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Navigational control strategy of humanoid robots using average fuzzy-neuro-genetic hybrid technique

Abstract

In this research paper navigational path planning of humanoid robots using developed average fuzzy-neuro-genetic hybrid technique has been analysed. Inputs to the hybrid controller are front, front-left and front-right obstacle distances and target location obtained from ultrasonic and image sensors of humanoid robot. Three Artificial Intelligence (AI) controllers such as, fuzzy logic, neural network and genetic algorithms have been used in parallel for robot navigation control. The outputs from sensors are fed as inputs to the hybrid controllers. The average output from the controller in the form of steering angle is used for robot dynamic movements while avoiding obstacles and reaching targets. A close agreement has been observed during comparison of simulation and experimental results.

Keywords: AI, humanoid, robots, genetic, fuzzy, neural

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Introduction

Several researchers around the world are working on control of robots in various terrains. During the research Ravanakar et al.[1] have discussed about robot navigation. In their paper they have discussed about various path smoothening method during navigation. McGuire et al.[2] have discussed about bug algorithms for indoor robotic navigation. They have shown their results in simulated environments.

Yang et al.[3] have studied double-layer ant colony optimisation technique for robot navigation. They have used tuning point optimisation technique along with ant colony optimisation technique to get a smooth path for the robot. Modular navigation framework for wheeled mobile robot has been discussed in paper.[4] This modular navigation framework has been verified on different robotic platforms. Xie et al.[5] have used stochastic switch for getting better performance in robot navigation. Fuzzy inference techniques have been used[6,7] for addressing robot navigational problems and problems related to engineering fields. Moreno et al.[8] have suggested auxiliary navigation waypoints for more suitable robot trajectory generation. They have demonstrated the results for robot navigation in simulation environments.

Chen et al.[9] have used graph convolution networks for mobile robot navigation in crowded environments for effective path planning. Liu et al.[10] have analysed a self-improving lifelong learning framework for robot navigation subjected to different environments. They have shown the results in experimental modes. Patle et al.[11] have used firefly algorithm for robot navigation. They have compared their results with other navigation technique. SLAM technology using RGB and depth images is incorporated in robot navigation and has been described in the paper.[12] The paper describes the integration of the knowledge graph and semantic descriptor for eliminating the dynamic objects during navigation and improves the positioning of robots.

Adaptive harmony search algorithm has been used in the robot navigation and is analysed in the paper.[13] The paper has shown both simulation and experimental results on robot navigation using harmony search algorithm. Hu et al.[14] have used deep reinforcement learning architecture to get the robot navigation instruction from simulated environment training data. They have also used the experimental model for navigational purpose. Control of biped robot using regression controller and navigation of humanoid robot have been reported in papers.[15–17] In these papers navigation control results of biped robot both in simulation and experimental modes have been demonstrated.

Kivrak et al.[18] have analysed on socially aware robot path planning. They have used A* global planner for the robot to avoid local minima during navigation. Naik et al.[19] have used semantic mapping method for mapping and robot navigation subjected to indoor environments.

In the current paper a new hybrid average Fuzzy-Neuro-Genetic controller has been analysed for navigation of humanoid robots in cluttered environments. The novelty of the work is to develop and analyse the proposed technique. The analysis is given in subsequent section.

Analysis of hybrid average fuzzy-neuro-genetic controller

The hybrid controller represented in this paper consists of Fuzzy logic (Figure 1), Neural Network (Figure 2) and Genetic Algorithm (Figure 3) techniques. The inputs to the Fuzzy logic technique are Front Obstacle Distance (FOD), Front-Left Obstacle Distance (FLOD), Front-Right Obstacle Distance (FROD) and Target Angle (TA). The output from the fuzzy controller is Steering Angle 1 (SA-1). Trapezoidal and Triangular membership functions (Fig. 1) are used as fuzzy membership functions for inputs and output. Very-Low, Low, Low-Medium, High-Medium, High and Very-High are used as linguistic terms for the fuzzy input and output members. Several rules are used to carry out the Fuzzy Inference and to find the SA-1 as per inputs.

The inputs to the Neural Controller (Figure 2) are Front Obstacle Distance (FOD), Front-Left Obstacle Distance (FLOD), Front-Right Obstacle Distance (FROD) and Target Angle (TA). The output from the Neural Controller is Steering Angle 2 (SA-2). The Back Propagation Neural Network consists of six layers (Input Layer-IL, four Hidden Layers- HL1-4 and Output Layer-OL). Several training patterns are used to train the Neural Controller.

The inputs to the Genetic Control System (Figure 3) are Front Obstacle Distance (FOD), Front-Left Obstacle Distance (FLOD), Front-Right Obstacle Distance (FROD) and Target Angle (TA). The output from the Genetic Controller is Steering Angle 3 (SA-3). The data pool is consisting of several data sets with possible inputs and corresponding outputs. The data sets as per the fitness value from fitness function are used as parents for particular set of inputs. The corresponding outputs (SA-3) are found out after crossover and mutation.

Figure 4 depicts the architecture of average Fuzzy-Neuro-Genetic hybrid control system. The inputs to fuzzy, neural and genetic segments are FOD, FLOD, FROD and TA. The outputs from each segment (SA-1, SA-2 and SA-3) are combined and the average is calculated to find out Final Steering Angle.

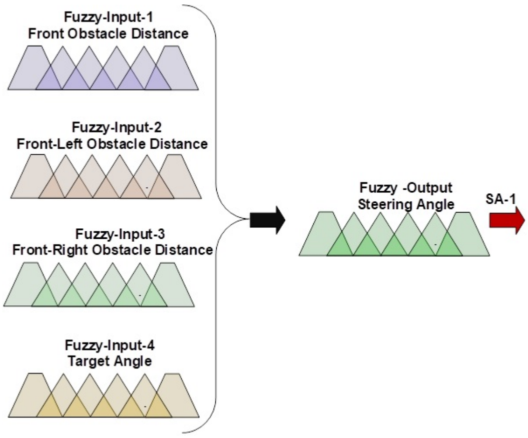

Figure 1 Architecture of fuzzy control system.

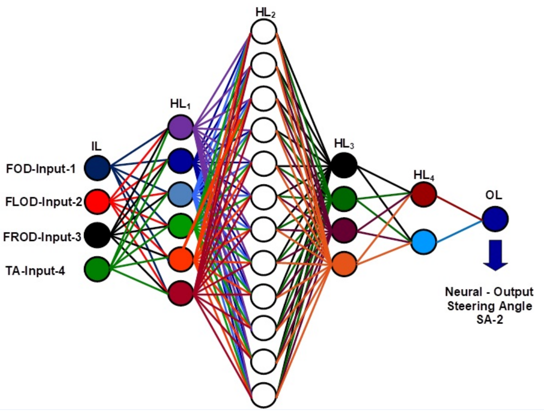

Figure 2 Architecture of neural control system.

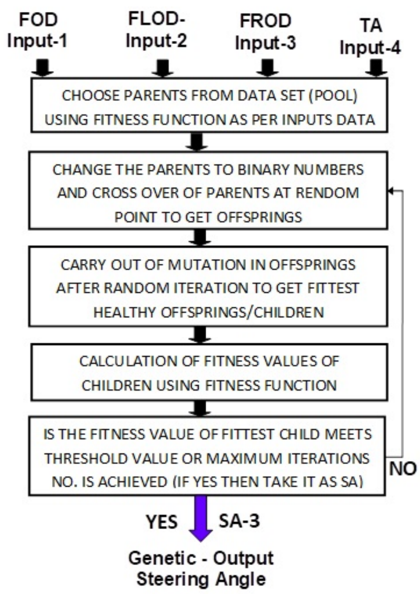

Figure 3 Architecture of genetic control system.

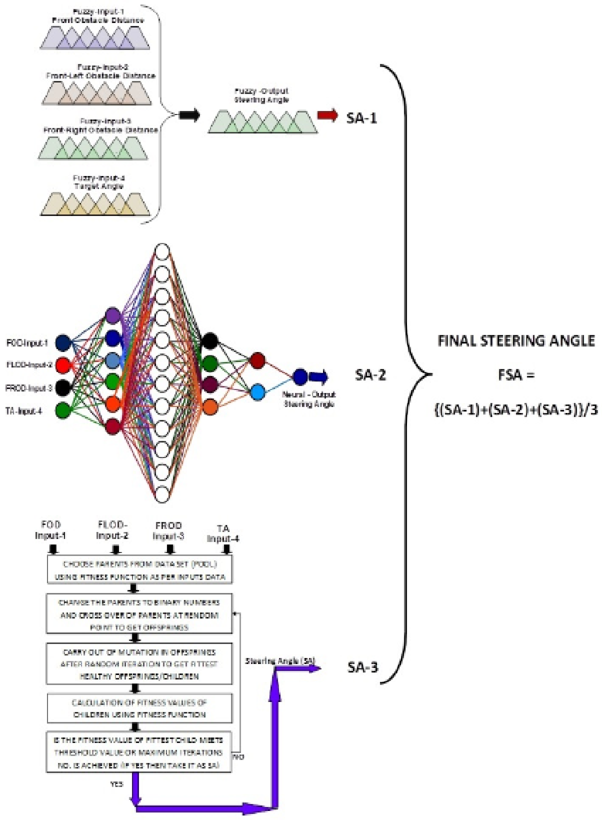

Figure 4 Architecture of average fuzzy-neuro-genetic hybrid control system.

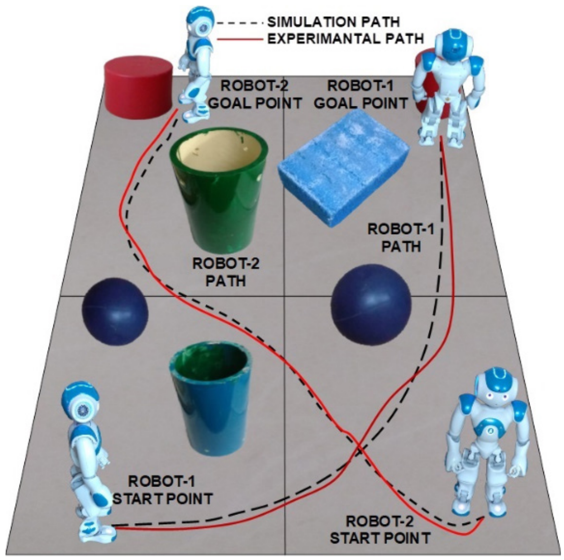

Figure 5 Navigational simulation and experimental result using fuzzy-neuro-genetic hybrid control system.

Results

Using average Fuzzy-Neuro-Genetic hybrid control system, simulations and experiments have been carried out using multiple NAO humanoid robots.[20] Figure 5 depicts the navigational paths of humanoid robots from start points to goal points while avoiding obstacles in simulation and experimental modes. Table 1 shows the comparison between simulation and experimental results in terms of path length and time taken for various exercises.

Experimental results are carried out carefully. During experiments linkages errors, slippage and hardware lagging have been noticed. Therefore gaps between simulation and experimental results have been observed. During comparisons among simulation and experimental results, deviations have been found within the limit of 5%. Both simulation and experimental results are found out by employing the proposed technique and are in agreement with each other.

Table 1 Path length and time taken by humanoid robots in various simulation and experimental exercises

Number of Exercise	Path Length in cm. Robot-1		Path Length in cm. Robot-2		Average Deviation In %	Time Taken in Sec Robot-1		Time Taken in Sec Robot-2		Average Deviation In %
	Sim.	Exp.	Sim.	Exp.		Sim.	Exp.	Sim.	Exp.	
1	141	143	119	122	1.96	5.22	5.33	4.4	4.54	2.64
2	175	178	162	166	2.09	6.48	6.62	6	6.19	2.66
3	310	315	334	339	1.55	11.48	11.74	12.37	12.62	2.14
4	211	214	176	180	1.84	7.81	7.98	6.51	6.72	2.7
5	437	445	384	392	1.95	16.18	16.58	14.22	14.58	2.5
6	531	541	624	632	1.58	19.66	20.18	23.11	23.56	2.29
7	675	683	538	547	1.42	25	25.43	19.92	20.42	2.11
8	376	382	447	456	1.8	13.92	14.24	16.55	16.97	2.41
9	253	258	289	294	1.85	9.37	9.63	10.7	10.99	2.74
10	481	487	359	364	1.32	17.81	18.15	13.29	13.54	1.89
	Path Length, Total Average Deviation in %				1.73	Time Taken, Total Average Deviation in %				2.4

Conclusion

In the current article fuzzy-neuro-genetic hybrid technique has been developed and has been investigated for navigational analysis of humanoid robot in complex environments. Ultrasonic and image sensors are used by the robots to map the environments. Inputs such as FOD, FLOD, FROD and TA are used in the hybrid controller to find out the Final Steering Angle. It has been observed that the robots have successfully avoided the obstacles while reaching targets in unknown environments. Several Simulation and Experimental results are found out while carrying out navigational tasks of humanoid robots from start points to goal points. The deviations between the results are found out to be within 5%. This method can be used by scientists and engineers for addressing various engineering problems.

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Conflicts of interest

The authors declare there are no conflicts of interest.

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