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Behaviour based navigational control of humanoid robot using genetic algorithm technique in cluttered environment

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ABSTRACT

Humanoids are popular than their wheeled counterparts by the virtue of their ability to mimic the human behaviour and replace human efforts if required. Navigation and path planning is a complex and challenging problem for humanoids as it involves careful consideration of the navigational parameters. This paper introduces the path planning of a humanoid robot utilizing genetic hereditary calculation. The objective of the paper is to design a navigational controller using genetic algorithm for path planning of a humanoid in a complex environment cluttered with obstacles. The basic working of a genetic algorithm has been explained and an objective function for path optimization has been formulated using the logic of the genetic algorithm. The working of the controller has been tested both in simulation and experimental platforms using NAO humanoid robot. Finally, the results obtained from both the environments have been compared against each other with a good agreement between them.

1. INTRODUCTION

Path planning in a cluttered environment is a challenging task especially when it comes to humanoid robot navigation. A humanoid robot is complex in the way it walks i.e. the robot is difficult to handle. It is quite perplexing to make it walk, then turn around and stop due to the dynamic effect and lack of support which makes it unstable. Hence, various methods have been proposed for its walking which would be helpful to carry out navigation. Kong et al. [1] have used Genetic Algorithm (GA) for gait generation of a humanoid robot. They proposed how to save electric power for smooth and optimal gait. Capi et al. [2] have proposed a revised GA approach humanoid gait analysis. Kundu et al. [3-4] have proposed several intelligent algorithms for path optimization of an underwater robot in obstacle prone environments. Weinberg et al. [5] have utilized GA in a musical system to create a collaboration between the human musician and robot player. The robot was designed in such a way that in a real time it can respond the human input in an acoustic and visual manner by listening the human by Musical Instrument Digital Interface (MIDI) and audio input. Mohammadi et al. [6] considered kinematic constraint data as input and proposed a wearable exoskeleton model for a disabled human arm for assisting in various operations. Kumar et al. [7-9] developed several intelligent methods for navigation of humanoids in complex environments. Clever and Mombaur [10] introduced an inverse optimal control based motion transfer from humans to humanoids by a 3D template model. Mohanty et al. [11-16] applied several nature-inspired algorithms for navigation of mobile robots in complex terrains. Das et al. [17] combined particle swarm optimization (PSO) with gravitational search algorithm (GSA) for path planning of multiple mobile robots. Razzazi and Sepahvand [18] used time complexity of two disjoint simple paths for path planning of mobile robots. Singh et al. [19-21] proposed navigational controllers for mobile robots by using the forward neural network in a real world dynamic environment. Nishiyama and Iba [22] analysed different robot motions using double learning experiments. Roberts et al. [23] have described regarding smoothing the Zero Moment Point (ZMP) using two GA tunings and tested their approach through multiple simulations. Pandey and Parhi [24-25] used a fuzzy based approach for navigation of multiple mobile robots in an environment with static obstacles. Villela et al. [26] have created a fast and stable walking humanoid robot for large degree of freedom and external variable. Parhi et al. [27-28] have described design, fabrication and analysis of an articulated mobile robot. To design the five degree of freedom arm, they have used many commercially robotic kits. Karkowski et al. [29] developed a real time path planning approach for humanoids using A* algorithm and adaptive 3D action set. Cruz and Zannatha [30] designed a walking humanoid robot with careful consideration of mechanical parameters for design, walking trajectories and feedback gains.

From the extensive survey of the literature, it can be inferred that most of the navigation and path planning problems have been applied on mobile robots only. A very few works have been reported towards the navigation of humanoids. However, they are applicable to specific environmental conditions only. There is need of a controller that can navigate a humanoid irrespective of the environmental conditions. Therefore, the current investigation is aimed to design and develop a navigational controller using GA as a potential navigation approach. The working of the controller has been verified in both simulation and experimental platforms.

2. BASIC OVERVIEW OF GENETIC ALGORITHM

A hereditary calculation is a sort of result seeking calculation in the worldwide territory. The principle of hereditary calculation is to find out ideal arrangement without differential equation. A humanoid robot has a complex structure, and its progression is difficult to solve. A genetic algorithm is an evolutionary computing approach that has been inspired by the principles derived from the natural genetics. The purpose of such an evolutionary approach is to apply the strategies to solve different real life application problems. GA has some basic characteristics similar to natural genetics which can be described as follows.

(i) Heredity: In nature, the child receives the characteristics of its parents using a process. The chain continues if the child reproduces after some time and transfers their properties (genes) to the new off springs.

(ii) Variation: To evolve the qualities of a species, there must be a mean by which variation is introduced in the population. Environmental conditions affect variation in creatures, and other factors or there may be some algorithm for change.

(iii) Selection: In most of the animals, not every adult gets a chance to be a parent and pass on its qualities to the next generation. Owing to this, there must be a mechanism that would select the ideal parents for reproduction. Such a mechanism will rely on some credits or fitness that would define the credibility of each participating element to become a potential parent.

3. GENETIC ALGORITHM APPLICATION

In a humanoid path planning, the primary idea is to avoid the obstacles that are present in the environment and reach the desired target position with path optimization. A humanoid robot heads towards its target from the source position without activation of any algorithm. After detection of any obstacle in the path, GA algorithm is provoked. Then, the GA controller proceeds with the basic operations like selection of parents, crossover, mutation and finally generation of best solution. According to the developed solution, the humanoid moves to its next position and again heads towards the goal.

3.1 Selection

In this paper, the objective of the path planning algorithm is to make a humanoid walk to its target without colliding against the obstacles present in the environment. With that in mind, a mix of variables must be considered while defining the parameters of GA algorithm. In selection operation, the parents must be a mixture of higher and lower qualities, or it may lead to premature convergence. In humanoid path planning, the parents are selected as the possible locations of the next potential positions where the humanoid can move in order to avoid the obstacle and reach nearer to the goal as per the fitness function.

3.2 Crossover

In natural genetics, the offspring produced after crossover inherit half the qualities from either of the parents. After selection of possible next points as parents, crossover operation is carried out to generate children. Children are added to the new data pool for further evaluation. After each step of crossover, there is an evaluation of the children qualities. GA continues to proceed through selection and crossover until the required qualities are met, or specific numbers of iterations are completed.

3.3 Mutation

Mutation is the property of adding new qualities to a population. These qualities may be inspired by external environmental conditions. It the process in which some of the genes of a particular child are exchanged to bring a variation in the population.

4. CONTROL ARCHITECTURE OF GENETIC ALGORITHM

In GA, the obstacle distances such as Front Obstacle Distance (FOD), Left Obstacle Distance (LOD) and Right Obstacle Distance (ROD) are selected as the input parameters. In this paper, each chromosome is considered to be having three genes (FOD, ROD, LOD) and each chromosome contains 12 bits. Figure 1 represents the basic control scheme of genetic algorithm.

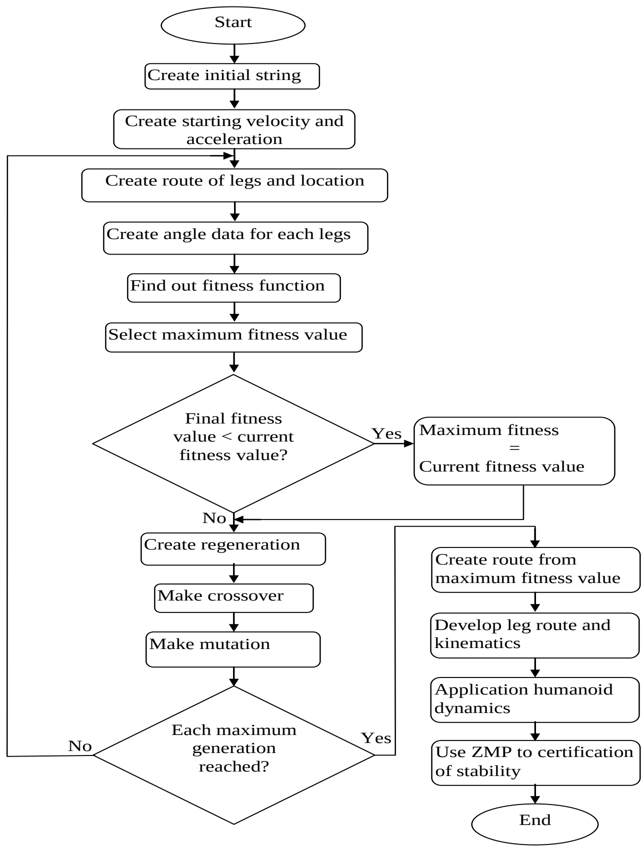

Figure 1. Flowchart of genetic algorithm

4.1 Steps used in GA

The steps used in GA can be explained as follows.

(i) First select all variables and objective function.

(ii) The GA starts elucidate the input variable whose values are to be increased. These are the dimensionless quantity.

(iii) Objective function = $\sqrt{(FOD_n - FOD_i)^2 + (LOD_n - LOD_i)^2 + (ROD_n - ROD_i)^2}$

where, FOD_n=front obstacle distance from rule 1 to n, FOD_i= front obstacle distance for input in current situation, ROD_n=Right obstacle e distance from rule 1 to n, ROD_i=Right obstacle distance for input in current situation, LOD_n=Left obstacle distance from rule 1 to n, LOD_i=Left obstacle distance for input in current situation, n = 1 to 100

(iv) For the analysis, the initial population containing two number of data sets. Crossover starts from the selected parents. We use two point crossovers. As we have taken the chromosomes containing twelve bits so we are choosing the crossover three bits left and right of the chromosome. Now the parents with the crossover points are as follows. Figure 2 represents the parent chromosomes for the current analysis.

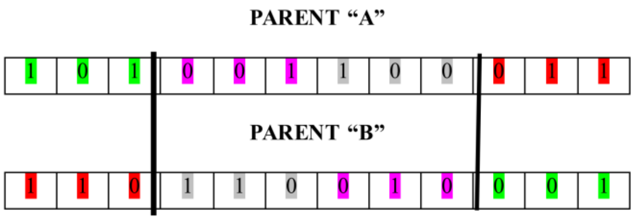

Figure 2. Parent chromosomes with crossover points

(v) Now we use two-point crossover in the GA. Figure 3 represents the scheme of crossover.

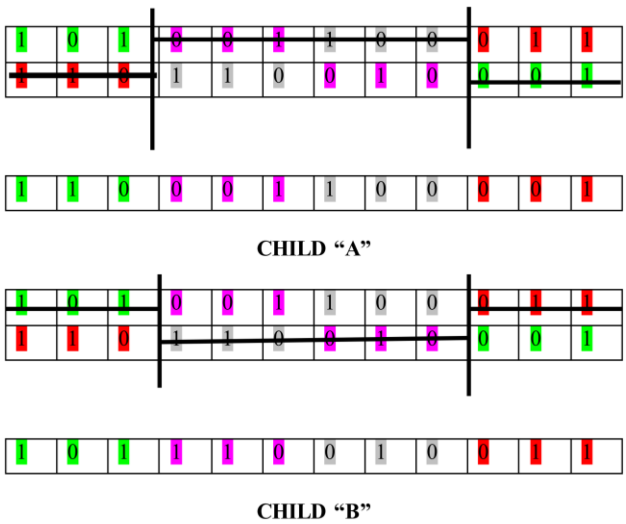

Figure 3. Two-point crossover implementation

(vi) After completion of crossover, mutation is started. For mutation, a binary encoding is used. As the mutation rate is 0.1% of the string, and the chromosomes contains 12 bits, so only two bits are taken therefore the GA for mutation is as follows. Figure 4 shows the mutation scheme used in the current work.

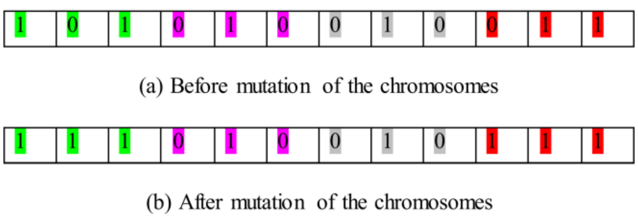

Figure 4. Mutation scheme

Now fitness evaluation of the parent and children are done by comparison of these two and the best fit member is selected. If the fitness value children come as a best fit, then it is added to the data. If parents come the best fit value, then the desired output is parent data, then the steps are repeated again.

5. IMPLEMENTATION OF GA IN HUMANOID PATH PLANNING

After designing the control architecture for humanoid path planning using GA, the working of the controller has been tested in both simulation and experimental platforms. V-REP has been selected as the simulation software for the navigational analysis of humanoid and NAO has been chosen as the humanoid platform for navigation. The path planning for humanoid robot in simulation has been carried out using one robot in the scene with five numbers of obstacles at random locations. The initial and final positions were defined for the humanoid. The humanoid was fed with the logic of GA algorithm and simulation was performed. Figure 5 and Figure 7 show the simulated path obtaining by the humanoid in scene 1 and scene 2 respectively.

To validate the simulation results, an experimental platform was designed under laboratory conditions. The obstacles were located at similar positions as of the simulation, and the humanoid was controlled through a Wi-Fi module. The actual humanoid control was performed through python programming. Figure 6 and Figure 8 show the snapshots taken during actual experiments conducted in laboratory. To compare the results obtained from both the environments, path length and time taken are selected as the two navigational parameters. These two are directly recorded from the simulation window of the software in the simulation platform and for the experimental platform, they are measured by the help of a measuring tape and stopwatch respectively. Table 1 represents the comparison of path length, and Table 2 represents the comparison of time taken between simulation and experimental environments.

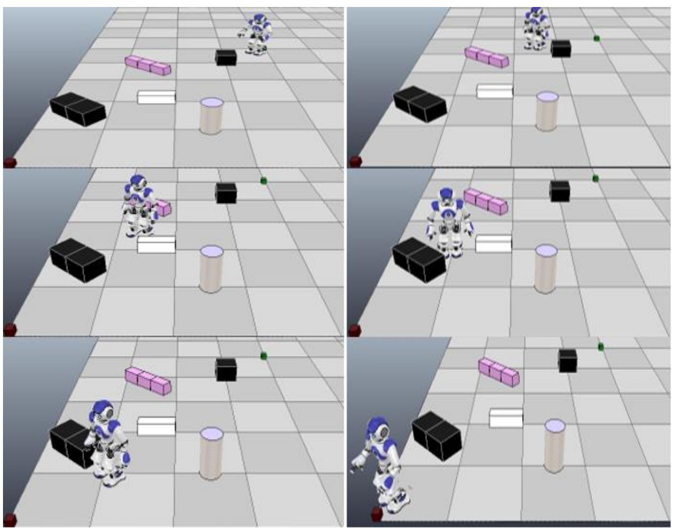

Figure 5. Simulation results for scene 1

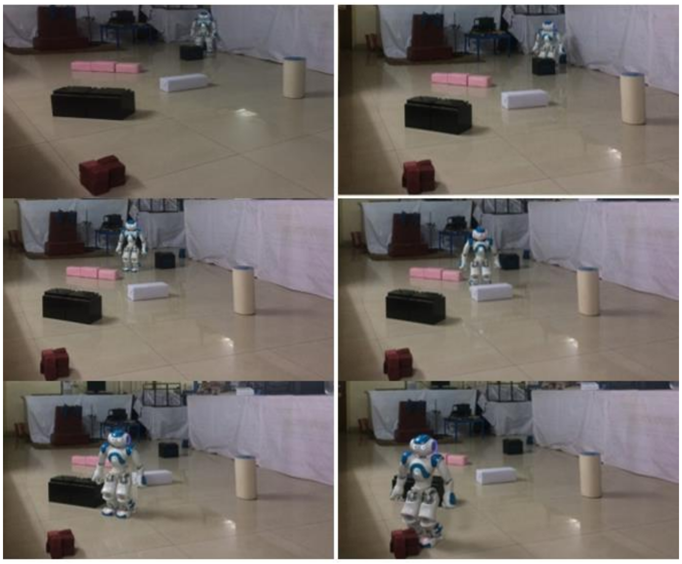

Figure 6. Experimental results for scene 1

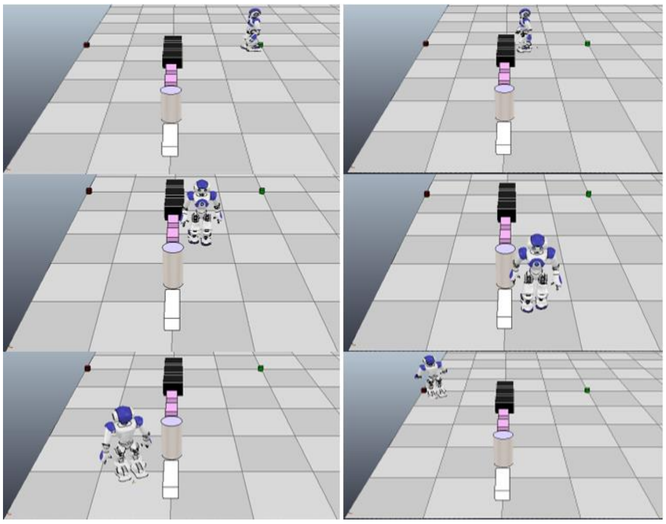

Figure 7. Simulation results for scene 2

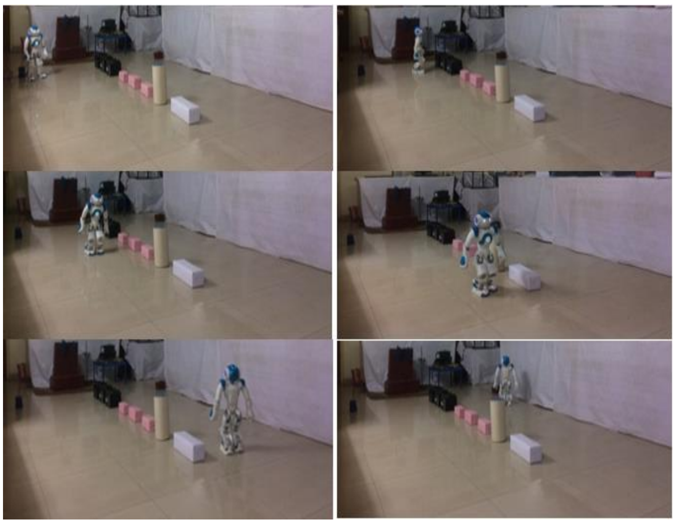

Figure 8. Experimental results for scene 2

Table 1. Comparison of simulated and experimental path length

Sl. No.	Simulation path length(m)	Experimental path length (m)	Deviation in path length (%)
1	3.02	3.14	3.82
2	3.0	3.23	2.2
3	2.9	3.1	2.08
4	3.25	3.48	6.6
5	3.04	3.2	5.0

Table 2. Comparison of simulated and experimental time taken

Sl. No.	Simulation Time taken(s)	Experimental time take (s)	Deviation in time (%)
1	53.0	55.5	4.5
2	51.5	53.1	3.01
3	48.6	50.9	4.51
4	55.7	58.2	4.29
5	51.7	53.8	3.9

From the simulation and experimental results, it can be observed that the humanoid is successful in avoiding the obstacles present in the environment and reach the final location with optimized path. The errors obtained from the comparison of navigational parameters are well within the acceptable limit. So, GA method can be used as a potential navigation approach for humanoids in complex scenarios.

6. CONCLUSION

With the development in use of current advanced technologies, robots have virtually become an integral part of human life. Navigation and path planning is an interesting yet challenging area of investigation that requires careful consideration of the navigational parameters. The classical methods available for navigational problems may not always be sufficient to provide an optimized pat as they may encounter the problem of being trapped at a local optimum. Therefore, in the current work, humanoid navigation was carried out using genetic algorithm as a potential navigational technique. The GA controller was designed considering the obstacle distances as the inputs, and the required turning angle was obtained as an output to avoid the obstacles present in the environment and reach the desired location safely. The working of the controller was verified through multiple simulations and experiments. The results obtained from both the environments were compared against each other, and a good agreement between them was observed with minimal percentage of errors. Therefore, GA can be successfully used for optimized humanoid robot path planning in a cluttered environment.

REFERENCES

[1] Kong JS, Lee BH, Kim JG. (2004). A study on the gait generation of a humanoid robot using genetic algorithm. In SICE 2004 Annual Conference IEEE 1: 187-191.

[2] Capi G, Nasu Y, Barolli L, Mitobe K, Yamanot M, Takedat K. (2002). A new gait optimization approach

based on genetic algorithm for walking biped robots and a neural network implementation. IPSJ Journal.

[3] Kundu S, Parhi R, Deepak BBVL. (2012). Fuzzy-neuro based navigational strategy for mobile robot. International Journal of Scientific & Engineering Research 3(6): 1-6.

[4] Kundu S, Parhi DR. (2016). Navigation of underwater robot based on dynamically adaptive harmony search algorithm. Memetic Computing 8(2): 125-146.

[5] Weinberg G, Godfrey M, Rae A, Rhoads J. (2007). A real-time genetic algorithm in human-robot musical improvisation. In International Symposium on Computer Music Modeling and Retrieval Springer, Berlin, Heidelberg 351-359.

[6] Mohammadi E, Zohoor H, Khadem SM. (2016). Design and prototype of an active assistive exoskeletal robot for rehabilitation of elbow and wrist. Scientia Iranica. Transaction B, Mechanical Engineering 23(3): 998.

[7] Kumar PB, Pandey KK, Sahu C, Chhotray A, Parhi DR. (2017). A hybridized RA-APSO approach for humanoid navigation. Nirma University International Conference on Engineering (NUiCONE) 1-6.

[8] Kumar A, Kumar PB, Parhi DR. (2018). Intelligent navigation of humanoids in cluttered environments using regression analysis and genetic algorithm. Arabian Journal for Science and Engineering 1-24.

[9] Rath AK, Parhi DR, Das HC, Muni MK, Kumar PB. (2018). Analysis and use of fuzzy intelligent technique for navigation of humanoid robot in obstacle prone zone. Defence Technology.

[10] Clever D, Mombaur KD. (2016). An inverse optimal control approach for the transfer of human walking motions in constrained environment to humanoid robots. In: Robotics: Science and Systems.

[11] Mohanty PK, Parhi DR. (2016). Optimal path planning for a mobile robot using cuckoo search algorithm. Journal of Experimental & Theoretical Artificial Intelligence 28(1-2): 35-52.

[12] Mohanty PK, Parhi DR. (2013). Cuckoo search algorithm for the mobile robot navigation. In: International Conference on Swarm, Evolutionary, and Memetic Computing 527-536.

[13] Mohanty PK, Parhi DR. (2014). A new intelligent motion planning for mobile robot navigation using multiple adaptive neuro-fuzzy inference system. Applied Mathematics & Information Sciences 8(5): 2527.

[14] Mohanty PK, Parhi DR. (2014). Navigation of autonomous mobile robot using adaptive network based fuzzy inference system. Journal of Mechanical Science and Technology 28(7): 2861-2868.

[15] Mohanty PK, Parhi DR. (2015). A new hybrid optimization algorithm for multiple mobile robots navigation based on the CS-ANFIS approach. Memetic Computing 7(4): 255-273.

[16] Mohanty PK, Parhi DR. (2014). A new efficient optimal path planner for mobile robot based on Invasive Weed Optimization algorithm. Frontiers of Mechanical Engineering 9(4): 317-330.

[17] Das PK, Behera HS, Panigrahi BK. (2016). A hybridization of an improved particle swarm optimization and gravitational search algorithm for multi-robot path planning. Swarm and Evolutionary Computation 28: 14-28.

[18] Razzazi M, Sepahvand A. (2017). Time complexity of two disjoint simple paths. Scientia Iranica. 24(3): 1335-1343.

[19] Singh MK, Parhi DR, Pothal JK. (2009). ANFIS approach for navigation of mobile robots. In: International Conference on Advances in Recent Technologies in Communication and Computing (ARTCom'09) 727-731.

[20] Parhi DR, Singh MK. (2009). Navigational strategies of mobile robots: A review. International Journal of Automation and Control 3(2-3): 114-134.

[21] Singh MK, Parhi DR. (2011). Path optimisation of a mobile robot using an artificial neural network controller. International Journal of Systems Science 42(1): 107-120.

[22] Nishiyama M, Iba H. (2015). Converting motion between different types of humanoid robots using genetic algorithms. International Journal of Computer Theory and Engineering 7(2): 97.

[23] Roberts JM, Kee D, Wyeth G. (2003). Improved joint control using a genetic algorithm for a humanoid robot. In: Proceedings of the 2003 Australasian Conference on Robotics and Automation. Australian Robotics and Automation Association Inc.

[24] Pandey A, Parhi DR. (2016). Multiple mobile robots navigation and obstacle avoidance using minimum rule based ANFIS network controller in the cluttered environment. International Journal of Advanced Robotics and Automation 1: 11.

[25] Pandey A, Parhi DR. (2014). MATLAB simulation for mobile robot navigation with hurdles in cluttered environment using minimum rule based fuzzy logic controller. Procedia Technology 14: 28-34.

[26] Villela LFC, Colombini EL, Técnico-IC-PFG R. (2017). Humanoid Robot Walking Optimization using Genetic Algorithms.

[27] Eliot E, BBVL D, Parhi DR. (2012). Design & kinematic analysis of an articulated robotic manipulator.

[28] Pothal JK, Parhi DR. (2015). Navigation of multiple mobile robots in a highly clutter terrains using adaptive neuro-fuzzy inference system. Robotics and Autonomous Systems 72: 48-58.

[29] Karkowski P, Oßwald S, Bennewitz M. (2016). Real-time footstep planning in 3D environments. In: IEEE-RAS 16th International Conference on Humanoid Robots (Humanoids) 69-74.

[30] Cruz RSN, Zannatha JMI. (2017). Efficient mechanical design and limit cycle stability for a humanoid robot: An application of genetic algorithms. Neurocomputing 233: 72-80.