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A Survey on Robot Path Planning using Bio-inspired Algorithms

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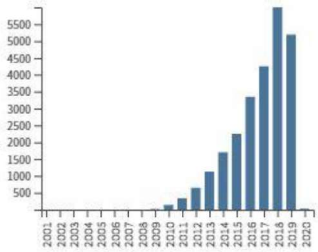
Abstract – **The path planning problem has been an essential topic in autonomous robotics. There are many new path planning methods that have been developed, and those using bio-inspired algorithms attract extensive attention. This paper analyzes several bio-inspired algorithms and surveys recent developments of robot path planning. Swarm intelligence, evolutionary algorithms, and neurodynamics are three primary robot path planning methods that are focused on in this survey. In addition, the pros and cons of these three methods are summarized and analyzed.**

Index Terms – bio-inspired algorithms, swarm intelligence, evolutionary algorithms, neurodynamics, path planning

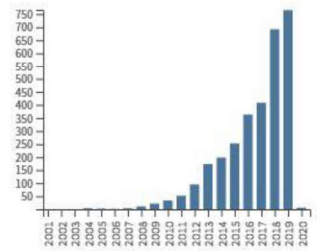
I. INTRODUCTION

Over the past decades, path planning has been attracting considerable interest because of the development of artificial intelligence. Fig. 1(a) shows the number of cited papers about path planning, which is retrieved from the Web of Science database in the past decades. There are many challenges in path planning problems due to the high computational complexity in complicated environments. It is hard for the traditional path planning methods based on mathematical models to generate a feasible path in complex environments. Bio-inspired optimization algorithms, which are inspired by nature, provide better results in complex environments [5]-[11]. Fig. 1(b) shows the number of cited papers about bio-inspired algorithms retrieved from the Web of Science database. Bioinspired algorithms have lately received significant attention for solving complex optimization problems because it usually finds the optimal solution that maintains the balance among its components. More recently, researchers paid considerable attention to using bio-inspired algorithms to deal with the path planning problems by treating it as optimization problems [1]-[4]. Many new methods have been proposed, but it is rather rare to find comprehensive reviews about robot path planning using bio-inspired algorithm. Thus, this paper analyzes several bio-inspired algorithms to illustrate the recent development of robot path planning. Swarm intelligence, evolutionary algorithms, and neurodynamics are the three primary robot path planning methods that are focused on in this survey. In addition, the pros and cons of these methods are also summarized and analyzed.

This paper is organized as follows. In Section II, the comprehensive review of three major bio-inspired algorithms is presented, including swarm intelligence, evolutionary algorithm, and neurodynamics methods. The pros and cons of these bio-inspired algorithms are discussed in Section III. Section IV presents a brief conclusion about this survey.



(a) The number of cited papers about path planning;



(b) The number of cited papers about the bio-inspired algorithm

Fig. 1. The number of cited papers about path planning and bio-inspired algorithm retrieved from the Web of Science database

II. PATH PLANNING USING BIO-INSPIRED ALGORITHM

In the recent three years, bio-inspired algorithms have attracted the consideration of attention in robot path planning [12]. The fundamental idea of bio-inspired algorithms is to incorporate successful strategies, mechanisms, and structures from a biological system into the designing of new algorithms to solve complex problems. The most three successful methods in bio-inspired algorithms are swarm intelligence, evolutionary algorithm, and neurodynamics. They are inspired by the self-organization behaviors of animals, natural evolution, and biological neural system.

Swarm intelligence and evolutionary algorithms are population-based algorithms. The optimization process has taken place in a set of candidate solutions. The candidate solutions are called population at each iteration. Although all

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these algorithms are very similar, they have different mechanisms or rules for selecting and modifying solutions. Neurodynamics method uses the neural network typically to plan the optimal path. The proposed neural network is not familiar with the neural network using in machine learning. The neural network using in machine learning has input and output layers. However, the neural network in the neurodynamics method is topologically organized. Therefore, neurodynamics is not a requirement for the learning process. Table I illustrates the source of inspiration and category of each algorithm mentioned in this paper.

TABLE I

INSPIRATION AND CATEGORY AMONG VARIOUS PATH PLANNING METHODS

Method	Inspiration	Category
Genetic algorithms (GA)	Evolution Theory	Evolutionary algorithms
Differential evolution (DE)	Evolution Theory	Evolutionary algorithms
Particle swarm optimization (PSO)	Coordinated movement of birds and fish school	Swarm intelligence
Ant colony optimization (ACO)	Ants foraging	Swarm intelligence
Bio-inspired neural network (BINN)	Biological neural system	Neurodynamics

A. Path Planning Based on Swarm Intelligence

In nature, large groups of animals show a more exceptional ability to solve complex tasks compared to smaller ones or lone individuals. It is well known as the navigation of flocks of birds, prey behavior of social insects, and the vigilant action of fishes. This collective and self-organization behavior in animals is called swarm intelligence [13]-[14]. Two popular algorithms in recent years are particle swarm optimization (PSO) and ant colony optimization (ACO).

a. Particle swarm optimization (PSO)

Kennedy and Eberhart firstly proposed PSO in 1998, and it is a global stochastic optimization method [15]. Researchers have paid much attention to using PSO to deal with the path planning problem because it is easy to implement and generate the optimal path efficiencies. Normally, in the PSO algorithm, each possible path is seen as the integration of particles. The position and speed of particles can be written as

$$v^{t+1} = v^t + \alpha\varepsilon_1[g^* - x_i^t] + \beta\varepsilon_2[x_i^* - x_i^t] \tag{1}$$

$$x_i^{t+1} = x_i^t + v^{t+1}, \tag{2}$$

where the v^t and x_i^t are respectively the speed and position of the individual particle. The v^{t+1} and x_i^{t+1} mean the speed and position of the particle in next time, respectively. ε_1 and ε_2 are the respectively random value from 0 to 1. α is the learning parameter. β is the acceleration parameter. Variable g^* is the best solution in the swarm, and x_i^* is the best solution for the individual. The equation shows that the new position of the particle is dependent on the previous position, globally optimal solution, and individually optimal solution. After working with multiple interactions, particles can achieve an optimal position, and the integration of these positions is the optimal path.

In recent three years, PSO is the most popular algorithm due to its high efficiency and easy to implement. However, PSO has some shortcomings in the application of path planning. The convergence speed is a big problem if the environment becomes complicated, and the computation complexity of the algorithm increases dramatically. More recently, a considerable amount of attention has been paid to the implementation of the multi-objective PSO algorithm. Thabit used multi-objective PSO to design new methods to generate the optimal path for a group of the robot in unknown environments [18]. They compared the proposed multi-objective PSO algorithm with other popular algorithms, and the multi-objective PSO can generate a smooth path with high convergence speed. By comparing with the above algorithm, the study associates the multi-objective PSO with another algorithm, such as Dijkstra's algorithm, to improve the convergence speed of PSO algorithms. In addition, the multi-objective PSO algorithm is beneficial in generating a smooth path. Wang and Cai combine the PSO algorithm with chaos optimization algorithm to generate the shortest path in the radioactive environment [17]. The experiment results showed that the robot could avoid the radioactive source in a complex environment. Researchers have modified the PSO to solve discrete optimization problems. Phung and Quach proposed an enhanced discrete PSO algorithm to plan the inspection path for version-based unmanned aerial vehicle [16]. According to theoretical analysis, they use the solution of the extended traveling salesman problem to replace the inspection path planning problem. Then, they solved the traveling salesman problem by using a discrete PSO algorithm. The proposed algorithm can efficiently generate the path. Therefore, PSO and its variance have drawn considerable attention in the robot path planning, and many researchers have developed their new PSO methods.

b. Ant colony optimization (ACO)

ACO was proposed by Dorigo and Di Caro in 1999 [19], firstly. The ants can find the shortest path between the nest and food by cooperating. The ants will generate the pheromone to guide other ants to follow the path. In the path planning problem, the probability of one ant moving from the position i to j can be written as

$$q_{i,j} = p_{i,j}^{\alpha} * \left(\frac{1}{d_{i,j}}\right)^{\beta}, \tag{3}$$

where $q_{i,j}$ is the probability of the ant moving from the position i to j. Variable $p_{i,j}$ is the concentration of pheromone from i to j. $d_{i,j}$ is the distance between i to j. α and β are impact parameters, respectively. The ant will choose the maximum probability to the next position, and update the pheromone can be written as

$$p_{i,j}^{t+1} = \rho * p_{i,j}^{t} + \frac{Q}{S}, \quad (4)$$

where $p_{i,j}^{t+1}$ is the new concentration of pheromone; Variable $p_{i,j}^{t}$ is the previous concentration of pheromone. ρ is volatile of pheromone. Q is a constant, and S is the sum of the distance moved. After working with multiple interactions, the optimal path is the highest concentration of the pheromone path.

ACO has slow convergence speed problems if the computation complexity increases rapidly, which occurs in the PSO algorithm as well. One of the improvement methods is to modify the process of state transition. Ma and Gong incorporated the alarm pheromone into the traditional guiding pheromone to develop a novel ACO algorithm based on a comprehensive model [21]. The simulation tests showed that the improved ACO algorithm has a better real-time performance by comparing it with other algorithms. More recently, researchers have paid attention to associating ACO with other algorithms. Xiong and Chen proposed a hybrid Voronoi-based ACO method to deal with the path planning problem for multiple autonomous marine vehicles in the ocean environment [20]. By comparing with other algorithms, simulation tests showed that the proposed ACO algorithm has a better performance of the effectiveness and robustness in maximizing data collection. Liu combined the pheromone diffusion with local geometric optimization into the global path planning [22]. The simulation results showed that the convergence speed of the improved ACO algorithm is faster than other algorithms.

By comparing PSO with ACO algorithms, there is no information exchange between each particle or ant. The particles and ants only modify themselves by following the objective function. Thus, the PSO algorithm is easy to be implemented. However, the simple structure of the algorithm also leads to the slow convergence speed when the environment becomes more complex, and the computation complexity of the algorithm increases dramatically.

B. Path Planning Based on Evolutionary Algorithms

Evolutionary algorithms are another essential part of the bio-inspired algorithm. Darwin's theory inspires evolutionary algorithms that animal populations adapt to their environment. In the path planning problem, evolutionary algorithms simulate the natural evolution for individuals, according to the process of selection, reproduction, crossover, and mutation. The crossover process can be considered as a randomization process. The randomization process increases the computational compacity of the algorithm. However, it also helps to find the global minimum solution. The Fig. 2 shows the benefit of the crossover process, and the crossover process can prove a chance to find the global minimum solution if the solutions are in the area of the local minimum. Two popular algorithms in recent years are the genetic algorithm (GA) and differential evolution (DE).

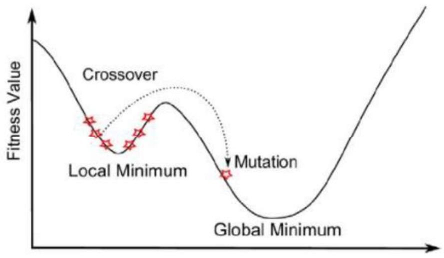


Fig.2. A comparison between crossover and mutation processes from [27]

a. Genetic algorithm (GA)

GA is a stochastic optimization algorithm, which was proposed by Holland in 1975 [23]. The natural selection of real environments inspires GA. Similar to animals adapting to their environment, the solution in the GA adapts to the fitness function during the iterative process using biological operators. Such as, crossovers, mutations, and inversions are used in the iterative process. In the path planning problems, each chromosome is a possible path. After multiple integrations, the best performance of the chromosome is the optimal path.

Even though GA can rapidly provide excellent results, it has some disadvantages in complex search environments. Firstly, the result of GA could be the local optimal when the algorithm uses an improperly-defined fitness function. Secondly, GA is challenging to operate on dynamic data sets. For some particular path planning problems, and given the same amount of computation time, the simple structure algorithm gets better solutions than GA. Researchers implemented GA to generate the collision-free path and then used another algorithm to get a smooth path [24]. The fitness function can be implemented in GA, for example, Shih applied the exponential effective function to the hybrid-GA [25]. The proposed algorithm was capable of discovering the optimal path reachability and efficiency. In addition, by increasing the number of offsprings, the convergence speed is significantly improved. Xin and Zhong used the multi-domain inversion to increase the number of offsprings [28]. The increasing number of offsprings could help to improve the efficiency of local path planning and increase the probability of generating excellent individuals. Patle presented a novel improved GA algorithm to deal with mobile robot navigation by using the binary code matrix in complex environments [26]. The proposed algorithm has satisfactory real-time performance. Elhoseny increased the exploration capabilities of the crossover process, which helps to generate the path locally in a subspace [27]. The robot's energy consumption is avoided in harsh environments in their simulation experiment.

b. Differential evolution (DE)

DE was proposed by Storn and Price in 1995 [29]. DE is similar to the GA, and both methods use the populations of individuals to find the optimal path. The main difference between GA and DE is the method to get the mutation solution. In GA, the individuals of small perturbations produce the changing of the genes to find the mutation solutions. However, in DE, the arithmetic combinations of individuals produce mutation solutions. The mutation process in DE can be written as

$$x_i = x_r + F * (x_p - x_q), \tag{5}$$

where x_i is the location of the mutation; Variable x_r, x_p, and x_q are respectively the location of its random parents. F is called a scaling factor, as it shrinks the length of the difference $(x_p - x_q)$.

Evolutionary parameters directly determine the efficiency of the DE algorithm. In the study of DE, many papers focus on the diversity of the population of parents, mutants, and offsprings. Zamuda designed a success-history based adaptive DE algorithm to provide the underwater path planning for continuous numerical optimization [32]. The new proposed algorithm can stably and competitively generate the paths. Sun and Wu applied an adaptive multi-objective DE algorithm to the multi-robot system [31]. The experiment results show that multiple unmanned aerial vehicle systems can generate multiple feasible paths in the aerial environment.

For evolutionary algorithms, crossover, mutation, and selection are three principal evolution operators. Because of these operators, the evolutionary algorithms can jump out of the local minimum due to the random crossover process. However, evolution operators increase the time complexity of algorithms. In complex environments, the real-time performance of evolutionary algorithms is unsatisfactory.

C. Path Planning Based on Neurodynamics

One limitation of bio-inspired algorithms is that most of the proposed algorithms are not able to provide good results in the real-time path planning problem. Because these bio-inspired algorithms require any learning process, such as the ants modifies the probability of choosing a path by following the objective function. Among all these bio-inspired algorithms, the bio-inspired neural network (BINN) has attracted extensive attention [33]. The BINN was proposed by Simon X. Yang [34]-[36], this model is inspired by the membrane model for the biological neural system [37] and the shunting model [38]. In this model, there is a special correspondence between each neuron and the position of the grid map. Each neuron can be represented by its neural activity. The neural activity is calculated as

$$\frac{d_{u_k}}{d_t} = -Au_k + (B - u_k)S_i^+(t) - (D + u_k)S_i^-(t), \tag{6}$$

where A is the passive decay rate, B and D are the upper and lower bounds of neural activity, respectively. Variable $S_i^+(t)$ and $S_i^-(t)$ are respectively the excitatory and inhibitory inputs from the neural network. The robot keeps searching for the location of maximum neural activity in environments until reaching the target. The connection between maximum neural activity positions is the optimal path. There is no learning process due to the BINN method is topologically organized. Thus, BINN shows great real-time performance in a dynamic and complex environment. The Fig. 3 shows a bio-inspired neural network structure diagram of local path planning.

Recently, researchers have paid considerable attention to using BINN method to deal with the real-time path planning problems. The BINN method can generate the shortest path efficiently in the complex underwater environment due to its excellent real-time performance. Ni and Wu proposed a dynamic BINN to generate the optimal path for AUV in three-dimensional unknown environments [39]. The dynamic BINN model only searches the neural activity in the vicinity of AUV. Thus the computation complexity could be decreased. In their simulation tests, the dynamic BINN model can efficiently generate the optimal path when AUV works in the large size environment, and the detection range of sensors is smaller than the size of obstacles. Ni and Zhang used the BINN model to optimize the fitness function of the PSO method [40]. The proposed algorithm is efficient to optimize the fitness function and generate the paths. Cao and Sun used an improved BINN method to the cooperation of multiple AUV to deal with the target search problem [41]. The simulation results show that this integrated algorithm is to generate the efficiency and adaptability of the path. Luo used BINN to model the workspace and guide multiple mobile robots to finish the complete area coverage mission [42]. The simulation results show that the BINN model is computationally efficient to generate the complete area coverage path.

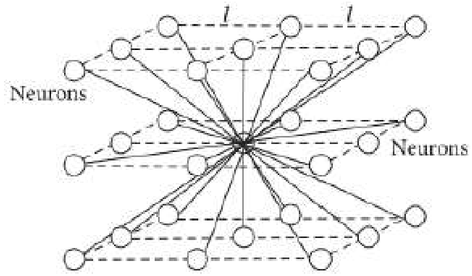


Fig. 3. Example of a BINN model form [39]

It is essential to be mentioned that the BINN model uses a neural network to generate the optimal path. However, it is different compared with the neural network using in machine learning. For the neural network using in machine learning, it usually has the input layer, the output layer, and the hidden layer. For BINN, there is not these layers and learning process. Therefore, it is also called a bio-inspired neurodynamic model.

III. Discussion

In section II, the path planning methods based on swarm intelligence, evolutionary algorithm, and neurodynamics are discussed. The summary of the pros and cons of these methods is shown in Table II.

Many researchers are focusing on the PSO algorithm. PSO is easy for implementation. However, premature convergence and slow convergence speed limit the practical use of the PSO algorithm. ACO algorithm can efficiently generate the optimal path in dynamic environments. However, the convergence time is uncertain.

Several path planning methods are based on evolutionary algorithms. Although GA can easily find the globally optimal solution, the convergence speed is highly influenced by mutation operators. DE is not required when using probability distribution to generate the offsprings. However, the performance of local path planning is unsatisfactory for DE.

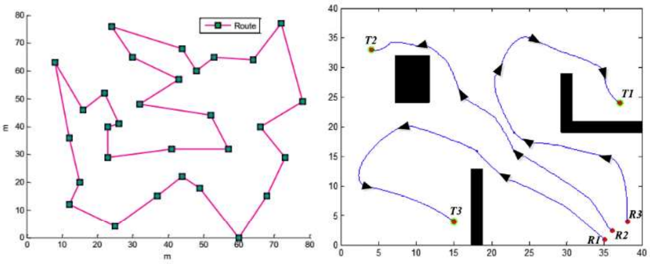
More recently, considerable attention has been drawn to the neurodynamics method. The BINN model becomes the most popular method due to its excellent real-time performance for complex path planning problems. The limitation of swarm intelligence and evolutionary algorithms is that these methods require some learning process. Thus, real-time performance is unsatisfactory. However, the BINN method is topologically organized; there is not any learning process. Thus, the real-time performance of BINN is better than other algorithms. The BINN model can associate with other algorithms, such as the PSO algorithm. In addition, Researchers have modified the BINN model to design new methods.

TABLE II.

COMPARISON OF VARIOUS PATH PLANNING METHODS

Method	Advantage	Disadvantage
PSO	• Easy to be implemented • No mutation calculation required	• Premature convergence • Slow convergence speed
ACO	• Efficiently work in a dynamic environment • No premature convergence problem	• Probability distribution changes by iteration • Convergence time is uncertain
GA	• Easy to find a globally optimal solution • Probabilistic mechanism with randomness	• The convergence speed is uncertain
DE	• No requirement for the continuity of the function	• Unsatisfactory local path planning performance • Many parameters need to be adjusted
BINN	• Real-time performance • No learning process • Not sensitive to obstacles	• Complex computing in large size environment

It is important to note that there is still a gap between the simulation results and its practical usage. Fig. 4 shows the simulation results from [17] and [41]. The improved BINN method generates a smooth path, as is shown in Fig. 4(b). There are many sharp inflection points on the optimal path in Fig. 4(a). Because of the kinematic constraints, such as the limit of the robot steering angle, the algorithms shown in Fig. 4(a) is very difficult to achieve good results. Thus, the efficiency of the algorithm is an important consideration, yet future research should consider whether it is possible to work for real applications.



(a) The simulation result from [17] (b) The simulation result from [41]

Fig. 4. The comparison of simulation results

IV. CONCLUSION

As artificial intelligence has become more prevalent in robotics, the amount of research on path planning has increased dramatically. Many new methods have been developed, but it is rare to see comprehensive reviews on robot path planning using bio-inspired algorithms. This paper analyzes several bio-inspired algorithms and surveys recent developments of robot path planning. Different bio-inspired algorithms have different pros and cons of these methods. One limitation of bio-inspired algorithms is that most of the proposed algorithms are not available to provide excellent results in the real-time path planning problem. The BINN model has no learning process, which is beneficial to real-time performance

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