Application of Evolutionary Artificial Potential Field in Robot Soccer System

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Abstract

Evolutionary Artificial Potential Field (EAPF) functions are utilized for mobile robot navigation in a micro-robot soccer (MiroSot) environment. In a micro-robot soccer system the robots are monitored using an overhead CCD Camera, making it suitable for real time application of the EAPF functions. The effectiveness of the EAPF functions in real time mobile robot navigation are verified through experimentation. The EAPF functions proposed are tested in different scenarios related to ball tracking and ball kicking, while facing competition from other robots.

1. Introduction

Autonomous path planning plays an important role in mobile robot systems. Various methods have been developed for mobile robot path planning. The path planning problem can be stated as seeking a collision free path between two locations with certain optimization criteria.

The two major directions in collision free navigation are the Artificial Intelligence (AI) and the potential field approaches. The AI direction focuses on global path planning with optimization algorithms. It involves complex computing, and can be resorted to when the information on the environment is ambiguous. The potential field direction provides freedom in selecting the potential field functions and is simple in realization. This research direction has attracted great interest among researchers. Currently the robot vision systems are capable to provide efficient image processing on the workspace in real time. As a result, the positions of objects in the workspace can be identified easily, making it easier to calculate the potential field.

Potential field functions have evolved from physical potential field functions at the beginning to the Artificial Potential Field (APF) functions. Diverse path planning methods based on APF have been developed recently. Research on APF problems covers from building artificial potential functions to surpassing the restrictions of the workspace [4, 9]. Some APFs are inspired by physical processes. A new artificial potential field method for path planning of non-spherical single-body robots is presented in [3], which simulates steady-state heat transfer with variable thermal conductivity. A tradeoff between the navigation performance and the real time computation is to be resorted to in real time applications. Simple and effective functions are preferred in dynamic environments where absolute accuracy is of less importance.

Recently the topic of Evolutionary Robotics (ER) has generated much attention as a tool for the creation and programming of robot control systems [1]. ER is an attempt to develop robots and their sensorimotor control system through an automatic design process involving artificial evolution [6]. The core technique of ER is Evolutionary Algorithm (EA), which is aimed at a coherent population-oriented methodology of structural and parametric optimization of a diversity of systems. The field of evolutionary computation has reached a stage of some maturity. The methods of evolutionary computation are among such technique. The stochastic algorithms model the natural phenomena like, genetic inheritance and Darwinian strife for survival. EAs offer an important ability to cope with realistic goals and design objectives reflected in the form of relevant fitness functions. In ER, a new approach has been developed, which emphasizes on co-evolution. From biological sciences it is learned that the animal brains and bodies have developed in parallel. By evolving the robot structure and control program in parallel it is hoped that ER can begin to solve more complex problems.

Research on APF with genetic algorithms is presented in [8]. Blended with EAs, a new potential field method-

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ology named Evolutionary Artificial Potential Field (EAPF) has emerged [2]. It 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 multi-objective evolutionary algorithm (MOEA) can be resorted to, to deal with the multiple objectives associated with mobile robot navigation. MOEA is a stochastic search technique inspired by the principles of natural selection and genetics. It has attracted significant attention from researchers in various fields due to its ability to search for a set of pareto optimal solutions. The resolution is not guaranteed to be the best, but it brings out fine control result in most time.

Robot Soccer System is one of the standard problems for the study on multi-agent systems, and can be used as a common test-bench for multi-agent systems [11, 12].

The robot soccer system is involved with diverse fields like robotics, intelligent control, communication, computer technology, sensor technology, image processing, mechatronics, artificial life, etc.

In a robot soccer system, the active environment is placid and continuous, with fixed bounds and goals. For such a known environment, APF approaches are convenient to be utilized for path navigation and collision avoidance. The robot soccer system is used to verify the usefulness of the EAPF functions for real time applications.

This paper is organized as follows. The EAPF functions and the fitness function are presented in Section 2. Simulation and experimental results are included in Section 3. Conclusion and future research direction are provided in Section 4.

2. The Artificial Potential Field

In the traditional artificial potential filed methods, an obstacle is considered as a point of highest potential, and a goal as a point of lowest potential [2]. The attractive force towards the goal (F_a) and the repulsive force (F_r) from an obstacle are defined respectively in Equations 1 and 2. The potential field angle is defined in Equation 3.

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

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

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

Where D_{rg} is distance between the robot and the goal, D_{ro} is distance between the robot and the obstacle; p and n are positive parameters that are to be optimized.

When the attractive and repulsive forces balance out, the robot is trapped. To avoid this, an escape force F_e (Equation 4) is utilized [2].

$$F_e^{(i)} = \frac{\left|\cos(\angle F_a^{(i)} - \angle \sum F_r^{(i)}) - \cos(c)\right|}{dD_{ro}^m} \tag{4}$$

The potential field angle θ acts as the control signal to the robot.

$$\theta = \angle F_a - \angle \sum F_r \tag{5}$$

The multi-objective evolutionary algorithm is used to optimize the parameters (p, n, c and d) associated with the potential field function. Fitness selection is the preliminary problem in optimization. The influence of cost terms in control policy and evolutionary program techniques is presented in [1, 7]. In this paper, the following (penalty) values are minimized using EA.

C_1 = Penalty value associated with the distance between the robot and goal.

C_2 = Penalty value considered on collision.

C_3 = Penalty related to the length of the path in configuration space.

C_4 = Penalty based on the robot turn-angle.

The fitness function is formulated in two ways: As a linear combination of penalty functions and through prioritization. The robot is desired to arrive at the goal point (Kicking the ball - C_1) through a collision free path (C_2). C_1 and C_2 have higher priority. The smoothness (C_4) of the path followed and path length (C_3) are of lesser priority.

3. Experimental results on a robot soccer system

The Micro-Robot Soccer System platform is used to test the navigation approach. The robots used in the setup are 7.5(cm) cubic in size, semi autonomous. The robots have driving mechanism, communication parts and, computational parts for velocity control and for processing the data received from a host computer. All

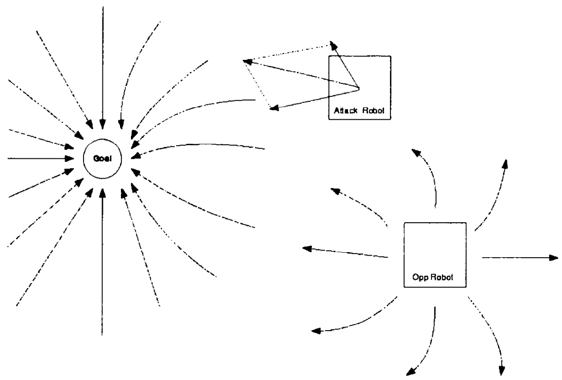

Figure 1. The Artificial potential field.

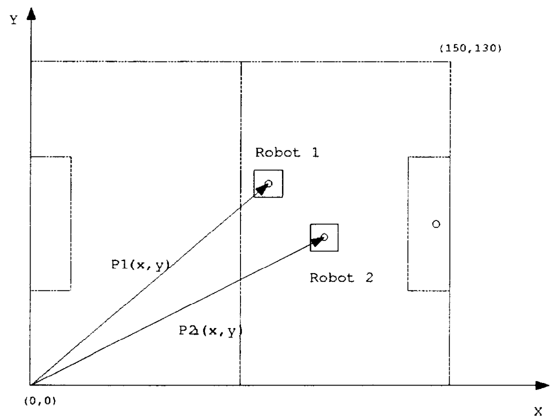

Figure 2. Position Representation of Robots.

the calculations for vision data processing and position control of robots are done on the host computer.

In the robot system considered, there are three robots per side, acting as attacker, defender and goalie. A CCD camera (vision system) grabs the positions of the ball (goal) and the other robots (obstacles). The play field is mapped onto a 2-D coordinate system. Positions of the robots and ball are represented by respective X and Y coordinates as illustrated in Figure 2. The home robot positions are presented by the vector $P_R(x_R, y_R)$, the opponent robots by $P_{Oi}(x_{oi}, y_{oi})$ $(i = 1, 2, 3)$, and of the ball as $P_G(x_g, y_g)$.

Distances of the robot from the goal point and obstacles are calculated with Equations 6 and 7:

$$D_{gr} = ||P_G - P_R|| \tag{6}$$

$$D_{ori} = ||P_R - P_{Oi}|| \tag{7}$$

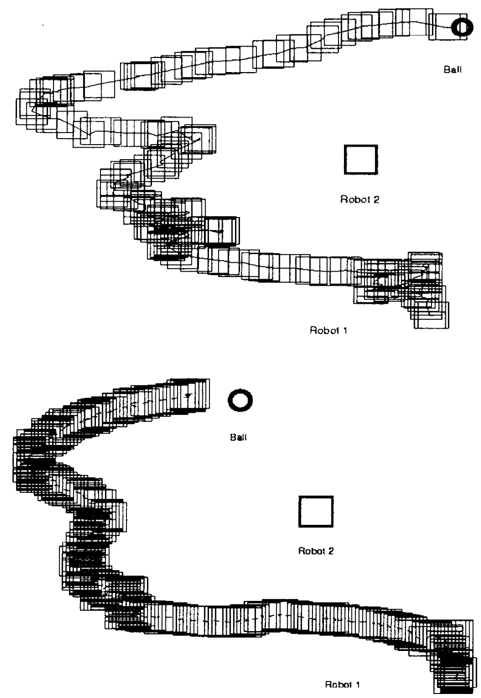

Figure 3. Robot motion.

The Potential field forces are defined as:

$$F_a = \frac{1}{||P_G - P_R||} \tag{8}$$

$$F_r = \frac{1}{(p||P_R - P_{Oi}||)^n} \tag{9}$$

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

The escape force F_e is defined as:

$$F_e = \frac{\left|\cos(\angle F_a^{(i)} - \angle \sum F_r^{(i)}) - \cos(c)\right|}{D_{min}} \tag{11}$$

where,

$$D_{min} = min(||P_R - P_{Oi}||) \quad i = 1, 2, 3 \tag{12}$$

$$\angle F_e = \Pi/4 \tag{13}$$

Once the escape status is reached, F_e is executed 3 times to ensure that the robot leaves the null-force area. The reason for such a design is that if the escape force becomes zero at the exact time interval when the robot is

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out of the escape area, the robot cannot move effectively enough to leave the null-force area. It may possibly fall into the escape status again and may take longer time to move towards the real target. The experimental results are illustrated in Figure 3.

The potential field angle (Equation 10) is the control input signal and the appropriate velocities proportional to the turn-angle are transmitted (RF) to the robots. The actual motor velocities of the left and right wheels are determined by the on-board micro-controller through a classical PID controller with velocity feedback (Equations 14 to 20).

$$v_{left} = v_c + v_\theta \cdot \theta_p \tag{14}$$

$$v_{right} = v_c - v_\theta \cdot \theta_p \tag{15}$$

where $K_p, K_i, K_d \in (0,1)$, and

$$\begin{aligned} v_c &= \frac{K_c}{1+\exp(-F_{total})}\, v_p && (16)\\ v_\theta &= K_p\theta_p + K_i\zeta_p + K_d\delta_p && (17)\\ \theta_p &= \angle F_{total} && (18)\\ \zeta_p &= \rho\zeta_p + \theta_p && (19)\\ \delta_p^{(i)} &= \theta_p^{(i)} - \theta_p^{(i-1)} \quad i-interval && (20) \end{aligned}$$

Where the parameters k_θ and v_c are related to the robot angle (θ) and robot to goal distance respectively.

To improve the performance of the robots, the status of robots are divided into several categories and different values are assigned to the parameters p and n of the repulsive function Equation 2.

In the experiments, the robot could reach the goal, but the path was not as satisfactory as in [2], as the path has departed from the ideal trail slightly. There are a couple of reasons for this mismatch: The processing time required to calculate the potential field angle in real time, the mapping of the potential field angle to the wheel velocities and the effectiveness of the velocity control. Further more, the robots move at a faster rate in comparison with the frame update rate. When the robot moves too fast, its motion is expected to deviate.

One of the main problems in EAPF is that the robot cannot pass between two obstacles, even the space in between the two is enough for the robot to move through. This happens as the direction of the sum of the two repulsive forces point away from the opening between the two close obstacles [10]. This problem will also affect the smooth motion of the robot.

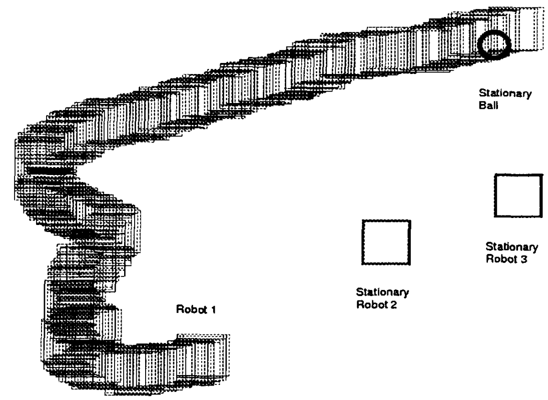

Figure 4. Ball tracking with two stationary robots.

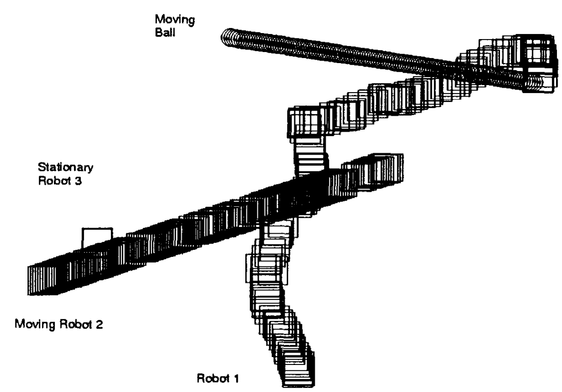

Figure 5. Ball kicking while competing with another.

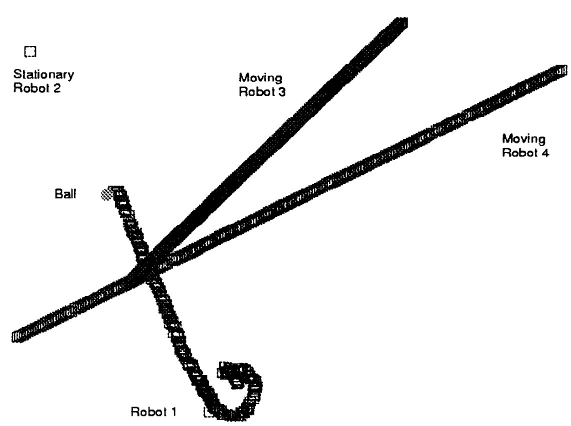

Figure 6. Ball tracking while in competition.

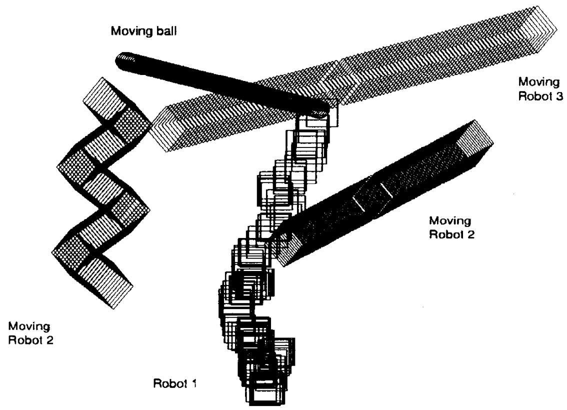

Figure 7. Ball kicking while competing with three other robots.

4. Conclusion

In this paper, the application of the evolutionary artificial potential field (EAPF) method in a micro-robot soccer environment is presented. The EAPF functions proposed were tested in different scenarios in ball tracking and kicking, while facing competition from other robots.

For more accurate solutions, it is required to optimize the parameters associated with the EAPF functions in real-time. Further research is needed to impart cooperative behaviors and learning capabilities to the mobile robots.

References

[1] Timothy E. Revello; Robert McCartney, "A Cost Term In An Evolutionary Robotics Fitness Function," Congress on Evolutionary Computation. Proceedings of, volume1.1, 2000, page 125 - 132 .

[2] Vadakkepat, P.; K. C. Tan; Wang M.-L., "Evolutionary artificial potential fields and their application in real time robot path planning,: Congress on Evolutionary Computation, Proceedings of the, 2000. Volume: 1, Page(s): 256 -263 vol.1 .

[3] Yunfeng Wang; Gregory S. Chirikjian," A New Potential Field Method for Robot Path Planning," Proceedings of the 2000 IEEE Int. Conference on Robotics & Automation, San Francisco, CA April 2000

[4] Ahmad A. Masoud, "Integrating Directional Constraints in Motion Planning Using Nonlinear, Anisotropic, Harmonic Potential Fields", Proceeding of the 1998 IEEE ISIC/CIRA/ISAS Joint Conference, Gaithersburg, MD, Sep 14-17, 1998

[5] Sukhan Lee; Javier Bautista, "Motion Control For Micro-Robots Playing Soccer Games"; Proceedings of the 1998 IEEE, Int. Conference on Robotics & Automation Leuven, Belgium May 1998

[6] Stefano Nolfi, "Evolutionary Robotics: Exploiting the full power of self-organization" Self-Learning Robots II: Bio-robotics (Digest No. 1998/248), IEE , 1998 Page(s): 3/1 -3/7

[7] Rana, A.S.; Zalzala, A.M.S., "An evolutionary algorithm for collision free motion planning of multi-arm robots", Genetic Algorithms in Engineering Systems: Innovations and Applications First International Conference on Page 123 -130, 1995

[8] Dozier, G.; Homaifar, A.; Bryson, S.; Moore, L. " Artificial potential field based robot navigation, dynamic constrained optimization and simple genetic hill-climbing," Evolutionary Computation Proceedings, 1998. IEEE World Congress on Computational Intelligence., 1998 Page(s): 189 -194

[9] Toshio T.; Pietro G. Morasso; Makoto Kaneko, " Trajectory Generation for Manipulators Based on Artificial Potential Field Approach with Adjustable Temporal Behavior", Intelligent Robots and Systems '96, IROS 96, Proceedings of the 1996 IEEE/RSJ International Conference on , Volume: 2 , 1996 Page(s): 438 -443 vol.2

[10] Yoram Koren; Hohann Borenstein," Potential Field Methods and Their Inherent Limitations for Mobile Robot Navigation," Proceeding of the 1991 IEEE, Int. Conference on Robotics and Automation,Sacramento, CA-April 1991

[11] J.-H. Kim and P. Vadakkepat, "Multi-Agent Systems: A Survey from the Robot-Soccer Perspective," Intelligent Automation and Soft Computing, Vol. 6, No. 1, P.3-18, 2000.

[12] H.S Sim, M.J Jung; H.S Kim; J.-H. Kim and P. Vadakkepat, "A Hybrid Control Structure for Vision Based Soccer Robot System," Intelligent Automation and Soft Computing, Vol. 6, No. 1, P.89-101, 2000.