ASSIGNMENT REPORT FOR AI6126: ADVANCED COMPUTER VISION

Homework Assignment

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1 Introduction: the Robot Soccer

A soccer match can be considered as a multi-agent system (MAS). There have been a lot of research and applications in this field around the most well-known competiton, the Robot Soccer World Cup[1], also known as RoboCup. There are several types of soccer games, such as real robotic soccer, simulation soccer, and keep-away soccer [19, 26].

The RoboCup is an annual international robotics competition. Founded in 1997, the event's ultimate mission is to field a robot team capable of beating the human soccer World Cup champions by 2050. This public but challenging appeal is considered a great platform to advance research in the agent-based Artificial Intelligence and Robotic domains. The RoboCup is designed as a standard task so that a range of technologies can be integrated and evaluated, including vision and objects recognition, multi-agent collaboration, strategic decision making, real-time reasoning, motor control, and many more. [12] According to the history on the official website, more than 40 real and simulated teams participated in the first RoboCup games and conference in 1997, which was attended by more than 5,000 spectators. Since then, RoboCup have been held every year, except for 2020, which was cancelled due to COVID-19, and will continue in Bordeaux in 2023.

Generally speaking, the RoboCup competition has two types of leagues, the "real" robot leagues and a "virtual" simulator league that relies on a software platform. The simulation league, also one of the oldest leagues in RoboCupSoccer, focuses on artificial intelligence and team strategy. In "virtual" competition, independently moving virtual robots, also known as agents, play soccer on a virtual field inside a computer. They are not real robots, but computer programs that play through a simulator provided by RoboCup, which is similar to a real soccer game in many ways. There are two subleagues of the simulation league: 2D and 3D. For the 2D Simulation League, the simulator is called SoccerServer[2], which provides a simulator environment with complex dynamics, noisy and limited virtual sensor information(visual, acoustic, and physical), noisy controls, and real-time matches. Players can also have restricted communication with the server and their teammates. On the other hand, they perform some basic commands(like dashing, kicking, and more) to influence their surrounding environment. Most importantly, players need to learn how to work together as a team to win a soccer match in the Soccer Server [16]. As for 3D simulation matches, an extra dimension and more complex physics are added compared to 2D ones, therefore increasing the realism of the simulation environment.

As one of the subcategories of Distributed Artificial Intelligence (DAI), unlike Distributed Problem Solving (DPS) that emphasizes information management capabilities, MAS highlights behavior management among agents who are independent of each other while engaging in a high degree of teamwork to achieve a common goal[25]. In other words, MAS studies the problem of collaboration among autonomous agents. Thus, from the MAS perspective, a soccer game is a very standard multi-agent environment, where we can consider each soccer team as a multi-agent system[12]. And robotic soccer (simulated) has numerous advantages as a MAS test platform. For instance, it is easy to access for researchers. Also,it also embodies a great deal of MAS issues, including agent heterogeneity, communication abilities, collaborative and adversarial issues, real-time reasoning, and many more[25]. Players on the same team have a common goal, and that is to score points and thus win the game. Players (or agents) on the same team have a common goal, and that is to score points and thus win the game. And both sides share this goal, which determines the obstructiveness of the environment for a team. At the same time, the game environment is also

[1] RoboCup `https://www.robocup.org`

[2] Soccer Server `https://www.robocup.org/leagues/24`

dynamic due to the frequent movements of their opponents and teammates. Besides, each player is required to act autonomously due to limited communication among players. Therefore, each team member needs to learn good behavior and coordinate in this dynamic, obstacle-filled environment to achieve their common goal.

2 Path Planning in A Dynamic Environment

As mentioned earlier, robotic soccer serves as a good testbed for MAS and allows for the study of a wide range of techniques, which also include navigation approaches. Navigation is a fundamental capability of autonomous mobile robotics, and path finding focuses on the best way from the starting position to the destination, based on certain evaluation criteria, such as path distance, time cost, or obstacle avoidance. In addition to navigation for soccer robots, pathfinding has also been extensively studied for use in many other areas, including intelligent transportation and weapons navigation [17].

Path planning algorithms vary according to the nature of the environment (static or dynamic), depending on whether the position of the obstacle changes over time [8]. For instance, given an environment which contains a collection of stationary obstacles and a target, most path planning strategies like the A-star algorithm[9] promise at least one optimal path in most cases.

However, multirobot scenario posese several challenges to navigation study. Firstly, the environment of a soccer game is highly dynamic because of the changeability and complexity of the robot (from adversaries and teammates). Even for 2D soccer simulation, motion planning is an NP-hard question[4]. Therefore, reactive motion planning methods are required to avoid collisions with moving obstacles, which cannot be overcome by classical strategies. At the same time, robots are also expected to achieve spatial positioning goals since the location of the ball is changing constantly.

Besides, the RoboCup soccer game is a very fast game where robots can move at over 2 m/s and the ball moves at speeds of up to 10 m/s. Accordingly, some time-consuming path planning algorithms cannot meet our requirements; instead, we need algorithms that are fast enough to have real-time response while coordinating with teammates flexibly[3].

In addition, for some leagues of the Robotics Cup, the challenges posed by limited information have plagued researchers. Depending on the rules of the game, in some competitions, robots have access to real-time game information, such as the location of the ball, their teammates, and their competitors, with the aid of sensors and a cloud-based information center. This global state information makes it possible for teammates to act strategically with each other, allowing them to plan their paths more efficiently to reach a common scoring goal. However, for robots with restricted information, there is a difficulty that needs to be addressed.

In conclusion, collision-avoidance and time-efficient path planning has been an obvious challenge for researchers in MAS field.

3 Recent Methodologies

Path planning strategies for robot motion are broadly divided into three classifications: classical and reactive methods[20]. Traditional algorithms were popular about one or two decades ago, which include cell decomposition (CD), probabilistic roadmap approach (RA), artificial potential field (APF). And there is rapidly-exploring random trees (RRT)[6, 13, 24, 2]. For instance, an improved iterative RRT method[2] is proposed for RoboCup Small Size robots, which finds ideal and near-optimal solutions in real time. However, they are becoming obsolete in an increasingly complex environment and in the growing need for responsiveness in real time. They are clearly not suitable for multi-robot soccer matches.

As for reactive approaches, also known as heuristic techniques, mainly refer to the neural networks (NN), genetic algorithms (GAs)[28, 10], Fuzzy Logic (FL), artificial potential field (APF), ant colony optimization (ACO), particle swarm optimization (PSO), and many more. Many of the above methods have their advantages and disadvantages. For instance, AI methods, such as neural networks and evolutionary algorithms, can find the optimal path better than traditional methods when faced with highly dynamic environments, but they are time-consuming and require high computational resources. Therefore, researchers often use a combination of different methods to achieve better performance[18]. Some reactive methods will be discussed below specifically (Section 3.1 for GA, Section 3.2 for FL, and Section 3.3 for ACO), along with their advantages and disadvantages.

3.1 Genetic algorithm (GA)

The genetic algorithm, inspired by the process of natural selection of biological evolution, is one of the most popular algorithms among researchers in recent years. Numerous variants of genetic algorithms have been commonly adopted to solve optimization and search problems in various fields of science and engineering, including the one of robot navigation.

There are three essential genetic operators: *crossover* for convergence in a subspace, *mutation* for escaping from a local optimum, and *selection* for choosing the best results[29].

In this algorithm, a population of candidate solutions (also called individuals) is randomly generated, then evolution goes with iterations wherein the population in each iteration is called a *generation*. Every member of the population is assigned with a *fitness* value F according to the objective functions $f(x)$. Then individuals with higher fitness values are randomly chosen to generate new solutions by combination and mutation, with a crossover probability p_c and a mutation probability p_m, respectively. And new solutions will be accepted if their fitness increase. Then the next generation will be selected for the next iteration. Finally, the algorithm is terminated if a termination condition is reached.

The genetic algorithm is used for multi-robot path planning frequently. For instance, Patle et al. [21] proposed the matrix binary code-based genetic algorithm in a static and dynamic environment for multiple robot systems, as well as the single robot one). In this work, the robot is capable of avoiding collisions and tracking moving goals while requiring short navigational time and path length. Elhoseny et al. [7] also proposed a Modified Genetic Algorithm (MGA) along with Bezier curve for the robot path planning to get more smooth paths in a dynamic field. Recently, Chen et al. [5] proposed a soccer path planning method based on S-adaptive genetic algorithm, which performs well in saving the effective solution, shortening the convergence time, and getting the optimal path. And the path obtained by this method achieves better obstacle avoidance performace in a short time. There are also some works focusing on a combination of GA and other reactive algorithms to achieve a hybrid and improved approach[27].

The genetic algorithm also shows its limitations, such as slow convergence rate, no guarantee to get satisfactory results, time-consuming evolution process to decide the mutation rate and population size, etc[20]. Despite these disadvantages, genetic algorithms still are widely used by researchers for modern nonlinear optimization[29]. For example, Jaesung Lee et al. [14]. proposed an effective GA initialization method to obtain high-quality paths in a short time.

3.2 Fuzzy logic (FL)

Fuzzy logic was firstly introduced by Zadeh in 1965, who was inspired by human ability to make decisions based on imprecise and non-numerical information. Fuzzy models have commonly applied in situations of ambiguity and lack of certainty, including pattern recognition, automatic control, decision making, data classification, and many more. In this algorithm, rules provided by humans (If-Then) are used and converted into their mathematical equivalents. The four basic parts of a fuzzy logic controller are: fuzzification that assigns input variables to fuzzy sets with some degree of membership, a knowledge base that includes IF-THEN rules and linguistic variables based on the fuzzy set theory, fuzzy reasoning that executes available rules to obtain output truth values, and defuzzification that obtains continuous variables from fuzzy truth values.

Nowadays, there are many works on FL for multi-robot path planning, some of which focus on the combination of FL and other techniques in a sensor-based environment. A neuro-fuzzy and fuzzy probabilistic coordination and path planning for multi-robot teams was proposed by Al-Jarrah et al.[11]. A first-order Sugeno fuzzy inference system is used as the leader of the high-level controller, while other follower robots will behave to achieve coordination. Besides, fuzzy logic algorithm is also used for path planning in 2D and 3D environments by Rath et al.[23] and Abbasi et al.[1], respectively.

Fuzzy logic has the ability to simulate human thinking and knowledge base, represented by linguistic variables and if-then rules, respectively. However, it has difficulties in choosing the most appropriate rules and membership functions, citeMAC201613.

3.3 Ant colony optimization (ACO)

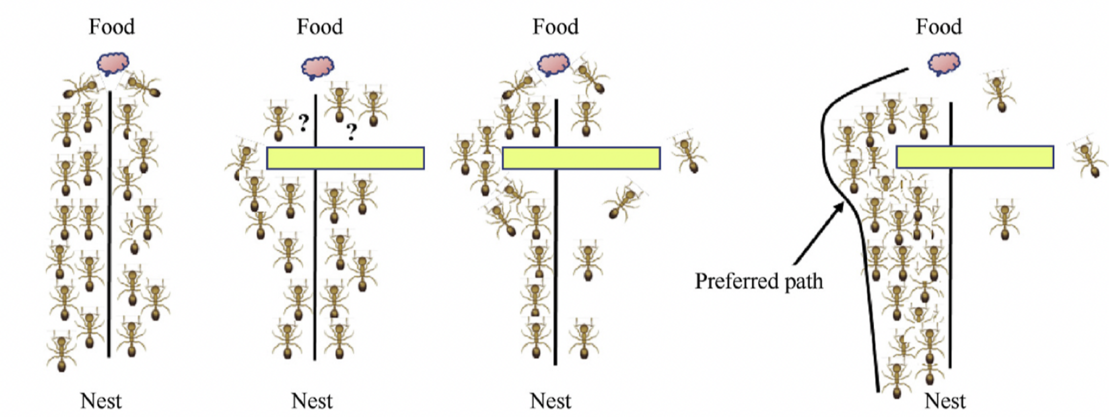

Figure 1: The behavior of ants while searching the food. reference [20]

Ant colony optimization (ACO) is a swarm intelligence algorithm and population-based approach for solving combinatorial optimization problems. This algorithm originates from the behavior of ants and their ability to take the shortest path from the nest to the food source. Recently, many methods have been proposed for path planning using ACO. For multi-robots, Liu et al.[15] proposed an anti-collision strategy for a static environment, which combines pheromone diffusion and geometric local optimization. For the dynamic environment, Rajput et al.[22] also proposed a novel pheromone updating technique to speed up convergence.

For real-time path planning of mobile robots, the adoption of ACO improves convergence speed, solution variation, computational efficiency and dynamic convergence behavior compared to other algorithms such as genetic algorithm[20].

However, the drawbacks of the ACO algorithm are also obvious. Increasing the parameter *alpha* produces earlier convergence, but this is also accompanied by producing (inferior) local solutions instead of global ones. In order to overcome this problem, algorithm combination methods have been proposed. For instance, Yen et al.[30] used rapidly-converging ACO coupled with fuzzy control to overcome the shortcoming that ACO is prone to fall into local optimal solutions and ensure that the mobile robot can avoid obstacles and reach the goal point smoothly.

4 New Approach

For solving multi-robot path planning, as other researchers have done, a combination of methods is necessary to obtain better performance. Therefore, a hybrid idea may be an alternative to solve the path finding problem in dynamic environments, i.e., using a fuzzy logic controller to find local paths avoiding obstacles and using GA-ACO as a convergent dual optimizer.

This is because FL methods have been shown to be real-time and effective for navigation in situations where the motion of obstacles and targets is difficult to predict, perhaps giving a high probability of good performance in simulated robotic soccer matches.

In addition, genetic algorithms have shown their advantages in recent years of research, producing good coordination in team tasks. Therefore, this approach can be used to achieve global optimality and to guarantee stability and performance in multi-agent training, allowing players of the same soccer team to show cooperative abilities. However, as mentioned earlier, GA has a defect of slow convergence speed. This drawback may be overcome by merging with the ACO algorithm, which is also a powerful metaheuristic. Thus, GA and ACO algorithms can be merged to achieve proper speed and performance as a dual optimizer.

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