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Self-learning Mobile Robot Navigation in Unknown Environment Using Evolutionary Learning

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Abstract: An autonomous mobile robot operating in an unstructured environment must be able to learn with dynamic changes to that environment. Learning navigation and control of mobile robot in an unstructured environment is one of the most challenging problems. Fuzzy logic control is a useful tool in the field of navigation of mobile robot. In this research, we optimized a performance of fuzzy logic controller by evolutionary learning technique. Two proposed approaches have been designed and implemented: Fuzzy Logic Controller (FLC) and Genetic-Fuzzy Controller (GA-FLC). The Genetic Algorithm is used for automatically learning to tune the membership function parameters for mobile robot motion control. Moreover, the performance of these approaches are compared through simulation.

Keywords: Robotics, Fuzzy Logic controller, soft computing, genetic algorithm, genetic- fuzzy algorithm
Categories: L.2, L.5.0, I.2.9, I.2.3

1 Introduction

Navigation of Mobile Robot is the control the movement of mobile robot from a start point to a destination point in a given environment with obstacle avoidance capabilities. The Environment can be classified as Structure (Known Environment), Semi-Structure (Partially Environment), and Unknown Environment. Navigation through Unknown Environment needs an approach that can deal with uncertainties situation [Hassanm and Deepika, 12]. Soft computing techniques Such as Fuzzy Logic, Evolutionary algorithms (Genetic Algorithm, Genetic Programming, Evolutionary Programming), and particle swarm optimization (PSO) are widely used in mobile robot navigation [Zhang, et al., 07]. The term Soft Computing has been proposed by LOTFI A. ZADEH, professor for computer science at the University of California in Berkeley in the early 90's [Zadeh , 94], it refer to a group of methodologies that aim to use approximation, uncertainty , and imprecision to achieve robust and low cost solution. Fuzzy Logic (FL) was initiated in 1965 by LOTFI A. ZADEH [Hellmann, 01], FL is a field of Artificial Intelligence that deal with mimic human thinking and decision making that allow intermediate values to be defined between traditional value like (yes/no , true /false , high /low ,etc.). The FL is successfully applied in many applications including: Mobile Robot Navigation, Image

Processing, Medical Chemistry, VLSI Design, etc. [Russo, 00]. For mobile Robot Navigation, there are several studies using Fuzzy Logic approach. In [Raguraman, et al., 09], authors proposed a sensor-based mobile robot navigation using fuzzy logic controller, and forty-eight fuzzy rules applied to obstacles avoidance and generate a safety path to the target [Parhi,05] describes a fuzzy logic to avoid obstacles in an unknown environment for mobile robot. In [Faisal, et al., 13] authors presented a fuzzy logic controller for navigation and obstacle avoidance in unknown environment. The performance of fuzzy logic depends on its rule-based and membership function, so in recent years, the hybrid method of fuzzy logic and Genetic Algorithm (GA) has been proposed to adjust the parameters of fuzzy logic controller and shown that it's very effectively. GA is clearly described in Goldberg book [Goldberg, 89]. In [Senthilkumar, 10] authors investigated a hybrid fuzzy-genetic technique for a target follow and obstacle avoiding for mobile robot. A priori knowledge in the form of linguistic variable, fuzzy rules, membership parameters, number of rules, etc. are easily integrated into a genetic design process. In the simulation , the robot receive information about start and target points then the rules were created randomly and compute fitness of each rule based on successfulness of the rule. This study concentrated on static obstacles in unknown environment.

In this paper, FLC is designed for mobile robot navigation and obstacle avoidance in unknown environment and optimized using evolutionary algorithm. This paper is organized as follows. Section 2 presents fuzzy logic controller. The proposed hybrid genetic-fuzzy logic algorithm is presented in section 3. Section 4 shows simulation results of proposed methods. Section 5 presents a conclusion.

2 Fuzzy Logic Controller (FLC)

In this work, we use two fuzzy logic behaviors: Motion to target behavior (FLC$_{I}$) and obstacle avoidance behavior (FLC $_{II}$). **The Motion to target behavior** is used to generate the right velocity and left velocity of the mobile robot, which allows the robot to move from start point to destination point using Fuzzy Logic. The FLC$_{I}$ has two inputs: Distance to the target, Angle error between robot and target and two outputs: Left Wheel Velocity (LV) and Right Wheel Velocity (RV).

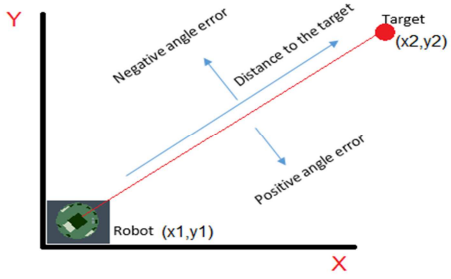

Figure 1: Robot and target in XY plane.

Figure (1) shows the distance and angle of robot in XY plane where (x1, y1):- current position of robot, (x2, y2):- target position. Equation (1) is used to calculate distance and angle between robot and target.

Dist. = $\sqrt{(y2-y1)^2+(x2-x1)^2}$ & Angle err. = atan2 ((y2-y1), (x2-x1)) (1)

The membership function is a graphical representation for the values of inputs and outputs. In this paper, seven 'Gaussian' membership functions are considered. The range of the distance to target is divided into seven linguistic variables, namely Zero (Z), Small (S), Near Mid (NM), Mid (M), Near Far (NF), Far (F), and Very Far (VF). For angle error between robot and target is divided into seven linguistic variables, namely Very Negative (VN), Near Negative (NN), Negative (N), Zero (Z), Near Positive (NP), Positive (P), and Very Positive (VP). Figure (2) illustrate the distributions of membership function for input variables of the FLC.

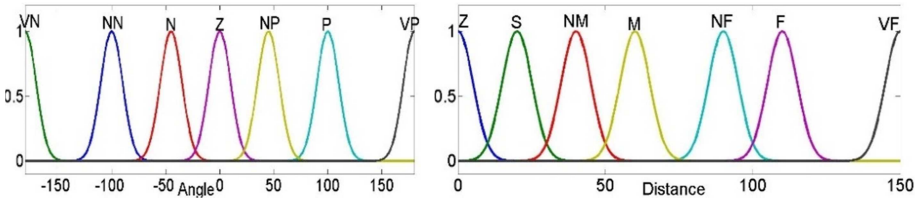

Figure 2: Distribution of membership function of input variables (Distance, Angle).

The range of left and right velocities is divided into seven linguistic variables, namely Zero (Z), Small (S), Near Mid (NM), Mid (M), Near High (NH), High (H), and Very High (VH). Figure (3) illustrate the distributions of membership function for output variables of the FLC.

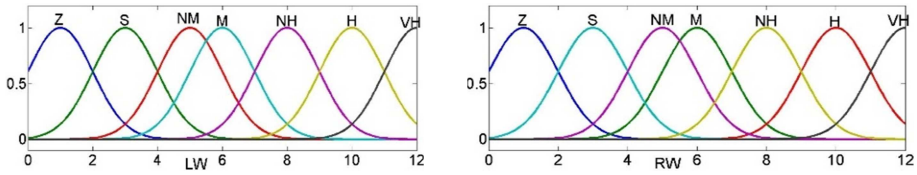

Figure 3: Distribution of membership function of output variables (LW, RW).

In obstacle avoidance behavior (FLC Ⅱ), this behavior is used to intelligent control the mobile robot among obstacles to reach the destination. The inputs of this fuzzy logic (FLCⅡ) are distances to obstacles that calculated from data sensors calculated as follow:-

Left Distance Obstacle (LD) = max (sensor reading (0), sensor reading (1))

Front Distance Obstacle (FD) = max (sensor reading (2), sensor reading (3))

Right Distance Obstacle (RD) = max (sensor reading (4), sensor reading (5))

The outputs of this fuzzy logic behavior are Left (LV) and Right velocities (RV). The range of Obstacle's distance is divided into three linguistic variables, namely Near (N), Medium (M), and Far (F). Figure (4) illustrates the distribution of membership function for input variables of the FLCII. For outputs variable, the range of LV, RV are divided into three linguistic variables, Small (S), Mid (M), and Fast (F). Figure (5) illustrates the distribution of membership function for output variables of the FLCII.

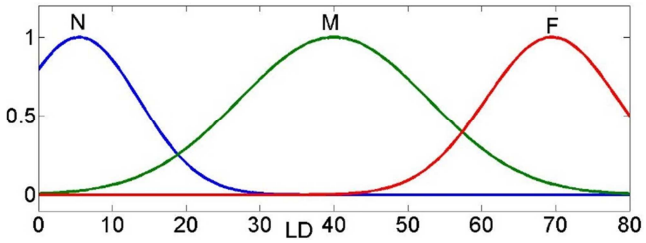

Figure 4: Distribution of membership function of input variables (LD, FD, and RD).

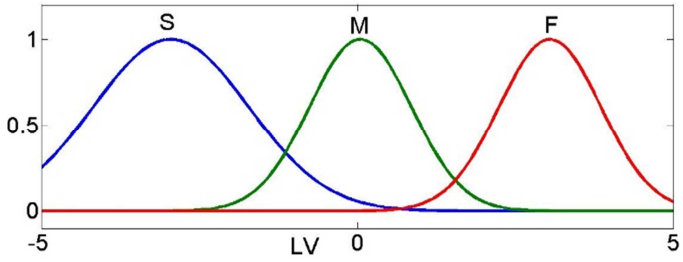

Figure 5: Distribution of membership function of output variables (LV and RV).

3 Genetic-Fuzzy Algorithm (GA-FLC)

A Genetic Algorithm (GA) is a model of evolutionary learning systems that use biological evolution in order to solve problems. A GA is a type of Evolutionary Algorithms and is an optimization tool in computer science. The solutions of a given problem are represented into chromosomes as a string of bits or any type of models and compute the fitness (cost function) for each solution. Crossover and Mutation are a main of GA operations, to apply crossover operator two solutions selected randomly based on fitness and combining, while mutation perform small change in a solution randomly. Figure (6) illustrates the general representation of proposed GA-FLC method. Firstly, we create initial population randomly. Each chromosome in population represents a solution (fuzzy logic controller). Second, simulate each chromosome using Simulator and assign fitness for each chromosome. Third, Select parents by fitness-proportionate selection technique called Roulette Wheel Selection. Finally, apply crossover and mutation to generate new population (offspring) and apply fitness-based selection technique to generate next population. We repeat these steps until reach number of generation.

3.1 Chromosome Representation

In this paper, we used a GA to tuning the Membership Function (MF) parameters of Motion to target behavior (FLC1). For this purpose, each MF of each input and output variables are represented in 2 bits **σ** represents the width of MF and **C** represents the center of MF. We use 56 bits as a length of each chromosomes: **4** (input and output variable) *** 7** (# of MF for each variable)*** 2** (for each MF) = **56.**

3.2 Fitness Function

GA require a fitness function in order to select the best chromosome (solution) for reproduction and new generation. The simulation (KIKS Simulator) is run for each solution to compute the fitness calculated by equation (3).

$$\text{Fitness } (chrom\ i) = A*DT + B*TR + C*DR \qquad (3)$$

Where, DT is a Distance Travelled by the robot to reach the target, TR is a Time required to reach target , DR is a Distance remaining to target (if the robot takes 1 minute and don't reach the target then, we add the remaining distance to fitness), and A, B, and C are a constant . The fitness function used should be minimized; figure (7) shows the fitness values through 100 generations.

Roulette wheel selection is used to select parents and apply crossover to generate offspring. The parameters of GA used in this work illustrates in table (1).

Number of Generation	100
Population size	50
Crossover	"Cut-and-crossfill"
Crossover rate	95%
Mutation rate	30%
Parent Selection	Roulette wheel selection
Generation selection	Fitness-based Selection

Table 1: Genetic Algorithm Parameters

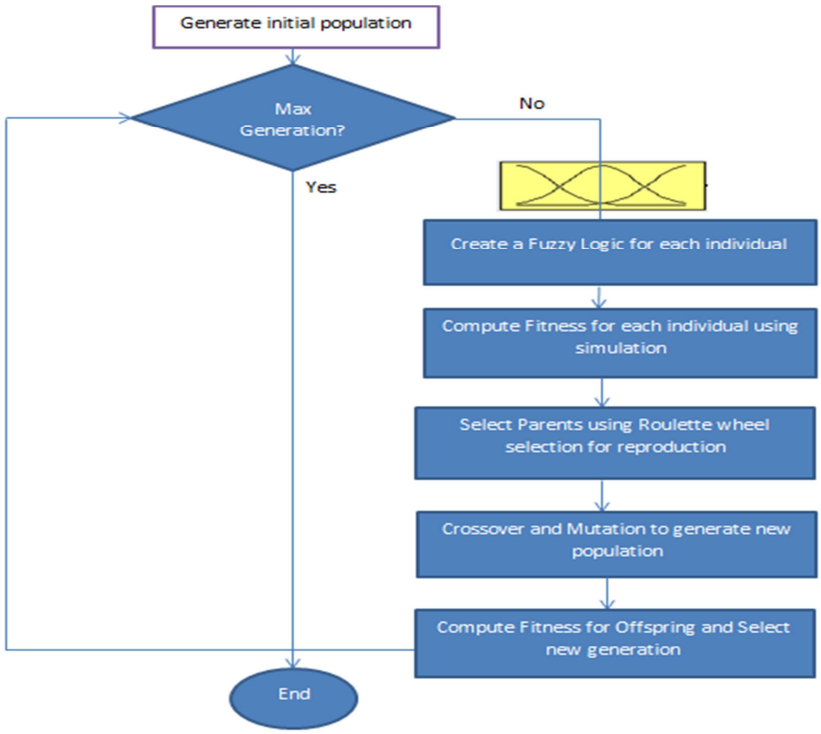

Figure 6: Genetic-Fuzzy Algorithm.

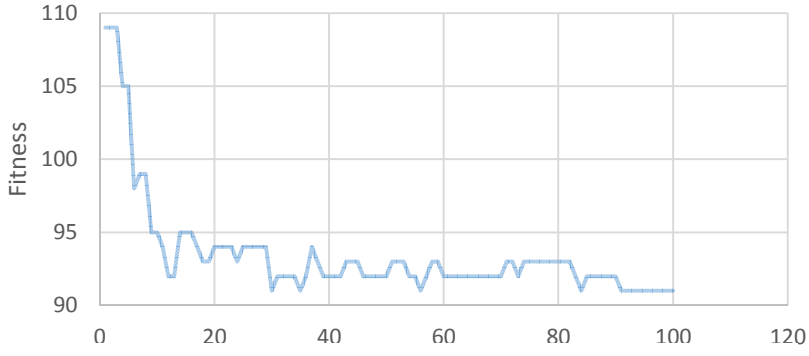

Figure 7: Relationship between Generation and fitness.

The membership functions of the motion to target behavior after we applied the genetic algorithm to learn and tune the membership functions are shown in figure (8).

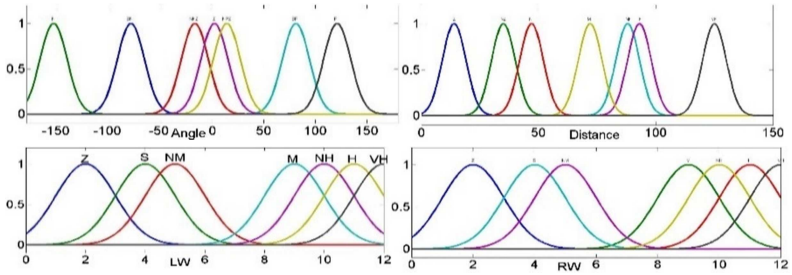

Figure 8: Membership function distribution of the best solution after 100 generations.

4 Simulation Results

The objective of this work is to optimize the fuzzy logic controller by tuning the membership function using genetic algorithm. In order to compare the two proposed methods (FLC & GA-FLC), we used a KiKS [Khepera Simulator, 10]. KiKS is a matlab application that simulates a Khepera robot in the way as real physical Khepera. Two criteria are considered to make comparison between these two proposed methods (Time required to reach the target, and the distance travelled from the start point to the target). The KiKS simulator have a monitor simulation details that use to compute Distance travelled and Time required. The comparison of robot navigation of proposed methods using several scenarios are presented in figs 9-14.

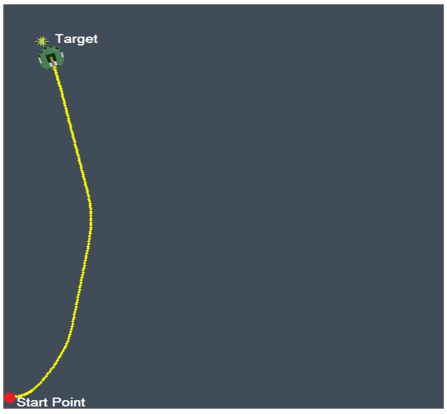

Figure 9: Scenario 1: robot navigation without Obstacle using FLC.

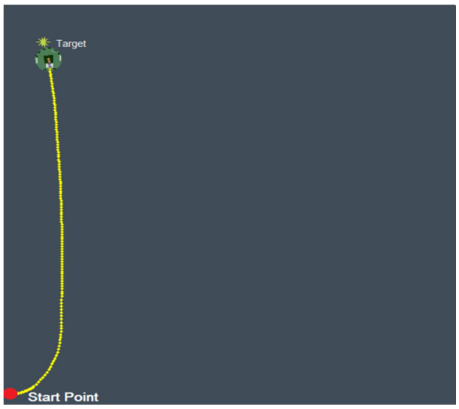

Figure 10: Scenario 1: robot navigation without Obstacle using GA-FLC.

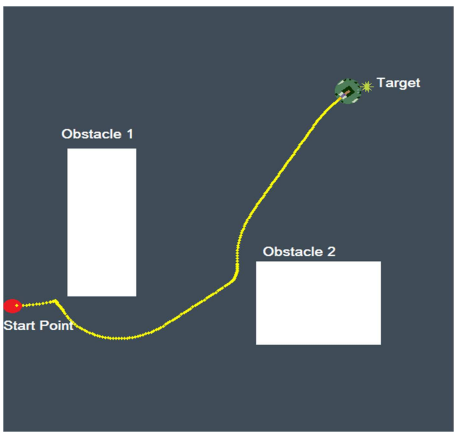

Figure 11: Scenario 2: robot navigation with two Obstacles using FLC.

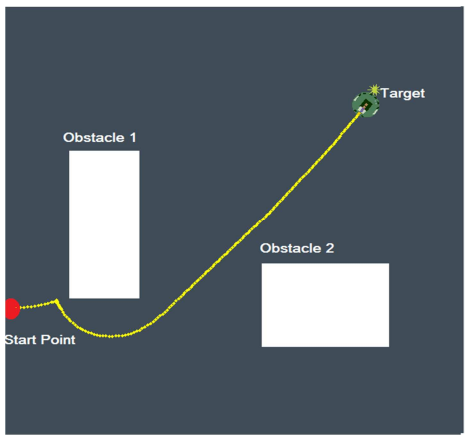

Figure 12: Scenario 2: robot navigation with two Obstacles using GA-FLC.

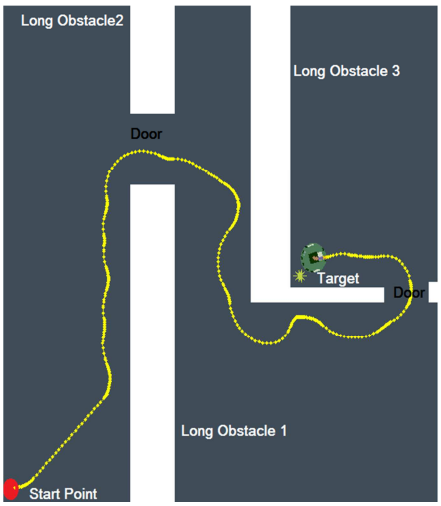

Figure 13: Scenario 3: robot navigation with Long Obstacles and Doors using FLC.

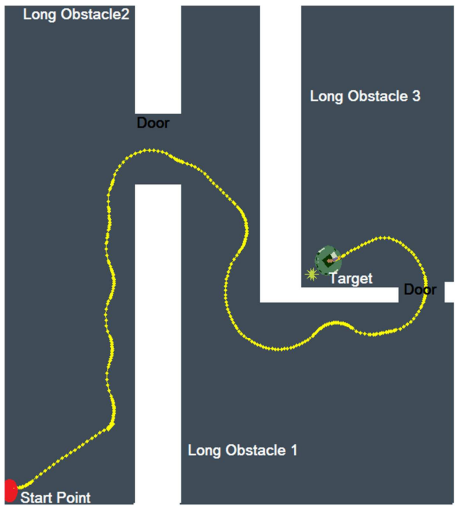

Figure 14: Scenario 3: robot navigation with Long Obstacles and Doors using GA-FLC.

Results of comparison of proposed methods in different scenarios with and without obstacles in unstructured environment are shown in table (2). Simulation results show that GA-FLC method gives the best result of distance travelled and time required used to reach the target for all scenarios.

Scenario	Method	Distance Travelled (cm)	Time Required (s)
Scenario 1	**FLC**	**89.1**	**23**
	GA-FLC	**86.5**	**19**
Scenario 2	**FLC**	**115.4**	**29**
	GA-FLC	**114.5**	**25**
Scenario 3	**FLC**	**219.0**	**52**
	GA-FLC	**211.6**	**49**

Table 2: Comparison for FLC and GA-FLC with different scenarios.

5 Conclusion

In this paper, we have shown how to apply an evolutionary learning algorithm to optimize the robot navigation in an unknown environment. Two approaches for mobile robot navigation in an unstructured environment with obstacle avoidance using fuzzy logic controller (FLC) and a hybrid genetic algorithm with fuzzy logic controller (GA-FLC) are discussed. KiKS simulator successfully tests the proposed methods. Simulation results show that the hybrid Genetic-Fuzzy Algorithm (GA-FLC) provide better performance compared with Fuzzy Logic Controller (FLC).

Acknowledgments

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References

[Faisal, et al., 13] Faisal, M., Hedjar, R., Al Sulaiman, M., and Al-Mutib, K., "Fuzzy Logic Navigation and Obstacle Avoidance by a Mobile Robot in an Unknown Dynamic Environment," Int J Adv Robotic Sy, vol. 10, no. 37, (2013).

[Goldberg, 89] Goldberg, D. E., "Genetic algorithms in search, optimization, and machine learning," 1989.

[Hassanm and Deepika , 12] Hassan, S., Deepika. S., "Fuzzy based mobile robot navigation in an unknown Environment," International Conference on Computing and Control Engineering, 2012.

[Hellmann, 01] Hellmann, M., "Fuzzy logic introduction," Université de Rennes, http://epsilon.nought.de/tutorials/fuzzy/fuzzy.pdf. (2001).

[KheperaSimulator, 10] KiKS is a Khepera Simulator, http://www.theodorstorm.se/index/2866.html .

[Parhi, 05] Parhi, D. R., “Navigation of mobile robots using a fuzzy logic controller,” Journal of Intelligent & Robotic Systems, vol. 42, no. 3, pp. 253–273 (2005).

[Raguraman, et al., 09] Raguraman, S. M., Tamilselvi, D., and Shivakumar, N., “Mobile robot navigation using Fuzzy logic controller,” in INCACEC 2009 pp. 1–5 (2009).

[Russo, 00] Russo, M., “Genetic fuzzy learning,” Evolutionary Computation, IEEE Transactions on, vol. 4, no. 3, pp. 259–273 (2000).

[Senthilkumar, 10] Senthilkumar, K. S., “Single Robot Motion Planning using Fuzzy-Genetic.”, Canadian Journal on Automation Control & Intelligent System Vol. 1, No. 1, (2010)

[Zadeh, 94] Zadeh, L. A., “Soft computing and fuzzy logic,” Software, IEEE, vol. 11, no. 6, pp. 48–56 (1994).

[Zhang, et al., 07] Zhang, H., Dai, X., Shi, Y., "State of the Art for Soft Computing Technologies in Mobile Robot Navigation," on ICICIC '07, pp.573, 5-7 (2007).