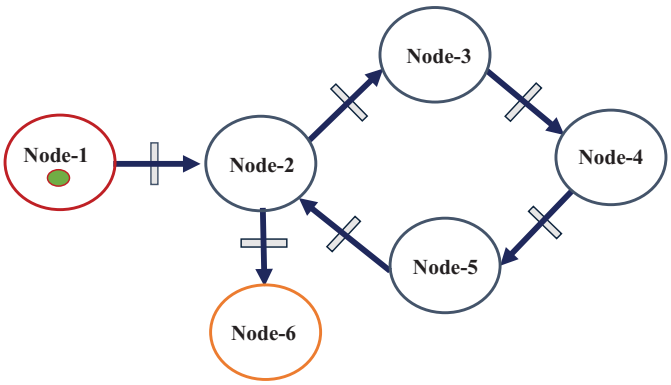


Fig. 5. Proposed Petri-Net strategy.

3.2. Integration of a petri-net strategy with the GO-based model

As already stated, the current investigation takes into account the navigational execution of both single and multiple humanoid robots. Although the proposed motion planning strategy can be executed in most of the complicated obstacle settings, yet, in the movement of multiple humanoids in a common platform, it may fail in avoiding possibility of inter-collisions. Therefore, to assign a priority in negotiation of a common obstacle by multiple agents, a Petri-Net strategy[30,31] has been integrated with the GO-based model. Figure 5 represents the Petri-Net strategy used in the current work.

Here, a circle represents the position of a robotic agent. The arrow mark states transition from one node to another. The elliptical shape represents the agent's current position. Node-1 states the initial command to begin which says that the agents are ready to move toward their respective targets. In Node-1, the agents do not have any information regarding other agent's location. Node-2 represents that the agents have headed toward their destination, and they begin to track each other's position. In Node-3, a dynamic obstacle is detected. Here, two agents have to set a priority regarding further movement. Hence, as per a general rule, the agent having least distance left toward the goal is given a higher priority, and it moves further, while the other agent acts as a stationary object. Node-4 represents the negotiation of priority. The agent having the least priority in Node-4 searches for possibility of any other conflicting situations. Node-5 represents the movement after resolution of all the conflicts. Node-6 is a special waiting state when an agent detects another set of agents already in a state of conflict. In such situations, the agent has to wait until all the previous conflicts are resolved. After resolution of the conflicts, the agent acquires Node-2 and proceeds further. Considering the above stated rules, navigational planning for multiple humanoids can be accessed in a common platform.

3.3. Motion planning for multiple humanoids

In motion planning for multiple humanoids, the arena size is kept constant. Two humanoids and five obstacles are used for the analysis, and individual source and target locations are set for each humanoid. Here, the logic of Petri-Net strategy is combined along with GO-based motion planning. The simulation results for motion planning execution is represented in Fig. 6. Similar pattern is also followed for the real-time setup, and motion planning is executed as was done for the navigation of single humanoid. The real-time results are represented in Fig. 7.

The simulation and real-time outcomes for navigation of multiple humanoids have also produced satisfactory results which prove the efficient working of the developed motion planning strategy. Tables III and IV represent the evaluation of simulation and real-time outcomes for navigation of multiple humanoids in terms of track stretch and period lapsed, respectively.

The evaluation or results in terms of navigational parameters also generate promising outcomes for motion planning of multiple humanoids.

4. Verification of the Proposed Motion Planning Strategy against Another Recognized Navigational Model

Although the proposed motion planning strategy has provided adequate results for the smooth movement of single as well as multiple humanoid robots, it is concurrently important to verify it against

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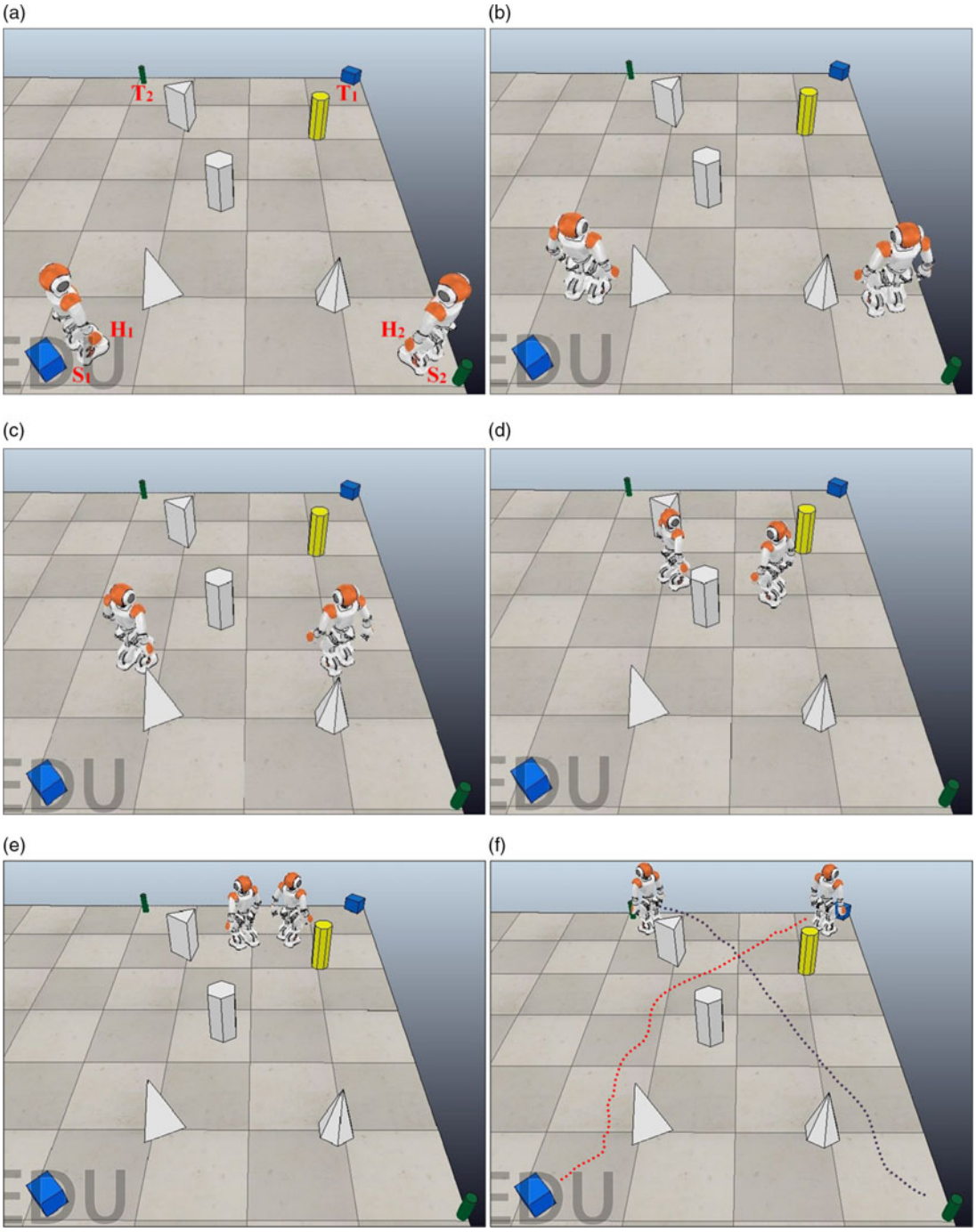


Fig. 6. Simulation results for multiple humanoids.

another recognized navigational model. To do so, a recurrent neuro-fuzzy approach developed by Chen and Richardson[32] is taken into consideration. Recurrent neuro-fuzzy is a well-established hybrid approach used for solving robot navigation problem. The arena mentioned in the stated approach is quite similar to the one used in the current investigation. Therefore, it has been used for the comparison purpose. Figure 8 represents the comparison of both the navigational models in terms of trajectory produced, and Table V represents the comparison in terms of track stretch.

The comparison of the proposed motion planning strategy has gained an improvement of about 7% over the recognized navigational model which gives a proof regarding the efficiency of the proposed strategy.

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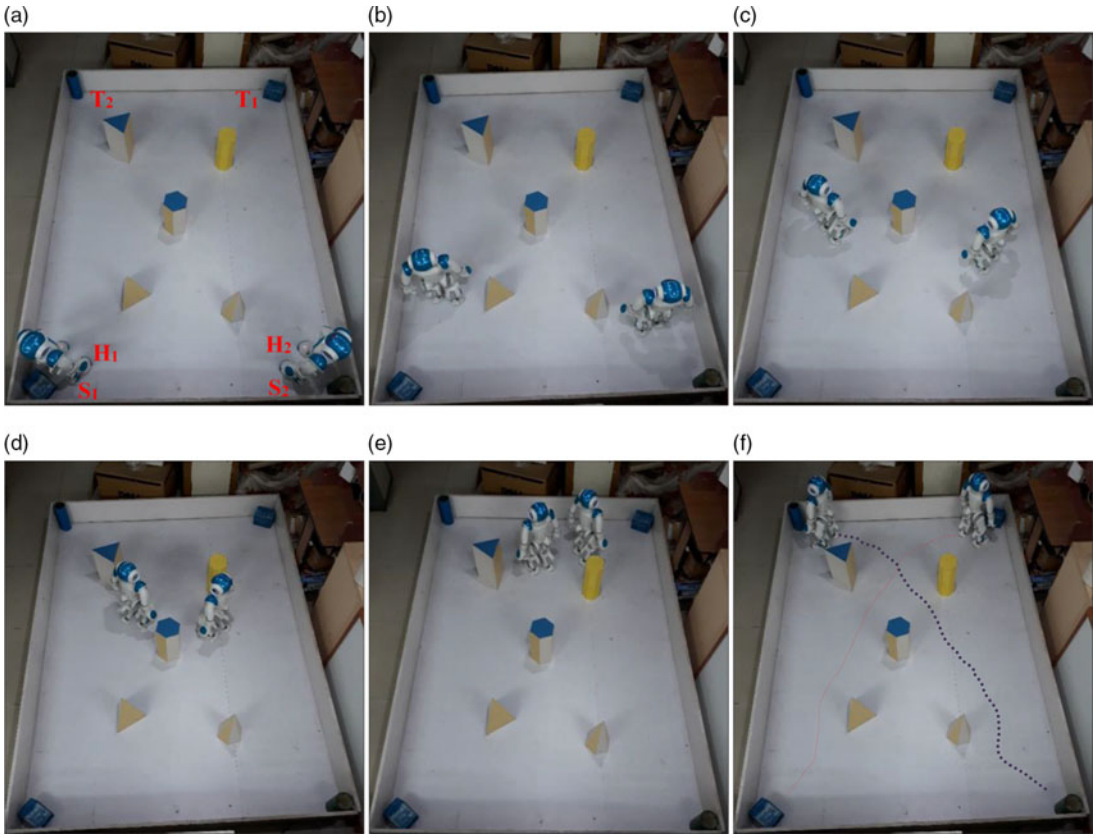


Fig. 7. Real-time results for multiple humanoids.

Table III. Evaluation of simulation arena against real-time arena in terms of track stretch for multiple humanoids.

	Simulation arena		**Real-time arena**		**% Error**	
	Track stretch (cm)					
Sl. No.	H_1	H_2	H_1	H_2	H_1	H_2
1	295.46	306.54	313.2	324.9	5.66	5.65
2	295.87	306.81	313.4	325.2	5.59	5.65
3	296.71	307.26	313.9	325.9	5.48	5.72
4	296.8	307.91	314.7	325.7	5.69	5.46
5	295.93	306.94	313.6	325.4	5.63	5.67
Average	296.15	307.09	313.76	325.42	5.61	5.63

Table IV. Evaluation of simulation arena against real-time arena in terms of period lapsed for multiple humanoids.

	Simulation arena		**Experimental arena**		**% Error**	
	Period lapsed (s)					
Sl. No.	H_1	H_2	H_1	H_2	H_1	H_2
1	40.62	42.24	42.96	44.6	5.45	5.29
2	40.84	42.35	43.29	44.82	5.66	5.51
3	41.03	42.67	43.78	44.97	6.28	5.11
4	41.17	42.49	43.82	45.26	6.05	6.12
5	40.95	42.17	43.18	45.03	5.16	6.35
Average	40.92	42.38	43.41	44.94	5.72	5.68

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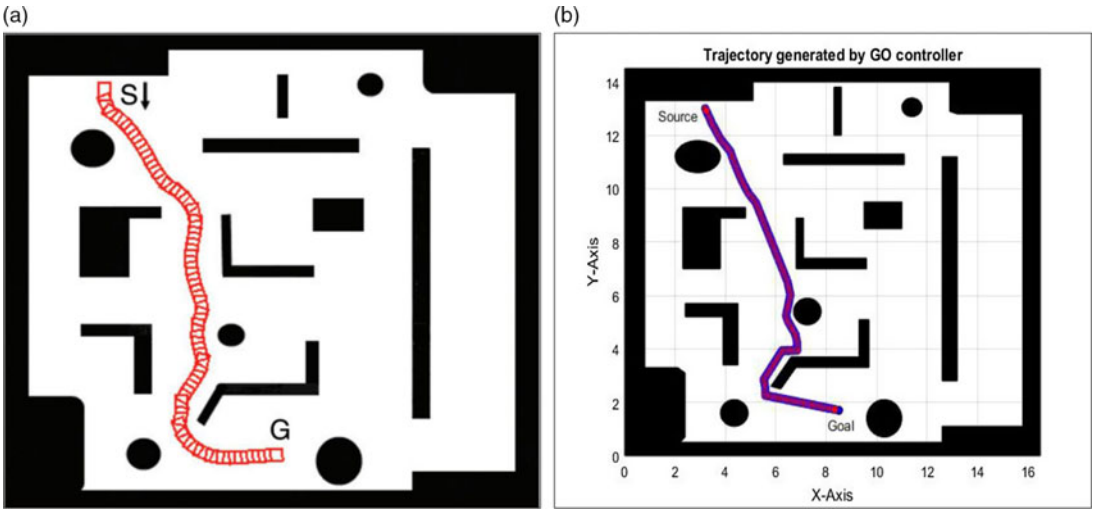


Fig. 8. (a) Trajectory generated by recurrent neuro-fuzzy approach.[32] (b) Trajectory generated by GO controller.

Table V. Comparison of recurrent neuro-fuzzy approach[24] with GO controller in terms of track stretch.

Technique used	**Track stretch in units**	**Improvement in %**
Recurrent neuro-fuzzy approach[32] (Fig. 8(a))	15.6	7.05
GO controller (Fig. 8(b))	14.5	

5. Conclusions

In the current investigation, a glowworm-based motion planning strategy is proposed for smooth and hassle-free movement of single as well as multiple humanoids. After detection of a potential obstacle by the sensory network of the humanoid, a swarm of virtual glowworms is created around the obstacle. By using the logic of GO algorithm, the next most feasible point to move is generated. The humanoid moves to the next step as per the generated ETA. The proposed strategy is implemented on a humanoid NAO in a V-REP simulation platform, and the simulation results are authenticated in a real-time setup. The results obtained from simulation and real-time arenas are evaluated against each other in terms of selected navigational parameters, and a proper agreement is found. To avoid possibility of inter-collision among multiple humanoids during their navigation in a common platform, a Petri-Net strategy is integrated along with the glowworm-based model. Finally, the proposed motion planning strategy is also verified against another recognized navigational model, and a significant performance improvement has been observed. The current investigation can be very much helpful in the utilization of humanoids in humanitarian platforms such as manufacturing and automation industries, medical assistance, elderly guidance, entertainment tool, etc. The proposed work can also be extended toward designing a robust hybrid controller using GO which can be considered as a future prospect. The proposed controller can also be tested for other forms of humanoids which is another future direction of the current work.

References

1. X. S. Yang, "Firefly algorithm, stochastic test functions and design optimization," *Int. J. Bio-Inspired Comput.* **2**(2), 78–84 (2010).
2. K. N. Krishnanand, P. Amruth, M. H. Guruprasad, S. V. Bidargaddi and D. Ghose, "Glowworm-Inspired Robot Swarm for Simultaneous Taxis Towards Multiple Radiation Sources," *Proceedings 2006 IEEE International Conference on Robotics and Automation* (2006) pp. 958–963.
3. K. N. Krishnanand and D. Ghose, "Detection of Multiple Source Locations Using a Glowworm Metaphor with Applications to Collective Robotics," *Proceedings 2005 IEEE Swarm Intelligence Symposium (SIS 2005)* (2005) pp. 84–91.
4. A. L. Christensen, R. OGrady and M. Dorigo, "From fireflies to fault-tolerant swarms of robots," *IEEE Trans. Evol. Comput*. **13**(4), 754–766 (2009).

https://doi.org/10.1017/S0263574720000892 Published online by Cambridge University Press

5. 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).
6. S. M. Ahmadi, H. Kebriaei and H. Moradi, "Constrained coverage path planning: Evolutionary and classical approaches," *Robotica* **36**(6), 904–924 (2018).
7. 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).
8. B. K. Patle, D. Parhi, A. Jagadeesh and O. P. Sahu, "Real time navigation approach for mobile robot," *JCP* **12**(2), 135–142 (2017).
9. A. Sathyan and O. Ma, "Collaborative control of multiple robots using genetic fuzzy systems," *Robotica* **37**(11), 1922–1936 (2019).
10. M. Brand and X. H. Yu, "Autonomous Robot Path Optimization Using Firefly Algorithm," **In:** *2013 IEEE International Conference on Machine Learning and Cybernetics*, vol. 3 (2013) pp. 1028–1032.
11. C. Liu, Z. Gao and W. Zhao, "A New Path Planning Method Based on Firefly Algorithm," **In:** *2012 Fifth IEEE International Joint Conference on Computational Sciences and Optimization* (2012) pp. 775–778.
12. L. Zhang, L. Liu, X. S. Yang and Y. Dai, "A novel hybrid firefly algorithm for global optimization," *PloS One* **11**(9), e0163230 (2016).
13. C. Liu, Y. Zhao, F. Gao and L. Liu, "Three-dimensional path planning method for autonomous underwater vehicle based on modified firefly algorithm," *Math. Prob. Eng.* (2015). doi: https://doi.org/10.1155/2015/561394.
14. M. H. Horng and T. W. Jiang, "Multilevel image thresholding selection based on the firefly algorithm," **In:** *7th International Conference on Ubiquitous Intelligence & Computing and 7th IEEE International Conference on Autonomic & Trusted Computing* (2010) pp. 58–63.
15. G. Wang, L. Guo, H. Duan, L. Liu and H. Wang, "A modified firefly algorithm for UCAV path planning," *Int. J. Hybrid Inf. Technol*. **5**(3), 123–144 (2012).
16. I. Fister, I. Fister Jr., X. S. Yang and J. A. Brest, "A comprehensive review of firefly algorithms," *Swarm Evol. Comput.* **13**, 34–46 (2013).
17. 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," *Proc. Comput. Sci.* **76**, 474–479 (2015).
18. W.U. Wei-guo and H. Yue-yang, "Research on Rapid Walking of Biped Robot Based on Parametric Surface Table Cart Model," **In:** *2009 IEEE International Conference on Robotics and Biomimetics (ROBIO)* (2009) pp. 463–468.
19. N. Scianca, D. De Simone, L. Lanari and G. Oriolo, "MPC for humanoid gait generation: Stability and feasibility," *IEEE Trans. Robot.* **36**(4), 1171–1188 (2020).
20. H. Yussof, M. Yamano, Y. Nasu and M. Ohka, "Design of a 21-DOF Humanoid Robot to Attain Flexibility in Human-Like Motion," **In:** *ROMAN 2006-The 15th IEEE International Symposium on Robot and Human Interactive Communication* (2006) pp. 202–207.
21. O. Pino, G. Palestra, R. Trevino and B. De Carolis, "The humanoid robot NAO as trainer in a memory program for elderly people with mild cognitive impairment," *Int. J. Soc. Robot.* **12**(1), 21–33 (2020).
22. G. Nava, F. Romano, F. Nori and D. Pucci, "Stability Analysis and Design of Momentum-Based Controllers for Humanoid Robots," **In:** *2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)* (2016) pp. 680–687.
23. D. Clever and K. D. Mombaur, "An Inverse Optimal Control Approach for the Transfer of Human Walking Motions in Constrained Environment to Humanoid Robots," **In:** *Robotics: Science and Systems* (2016).
24. P. B. Kumar and D. R. Parhi, "Intelligent hybridization of regression technique with genetic algorithm for navigation of humanoids in complex environments," *Robotica* **38**(4), 565–581 (2020).
25. P. B. Kumar, C. Sahu and D. R. Parhi, "Intelligent navigation of a self-fabricated biped robot using a regression controller," *Sci. Iran.* **27**(1), 262–272 (2020).
26. P. B. Kumar, M. K. Muni and D. R. Parhi, "Navigational analysis of multiple humanoids using a hybrid regression-fuzzy logic control approach in complex terrains," *Appl. Soft Comput.* **89** 106088 (2020).
27. A. S. Baskoro and M. G. Priyono, "Design of Humanoid Robot Stable Walking Using Inverse Kinematics and Zero Moment Point," **In:** *2016 International Electronics Symposium (IES).* IEEE (2016) pp. 335–339.
28. F. Göngör and Ö Tutsoy, "Design and implementation of a facial character analysis algorithm for humanoid robots," *Robotica* **37**(11), 1850–1866 (2019).
29. 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).
30. J. L. Peterson, *Petri Net Theory and the Modeling of Systems* (Prentice-Hall, 1981).
31. 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).
32. C. Chen and P. Richardson, "Mobile robot obstacle avoidance using short memory: a dynamic recurrent neuro-fuzzy approach," *Trans. Inst. Meas. Cont.* **34**(2–3), 148–164 (2012).

https://doi.org/10.1017/S0263574720000892 Published online by Cambridge University Press