Evolutionary Artificial Potential Fields and Their Application in Real Time Robot Path Planning

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Abstract- A new methodology named Evolutionary Artificial Potential Field (EAPF) is proposed for real-time robot path planning. The artificial potential field method is combined with genetic algorithms, to derive optimal potential field functions. The proposed Evolutionary Artificial Potential Field approach is capable of navigating robot(s) situated among moving obstacles. Potential field functions for obstacles and goal points are also defined. The potential field functions for obstacles contain tunable parameters. Multi-objective evolutionary algorithm (MOEA) is utilized to identify the optimal potential field functions. Fitness functions like, goal-factor, obstacle-factor, smoothness-factor and minimum-path-length-factor are developed for the MOEA selection criteria. An algorithm named escape-force is introduced to avoid the local minima associated with EAPF. Moving obstacles and moving goal positions were considered to test the robust performance of the proposed methodology. The simulation results showed that the proposed methodology is efficient and robust for robot path planning with non-stationary goals and obstacles.

1 Introduction

The robot path planning problem can be typically described as follows [17]: given a robot and a description of its working environment, plan a collision free path between two specified locations that satisfies certain optimization criteria. Path planning has been studied and applied in many research fields. Collision-free path planning algorithms for robot manipulators are proposed in [1] and [2]. Path-planning methods for autonomous vehicles working in natural sites are suggested in [6]. Path planning schemes for multiple robots are discussed in [11] and [12]. Depending on the field of application, robot path-planning methods differ. In general, path-planning methods can be classified in to two: the artificial potential field (APF) methods [6, 7, 8, 9, 10] and the artificial intelligence (AI) methods [1, 2, 3, 4, 5].

Many artificial intelligence methods exist for path planning, based on tools like, genetic algorithms (GA) [3, 4, 5], fuzzy [22, 23] and artificial neural network [24, 25]. These methods are associated with optimization algorithms, resulting in optimal global path planning. However, optimization algorithms are relatively complex, time-consuming, and are not very useful for real time applications. Artificial intelligence methods can be resorted to when the available information on the environment is ambiguous. The artificial potential field approaches are much convenient than AI methods for their high efficiency in path planning provided that the working environment is known.

Artificial potential fields are in use, in the context of obstacle avoidance, since Khatib [18]. In this approach a mobile robot applies a force generated by the artificial potential field as control input to its driving system. The traditional artificial potential field approaches were often purely reactive in nature and do not optimize the path arrived at [19, 20]. Modified potential field approaches with robust and improved performance have been reported lately: Chanclou B. [6] suggested path planners to impart robust features to the artificial potential field functions. This approach relies on two path-planners, one for global planning through physical computations, and the other for local planning though a physical simulation of the vehicle within the environment. These two planners work together to arrive at a suitable path through a natural terrain.

Akishita S. et. al. [8] proposed a navigator function to deal with the local minima associated with the traditional potential fields. A hydrodynamic potential field is utilized in this work to guide a mobile robot towards the goal while avoiding moving obstacles. The workspace for the robot is compared with a flow field, and the path to a streamline in this approach. Makita, Y. et. al. [9] proposed an hybrid method to improve the performance of the artificial potential fields. The hybrid method combined fuzzy control rules with potential field functions, for vehicle navigation and control in presence of obstacles. The potential field was generated based on Plumer's [7] technique, and the path using fuzzy rules. Such an approach resulted in less number of fuzzy antecedent input variables and prevented the control rules from being complex. Kun et. al. [10] proposed an adaptive fuzzy controller for robot path planning, to improve the flexibility of the artificial potential field method. Genetic algorithm (GA) is used to adjust the fuzzy control rules in the above work. The system will switch to the fuzzy tracking mode, when a robot is trapped in a local minimum. The fuzzy tracking mode controller continuously modifies the path, by tracking the obstacles, until the robot is able to escape from the local minimum. Compared with the traditional artificial potential field methods, the above methods provide robust and improved performance. However, these methods are complex for fast and real time path planning, and are not being applied in situations

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with moving obstacles and moving goal positions.

In this work, the artificial potential field method is combined with AI, to derive an optimal and efficient path planning method. An evolutionary artificial potential field (EAPF) method is proposed for real-time path planning. The objectives of this work are:

- To design a simple artificial potential field function with tunable parameters, for real time application,
- To derive the associated cost functions,
- To optimize the parameters of the potential field function with the multi-objective evolutionary algorithm (MOEA), and,
- To use the proposed evolutionary artificial potential field for real time robot navigation with moving obstacles around, and for moving goal positions.

The rest of the paper consists of four sections. Section 2 introduces the evolutionary artificial potential field method. The implementation of the proposed evolutionary artificial potential field is described in Section 3. Section 4 contains simulation results, followed by conclusions and suggestions for future research in section 5.

2 The Evolutionary Artificial Potential Field

2.1 The traditional artificial potential field methods

In the traditional artificial potential field methods, an obstacle is considered as a point of highest potential, and a goal as a point of lowest potential. In the domain of robot path planning, a robot always moves from a high potential point to a low potential point. In general, these procedures involve the following basic steps:

1. Setting up a potential field function Φ which can be a function of distance D, such as: $\Phi = 1/D$ [10],
2. Use of special algorithms to locate a minimum potential point,
3. Navigating a robot towards the minimum potential point arrived at, and,
4. The repetition of steps 2 and 3, until the robot reaches the goal position.

Traditional artificial potential field methods are efficient in identifying safe paths for robots. However, if an optimal path is required, it is needed to include the relevant optimization functions and associated constraints. The constraints invariably introduce complex computations, and the local minimum will be difficult to define and tackle.

2.2 The Evolutionary Artificial Potential Field (EAPF)

In the traditional artificial potential field function approach, no optimization process is involved in. The path generated through this approach will be safe but not optimal. In order to optimize the path arrived at; a new method named the Evolutionary Artificial Potential Field (EAPF) is proposed. In the evolutionary artificial potential field method, evolutionary algorithms optimize the potential field functions.

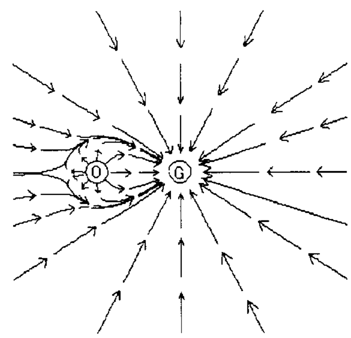

Figure 1: Evolutionary Artificial Potential Field

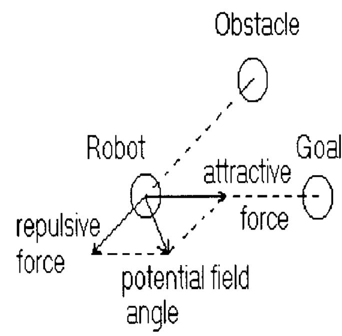

Figure 2: Resultant Angle direction in EPAF

Inspired by the natural potential fields, it is assumed that a robot moves in a direction along the potential field angle. The angle direction at any point in the field is along the resultant of a repulsive force from the obstacle and an attractive force towards the goal (Figure 2). The complete field associated with an evolutionary artificial potential field can be derived, once the repulsive and attractive forces at each point in the potential field are known (Figure 1).

Unlike the traditional approaches, different potential functions for obstacles and the goal are considered in the proposed approach. Evolutionary algorithm is used to optimize the obstacle potential field functions. The associated steps are:

- Designing a standard attractive force function for the goal point, and repulsive force functions with tunable parameters for different obstacle types. At each point in the field, the resulting potential field angle is along the angle of the resultant of the attractive and repulsive forces. Potential field functions are always considered as functions of distance. The attractive force towards the goal F_a, and the repulsive force from an obstacle F_r are defined in Equations 1 and 2, respectively.

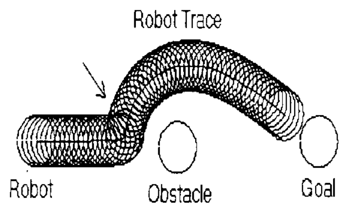

Figure 3: Robot trace without the escape-force function in EAPF

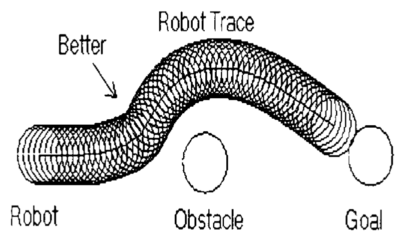

Figure 4: Robot trace with the escape-force function in EAPF

$$F_a = \frac{1}{D_{rg}} \tag{1}$$

$$F_r = \frac{1}{(aD_{ro})^n} \tag{2}$$

$$\text{Potential field angle} = \angle(F_a + \sum F_r) \tag{3}$$

Where, F_2 and F_r represent the attractive and repulsive forces. D_{rg} is the distance between the robot and the goal. D_{ro} is the distance between the robot and an obstacle. The parameters, a and n are to be optimized.

- Designing potential field cost functions for the system. The cost functions determine the fitness of a potential field function, otherwise known as a string. By comparing the cost functions of two such strings, it is possible to determine which of the two potential field functions is the best for the system.
- Use of the multi-objective evolutionary algorithm (MOEA) [14], to optimize the parameters of each of the potential field functions of the obstacles. The MOEA has four operations involved with; selection, crossover, mutation and ranking. Selection is the process of choosing a user-specified population size from a pool of population. In the crossover operation genes are exchanged between two strings. Mutation is used to randomly alter the genes of a string. The rank of a string is one plus the number of other superior strings within the population. The rank is related to a string's overall superiority within the population, and is used in the selection process to choose the strings to generate a temporary population. The MOEA is used till a satisfied result is obtained.
- Use of the evolutionary potential field function to navigate the robot(s).

Figure 5: The goal factor

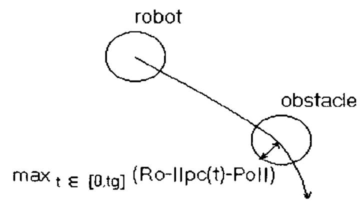

Figure 6: The obstacle factor

The resulting evolutionary artificial potential field function will be the optimal potential field function for an obstacle. The same function can be used in a multi-obstacle environment, where all the obstacles are of the same size. In the proposed EAPF method, only the information of the positions of the robot(s), obstacles and the goal point are required to plan the path. Due to this, the algorithm is suitable in situations where moving obstacles and moving goal point exist. The resulting robot navigation procedure is simple and fast.

If obstacles are of different sizes, it is needed to find optimal potential field functions for each of the obstacles. The rest of the procedure remains the same.

2.3 The Local Minimum associated with EAPF

The local minimum is a problem to be tackled in the artificial potential field methods. A robot navigated along an artificial potential field may be stable or may oscillate at the local minimum. Due to complex computations associated with, the traditional APF approaches trouble shoot at the local minimum. The evolutionary artificial potential field approach also suffers from the local minimum. However, as the associated computation is simple, the local minimum is easy to define and, it is easy to include additional algorithm to tackle the same. In this work, an additional algorithm named 'escape-force' is introduced to avoid the local minimum.

In the evolutionary artificial potential field, local minima exist within the areas around the null-potential points. The null-potential point condition is:

$$F_a + \sum F_r = 0 \tag{4}$$

A local minimum is identified when the following two conditions are satisfied (Equations 5 and 6).

$$\frac{F_a - \sum F_r}{\sum F_r} < b \tag{5}$$

$$\cos(\angle F_a - \angle \sum F_r) < -\cos(c) \tag{6}$$

When Equations (4) and (5) are satisfied, an additional escape force is applied:

$$F_e = \left(\frac{1}{dD_{ro}^m}\right)\left(\left|\cos(\angle F_a - \angle \sum F_r) - \cos(c)\right|\right) \tag{7}$$

Where, F_e represents the escape force. The parameters, b, c, d and m are to be optimized with the multi-objective evolutionary algorithm

Figures 3 and 4 show the results with and without the escape-force function. The result is better in Figure 4 with the escape force function.

3 Implementation of the evolutionary artificial potential field approach

3.1 The attractive and repulsive force functions in EAPF

In this section, the implementation of the evolutionary artificial potential field is discussed. It is assumed that there are several obstacles of equal size and a single goal within the environment. The aim is to plan an optimal collision-free path for the robot. EAPF is used to navigate the robot. The obstacles and goal are considered as different potential field resources. The potential field functions for the attractive and repulsive forces are (described in Section 2.2):

$$F_a = \frac{1}{D_{rg}} \tag{8}$$

$$F_r = \frac{1}{(aD_{ro})^n} \tag{9}$$

$$\text{Potential field angle} = \angle(F_a + \sum F_r) \tag{10}$$

3.2 The cost function

Three fitness functions, namely, the goal-factor, the obstacle-avoidance-factor, and the minimum-path-length-factor are utilized in the proposed approach while arriving at an optimal path. The associated cost functions are defined in Equations 8, 9 and 10. The goal-factor is zero when the robot is at the target point. The obstacle-factor is zero as long as the robot is not in collision with an obstacle. The minimum-path-length-factor denotes the path length of the shortest path.

Goal-factor (Figure 5):

$$f_p = \begin{cases} 0 & \text{robot at target point} \\ F_p + min_{t\in[0,t_g]}\left(||p(t) - P_g||\right) & \text{otherwise} \end{cases} \tag{11}$$

Obstacle-factor (Figure 6):

$$f_o = \begin{cases} 0 & \text{no collision} \\ F_o + max_{t\in[0,t_g]}\left(R_o - ||pc(t) - P_o||\right) & \text{otherwise} \end{cases} \tag{12}$$

Minimum-path-length-factor:

$$f_{\text{path length}} = \text{whole length of the planned path} \tag{13}$$

Through evolution it is desired to have zero values for the goal-factor and the obstacle-factor. Smaller minimum-path-length-factor means better performance of the potential function.

3.3 Optimization of the evolutionary potential field function using MOEA

The multi-objective evolutionary algorithm is used to optimize the parameters of the potential field function. The multi-objective evolutionary algorithm (MOEA) is a stochastic search technique inspired by the principles of natural selection and natural genetics. It has attracted significant attention from researchers and technologists in various fields, because of its ability to search for a set of Pareto optimal solutions. In this paper, the MOEA toolbox [14] is used to facilitate the optimization process. The MOEA toolbox is developed at The National University of Singapore as a tool for multi-objective optimization. Figure 7 shows the necessary settings to run MOEA toolbox.

4 Simulation Results

The evolutionary artificial potential field was implemented on different tasks in diversity situations to test its robust performance.

Figure 8 shows four path planning tasks with a stationary obstacle and a stationary goal situation. In each task, the obstacle is kept at different locations. Collision free optimal paths were obtained in all the four cases.

Figure 9 shows four path-planning tasks with a moving obstacle and a moving goal situation. In the first three cases in Figure 9, the goal point and the obstacle move in different directions. To show the robustness of the proposed EAPF, the goal point and the obstacle are considered on the move in a random fashion in the last case in Figure 9.

Figure 10 shows four path-planning tasks in a multi-obstacle situation with a single stationary goal point. In the

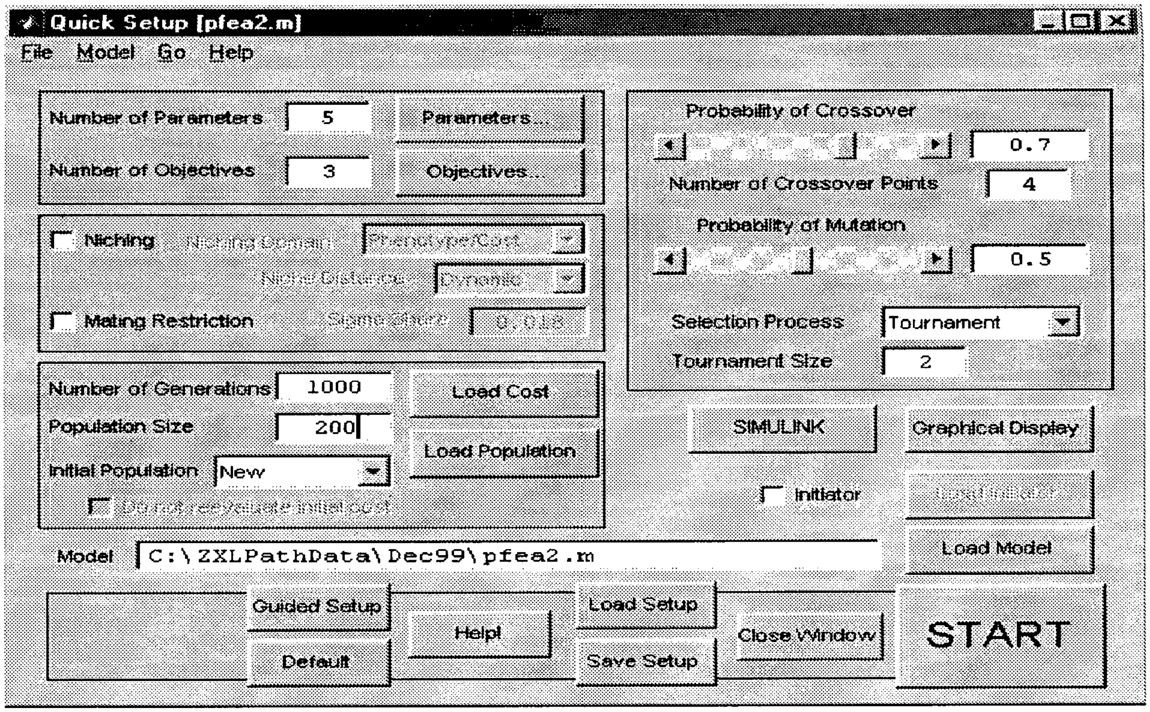

Figure 7: MOEA Toolbox settings

first case in Figure 10, the robot could reach the stationary goal avoiding the two stationary obstacles. In the next two cases in Figures 10, the robot could seek the moving goal point while avoiding several moving obstacles. In the last case in Figure 10, the robot was able to seek the random moving goal while avoiding three randomly moving obstacles.

From the above results, it is observed that the proposed evolutionary artificial potential field method can always plan an optimal smooth path, irrespective of whether the obstacles and the goal point are stationary or on the move.

5 Conclusion and suggestions for future research

In this paper, an evolution artificial potential field method is proposed for robot path planning. The proposed method is capable of navigating robots among moving obstacles and is able to seek the moving goal points as well. Compared with the traditional potential field method, the resulting paths are always smooth and optimal. Added to that, the path planning process is simple and fast.

Future research is still needed on the following points:

- Further improvement on path planning performance. Although the multi-objective evolutionary algorithm optimizes the potential function, the path planning performance is still limited by the basic model of the potential field function. To further improve the path-planning performance, optimal algorithms for the basic model of the potential field function are to be derived.
- This paper considered only obstacles of equal size. Without any loss of generality, the same algorithm can be extended to environments where the obstacle sizes differ.
- Recently, several methods have been reported, which combined the fuzzy and neural network tools with the artificial potential field [7,10]. A combination of these methods with the proposed method will be interesting to look into.

Bibliography

[1] Baba, N. and Kubota, N. (1994) "Collision avoidance planning of a robot manipulator by using genetic algorithm. A consideration for the problem in which moving obstacles and/or several robots are included in the workspace," Evolutionary Computation. IEEE World Congress on Computational Intelligence, Proceedings of the First IEEE Conference on, 1994, Page(s): 714 -719 vol.2

[2] Rana, A.S. and Zalzala, A.M.S. (1995) "An evolutionary algorithm for collision free motion planning of multi-arm robots," Genetic Algorithms in Engineering Systems: Innovations

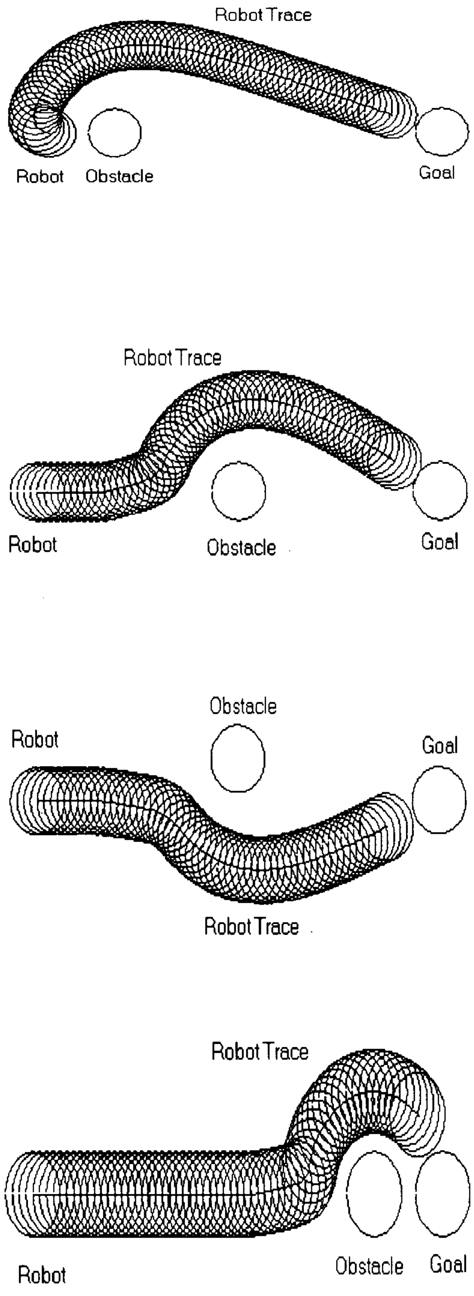

Figure 8: Path planning for one obstacle and one stationary goal

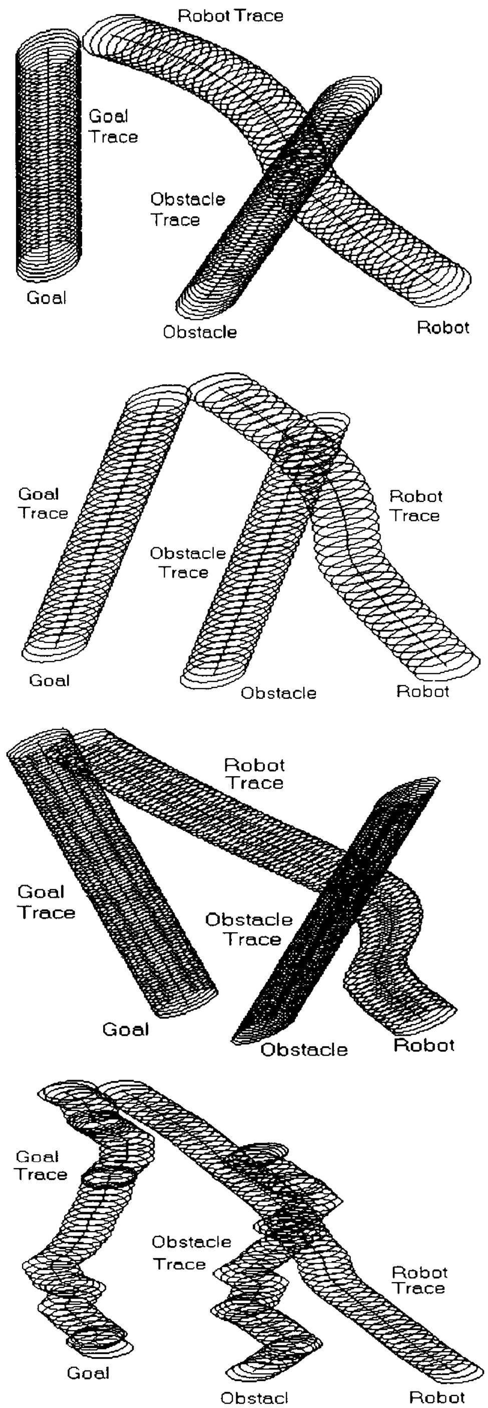

Figure 9: Path planning for one moving obstacle and one moving goal

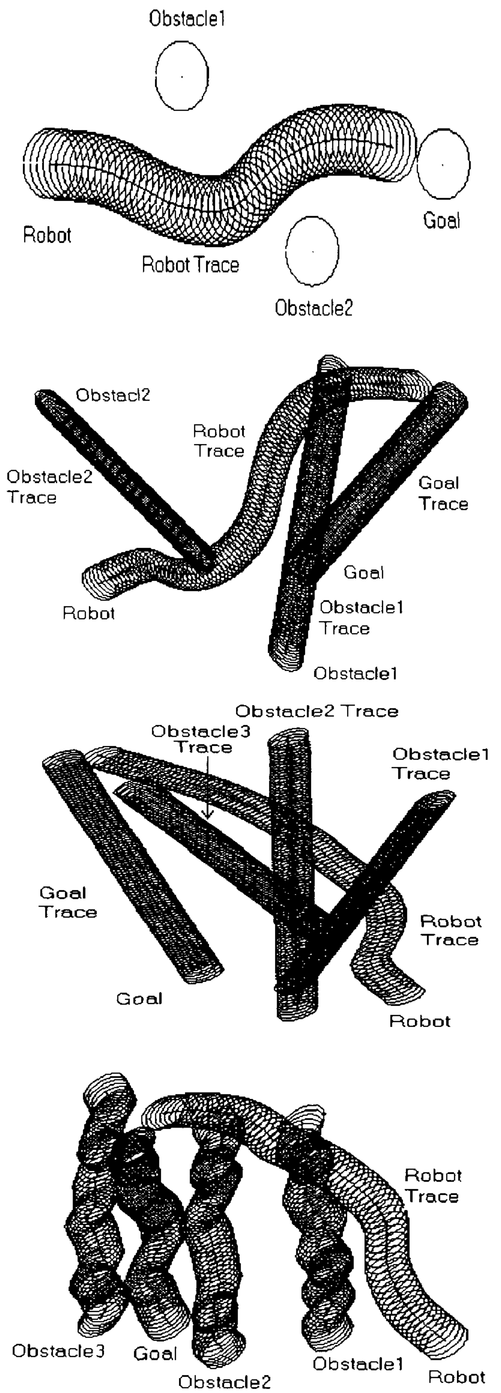

Figure 10: Path planning with multiple obstacles and one goal

and Applications, 1995. GALESIA. First International Conference on, Page(s): 123 -130

[3] Byoung-Tak Zhang and Sung-Hoon Kim,(1997) "An evolutionary method for active learning of mobile robot path planning", Computational Intelligence in Robotics and Automation, 1997. CIRA'97, Proceedings, 1997 IEEE International Symposium on, 1997, Page(s): 312 -317

[4] Dozier, G.; McCullough, S.; Homaifar, A.; Tunstel, E. and Moore, L., (1998) "Multiobjective evolutionary path planning via fuzzy tournament selection", Evolutionary Computation Proceedings, 1998. IEEE World Congress on Computational Intelligence, The 1998 IEEE International Conference on, 1998, Page(s): 684 -689

[5] Gerke, M., (1999) "Genetic path planning for mobile robots", American Control Conference, 1999. Proceedings of the 1999 Volume: 4, 1999, Page(s): 2424 -2429 vol.4

[6] Chanclou, B. and Luciani, A. (1996) "Global and local path planning in natural environment by physical modeling", Intelligent Robots and Systems '96, IROS 96, Proceedings of the 1996 IEEE/RSJ International Conference on Volume: 3, 1996, Page(s): 1118 -1125 vol. 3

[7] E.S.Plumer, (1992) "Neural network structure for navigation using potential fields," in Proc. Int. Joint Conf. Neural Networks (IJCNN-92), vol. 1, pp. 327-332, 1992.

[8] (1993) Akishita, S.; Hisanobu, T. and Kawamura, S., (1993) "Fast path planning available for moving obstacle avoidance by use of Laplace potential", Intelligent Robots and Systems '93, IROS '93. Proceedings of the 1993 IEIEE/RSJ International Conference on Volume: 1, 1993, Page(s): 673 -678 vol.1

[9] Makita, Y.; Hagiwara, M. and Nakagawa, M., (1994) "A simple path planning system using fuzzy rules and a potential field", Fuzzy Systems, 1994. IEEE World Congress on Computational Intelligence, Proceedings of the Third IEEE Conference on, 1994, Page(s): 994 -999 vol.2

[10] Kun Hsiang Wu; Chin Hsing Chen and Jiann Der Lee, "Genetic-based adaptive fuzzy controller for robot path planning", Fuzzy Systems, 1996, Proceedings of the Fifth IEEE International Conference on Volume: 3, 1996, Page(s): 1687 -1692 vol.3

[11] Woong-Gie Han; Seung-Min Baek and Tae-Yong Kuc, (1998) "GA based online path planning of mobile robots playing soccer games", Circuits and Systems, 1997. Proceedings of the 40th Midwest Symposium on Volume: 1, 1998, Page(s): 522 -525 vol.1

[12] Jong-Hwan Kim; Kwang-Choon Kim; Dong-Han Kim; Yong-Jae Kim and Vadakkepat, Prahlad, (1998) "Path planning and role selection mechanism for soccer robots", Robotics and Automation, 1998. Proceedings. 1998 IEEE International Conference on Volume: 4 , 1998 , Page(s): 3216 -3221 vol. 4

[13] Hong, C.S.; Chun, S.M.; Lee, J.S. and Hong, K.S., "A vision-guided object tracking and prediction algorithm for soccer robots"

[14] Tan. K. C.; Wang, Q. G.; Lee, T. H.; Khoo, T. T. and Khor, E. F., (1999) "A Multi-Objective Evolutionary Algorithm Toolbox for Matlab", (http://vlab.ee.nus.edu.sg/~kctan/moea.htm), 1999

[15] Heung-Soo Kim; Hyun-Sik Shim; Myung-Jin Jung and Jong-Hwan Kim, (1997) " Action selection mechanism for soccer robot", Computational Intelligence in Robotics and Automation, 1997. CIRA'97, Proceedings, 1997 IEEE International Symposium on, 1997, Page(s): 390 -395

[16] Jong-Hwan Kim; Hyun-Sik Shim; Heung-Soo Kim; Myung-Jin Jung and Vadakkepat, P. (1998) " Action selection and strategies in robot soccer systems", Circuits and Systems, 1997. Proceedings of the 40th Midwest Symposium on Volume: 1, 1998, Page(s): 518 -521 vol.1

[17] C. -K. Yap, (1987) "Algorithmic motion planning", in the Advances in Robotics, Vol. 1: Algorithmic and Geometric Aspects of Robotics, J. T. Schwart and C. -K. Yap, Eds. Hillsdale, NJ: Lawrence Erlbaum, 1987, pp. 95-143

[18] O. Khatib, (1986) "Real-time obstacle avoidance for manipulators and mobile robots", Int. J. for Robotics Research, Vol. 5, NO.1, pp90-99, 1986

[19] J. Borenstein; Y.Koren, (1991) "The vector field histogram-Fast obstacle avoidance for mobile robots", IEEE Trans. Robot. Automat., vol.7, no. 3, pp. 278-287, June 1991

[20] V. J. Lumelsky, (1991) "A comparative study on the path length performance of maze-searching and robot motion planning algorithms", IEEE Trans. Robot. Automat., vol. 7, no. 1, pp. 57-66, Feb. 1991

[21] http://www.fira.net

[22] Gerke, M. and Hoyer H., (1995) "Fuzzy collision avoidance for industrial robots", Intelligent Robots and Systems 95. 'Human Robot Interaction and Cooperative Robots', Proceedings. 1995 IEEE/RSJ International Conference on Volume: 2, 1995, Page(s): 510 -517 vol.2

[23] Liu, K. and Lewis, F.L., (1994) "Fuzzy logic-based navigation controller for an autonomous mobile robot", Systems, Man, and Cybernetics, 1994. Humans, Information and Technology, 1994 IEEE International Conference on Volume: 2, 1994, Page(s): 1782 -1789 vol.2

[24] Koh, K.C.; Beom, H.R. and Kim, J.S., (1994) "A neural network-based navigation system for mobile robots", Neural Networks, 1994. IEEE World Congress on Computational Intelligence, 1994 IEEE International Conference on Volume: 4, 1994, Page(s): 2709 -2714 vol.4

[25] Lee, S. and Kardaras, G., (1997) "Collision-free path planning with neural networks", Robotics and Automation, 1997. Proceedings, 1997 IEEE International Conference on Volume: 4, 1997, Page(s): 3565 -3570 vol.4