

A Survey on Robot Path Planning using Bio-inspired Algorithms

Junfei Li, Simon X. Yang and Zhe Xu

School of Engineering
University of Guelph
Guelph, Ontario, Canada

{jli64; syang; zxu02}@uoguelph.ca

Abstract – Path planning problem has been an important topic in autonomous robotics. There are many new path planning methods have been developed, and those using bio-inspired algorithms attract more attention. This paper analyzes several bio-inspired algorithms and surveys recent developments of robot path planning. Swarm intelligence, evolutionary algorithms, and neurodynamics are three major 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.

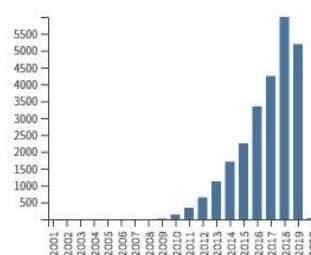
Index Terms – bio-inspired algorithms, swarm intelligence, evolutionary algorithm, neurodynamics, path planning

I. INTRODUCTION

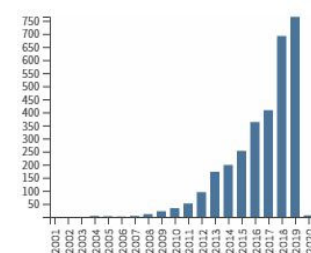
Over the past decades, path planning has been attracting an extensive interest based on the development of artificial intelligence. Fig. 1(a) shows the number of cited papers about path planning, which is retrieved from the Web of Science database in the past decades. There are many challenges in path 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 feasible path in complex environments. Bio-inspired optimization algorithms, which are inspired from nature, provide better results in complex environments [5]-[11]. Fig. 1(b) shows the number of cited papers about bio-inspired algorithm retrieved from the Web of Science database. Bioinspired algorithms have lately received great attention for solving complex optimization problems because it normally finds the optimal solution that maintain the balance among its components. More recently, researchers paid considerable attention on 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 major robot path planning methods that are focused on in this survey. In addition, the pros and cons of these methods are also summarized and analysed.

This paper is organized as follows. In Section II, the comprehensive review of three major bio-inspired algorithms

are presented, including the 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 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 recent three years, bio-inspired algorithms have attracted the consideration attention in robot path planning [12]. The fundamental idea of bio-inspired algorithms is to incorporate successful strategies, mechanisms, and structures from 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, which are inspired by the self-organization behaviours 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

these algorithms are very similar, they have different mechanisms or rules for selecting and modifying solutions. Neurodynamics method normally uses the neural network 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 layer, however, the neural network in neurodynamics method is topologically organized, which 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 greater 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)

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

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

$$x_i^{t+1} = x_i^t + v^{t+1}, \quad (2)$$

where the v^t and x_i^t are respectively the speed and position of individual particle. The v^{t+1} and x_i^{t+1} mean the speed and position of particle in next time, respectively. ε_1 and ε_2 are respectively the 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 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 more 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 robot in unknown environments [18]. They compared the proposed multi-objective PSO algorithm with other popular algorithms, the multi-objective PSO can generate smooth path with high convergence speed. By comparing with above algorithms, these studies associate 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 to generating the smooth path. Wang and Cai combine the PSO algorithm with chaos optimization algorithm to generate the shortest path in radioactive environment [17]. The experiment results showed that the robot is able to avoid the radioactive source in the 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 travelling salesman problem to replace the inspection path planning problem. Then, they solved the travelling salesman problem by using discrete PSO algorithm. The proposed algorithm can efficiently generate the path. Therefore, PSO and its variance have drawn a great 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 with each other. The ants will generate the pheromone to guide other ants to follow the path. In path planning problem, the probability of one ant moving from the position i to j can be written as

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

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 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 the volatile of pheromone. Q is a constant and S is the sum of the distance moved. After working with multiple interaction, the optimal path is the highest concentration of pheromone path.

ACO has slow convergence speed problems if the computation complexity increases rapidly, which occurs in PSO algorithm as well. One of 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 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 another 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 geometric local 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 not 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 important part of bio-inspired algorithm. Evolutionary algorithms are inspired by Darwin's theory that animal populations adapt to their environment. In path planning problem, evolutionary algorithms simulate the nature 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 algorithm, however it also helps to find the global minimum solution. The Fig. 2 shows the benefit of crossover process, the crossover process can prove a chance to find the global minimum solution if the solutions are in the area of local minimum. Two popular algorithms in recent years are genetic algorithm (GA) and differential evolution (DE).

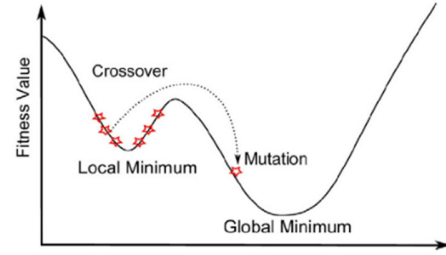


Fig.2. A comparison between crossover and mutation processes from [27]

a. Genetic algorithm (GA)

GA is a stochastic optimization algorithm, which was proposed by Holland in 1975 [23]. GA is inspired by the natural selection of real environments. 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 chromosome is the optimal path.

Even though GA can rapidly provide good results, it has some disadvantages in difficult search environments. Firstly, the result of GA could be the local optimal when the algorithm uses an improperly-defined fitness function. Secondly, GA is difficult 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 smooth path [24]. The fitness function can be implemented in GA, for example, Shih applied 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 the 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, 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 the mutation solutions. The mutation process in DE can be written as

$$x_i = x_r + F * (x_p - x_q), \quad (5)$$

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 $(x_p - x_q)$.

The efficiency of DE algorithm is directly determined by evolutionary parameters. 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 experiments results show that the multiple unmanned aerial vehicle system can generate multiple feasible paths in the aerial environment.

For evolutionary algorithms, crossover, mutation and selection are three key evolution operators. Because of these operators, the evolutionary algorithms are able to jump out the local minimum due to the random crossover process. However, the 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

$$\frac{du_k}{dt} = -Au_k + (B - u_k)S_i^+(t) - (D + u_k)S_i^-(t), \quad (6)$$

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 the location of maximum neural activity in environments until reaching the target. The connection of 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 the dynamic and complex environment. The Fig. 3 shows a bio-inspired neural network structure diagram of local path planning.

Recently, researchers have paid consideration attention to using BINN method to deal with the real-time path planning problems. The BINN method is able to generate the shortest path efficiently in complicated underwater environment due to its great 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 search 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 BINN model to optimize the fitness function of 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 target search problem [41]. The simulation results show that this integrated algorithm is to generate the paths efficiency and adaptability. Luo used BINN to model the workspace and guide multiple mobile robots to finish complete area coverage mission [42]. The simulation results show that the BINN model is computationally efficient to generate the complete area coverage path.

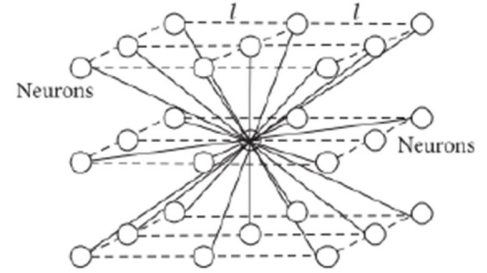


Fig. 3. Example of a BINN model form [39]

It is important to be mentioned that the BINN model use neural network to generate the optimal path, however, it is totally 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 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 the premature

convergence and slow convergence speed limit the practical use of 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.

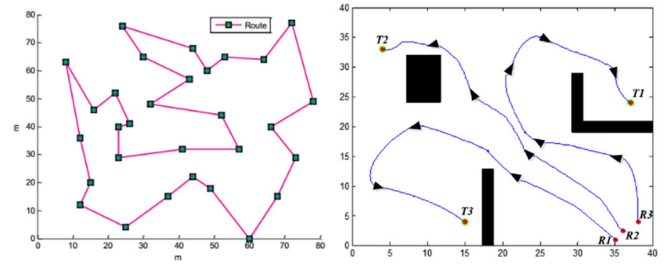
More recently, considerable attention has been drawn to neurodynamics method. The BINN model becomes the most popular method due to its great real-time performance for complex path planning problems. The limitation of swarm intelligence and evolutionary algorithms is that these methods require some learning process. Thus, the real-time performance is unsatisfactory. However, BINN method is topologically organized, there is not any learning process. Thus, the real-time performance of BINN is better than other algorithms.

TABLE II.

COMPARISON AMONG VARIOUS PATH PLANNING METHODS

Method	Advantage	Disadvantage
PSO	<ul style="list-style-type: none"> • Easy to be implemented • No mutation calculation required 	<ul style="list-style-type: none"> • Premature convergence • Slow convergence speed
ACO	<ul style="list-style-type: none"> • Efficiently work in a dynamic environment • No premature convergence problem 	<ul style="list-style-type: none"> • Probability distribution changes by iteration • Convergence time is uncertain
GA	<ul style="list-style-type: none"> • Easy to find a global optimal solution • Probabilistic mechanism with randomness 	<ul style="list-style-type: none"> • The convergence speed is uncertain
DE	<ul style="list-style-type: none"> • No requirement for the continuity of the function 	<ul style="list-style-type: none"> • Unsatisfactory local path planning performance • A lot of parameters need to be adjusted
BINN	<ul style="list-style-type: none"> • Real-time performance • No learning process • Not sensitive to obstacles 	<ul style="list-style-type: none"> • 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 the smooth path as is shown in Fig. 4(b). There are many sharp inflection points on the optimal path in Fig. 4(a). In real application, because of the kinematic constraints of the robot 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 the future research should consider whether it is possible to work for real application.



(a) The simulation result from [17] (b) The simulation result from [41]
Fig. 4. The comparison of simulation results

IV. CONCLUSION

As the artificial intelligence has become more popular in robotics, the amount of research on path planning has increased greatly. 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. Swarm intelligence, evolutionary algorithms, and neurodynamics are three major robot path planning methods that are focused on in this survey. In addition, the pros and cons of these methods are summarized and analyzed.

REFERENCES

- [1] C. D. B. Borges, A. M. A. Almeida, I. C. P. Júnior, and J. J. D. S. M. Junior, "A strategy and evaluation method for ground global path planning based on aerial images," *Expert Systems with Applications*, vol. 137, pp. 232-252, December 2019.
- [2] P. Yang, S.-W. Li, and Z.-Z. Hu, "A self-learning dynamic path planning method for evacuation in large public buildings based on neural networks," *Neurocomputing*, vol. 365, pp. 71-85, November 2019.
- [3] H. Yu, J. Chen, H. Wang, and G. Su, "A method of 3D path planning for solar-powered UAV with fixed target and solar tracking," *Aerospace Science and Technology*, vol. 92, pp. 831-838, September 2019.
- [4] O. Saha, P. Dasgupta, and B. Woosley, "Real-time robot path planning from simple to complex obstacle patterns via transfer learning of options," *Autonomous Robots*, vol. 43, pp. 1-23, May 2019.
- [5] H. Li, D. Yang, W. Su, J. Lü, and X. Yu, "An overall distribution particle swarm optimization MPPT algorithm for photovoltaic system under partial shading," *IEEE Transactions on Industrial Electronics*, vol. 66, no. 1, pp. 265-275, January 2019.
- [6] F. Wang, H. Zhang, K. Li, Z. Lin, J. Y. and X.-L. Shen, "A hybrid particle swarm optimization algorithm using adaptive learning strategy," *Information Sciences*, vol. 436, pp. 162-177, April 2018.
- [7] C. Qi, A. Fourie, and Q. Chen, "Neural network and particle swarm optimization for predicting the unconfined compressive strength of cemented paste backfill," *Construction and Building Materials*, vol. 159, pp. 473-478, January 2018.
- [8] D. Wu, J. Xu, and H. Zhao, "An improved ant colony optimization algorithm based on hybrid strategies for scheduling problem," *IEEE access*, vol. 7, pp. 20281-20292, January 2019.
- [9] J. Santos, A. Ferreira, and G. Flintsch, "An adaptive hybrid genetic algorithm for pavement management," *International Journal of Pavement Engineering*, vol. 20, no.3, pp. 266-286, March 2019.

- [10] R. Zhang and J. Tao, "A nonlinear fuzzy neural network modeling approach using an improved genetic algorithm," *IEEE Transactions on Industrial Electronics*, vol. 65, no. 7, pp. 5882-5892, July 2017.
- [11] H. Hong, M. Panahi, A. Shirzadi, T. Ma, J. Liu, A.-X. Zhu, W. Chen, I. K. and N. Kazakis, "Flood susceptibility assessment in Hengfeng area coupling adaptive neuro-fuzzy inference system with genetic algorithm and differential evolution," *Science of The Total Environment*, vol. 621, pp. 1124-1141, April 2018.
- [12] Q. Yang, and S.-J. Yoo, "Optimal UAV path planning: Sensing data acquisition over IoT sensor networks using multi-objective bio-inspired algorithms," *IEEE Access*, vol. 6, pp. 13671-13684, January 2018.
- [13] A. M. Anter, Y. Wei, J. Su, Y. Yuan, B. Lei, G. Duan, W. Mai, X. Nong, B. Yu, C. Li, Z. Fu, L. Zhao, D. Deng and Z. Zhang, "A robust swarm intelligence-based feature selection model for neuro-fuzzy recognition of mild cognitive impairment from resting-state FMRI," *Information Science*, vol. 503, pp.670-687, November 2019.
- [14] A. ŞİMŞEK and K. A. R. A. Resul, "Using swarm intelligence algorithms to detect influential individuals for influence maximization in social networks," *Expert Systems with Applications*, vol. 114, pp. 224-236, December 2018.
- [15] Y. Shi and Eberhart, "Particle swarm optimization: developments, applications and resources," *Proceedings of the 2001 congress on evolutionary computation*, vol. 1, pp. 81-86, 2001..
- [16] M. D. Phung, C. H. Quach, T. H. Dinh and Q. Ha, "Enhanced discrete particle swarm optimization path planning for UAV vision-based surface inspection," *Automation in Construction*, vol. 81, pp. 25-33, September 2017.
- [17] Z. Wang, and J. Cai, "The path-planning in radioactive environment of nuclear facilities using an improved particle swarm optimization algorithm," *Nuclear Engineering and Design*, vol. 326, pp. 79-86, January 2018.
- [18] S. Thabit and A. Mohades, "Multi-robot path planning based on multi-objective particle swarm optimization," *IEEE Access*, vol. 7, pp. 2138-2147, January 2018.
- [19] M. Dorigo, V. Maniezzo, and A. Colomi, "Ant system: optimization by a colony of cooperating agents," *IEEE Transactions on Systems*, vol. 26, no. 1, pp. 29-41, February 1996.
- [20] C. Xiong, D. Chen, D. Lu, Z. Zeng and L. Lian, "Path planning of multiple autonomous marine vehicles for adaptive sampling using Voronoi-based ant colony optimization," *Robotics and Autonomous Systems*, vol. 115, pp. 90-103, May 2019.
- [21] Y. Ma, Y. Gong, C. Xiao, Y. Gao, and J. Zhang, "Path Planning for Autonomous Underwater Vehicles: An Ant Colony Algorithm Incorporating Alarm Pheromone," *IEEE Transactions on Vehicular Technology*, vol. 68, no.1, pp. 141-154, January 2018.
- [22] J. Liu and J. Yang, "An improved ant colony algorithm for robot path planning," *Soft Computing*, vol. 21, no. 19, pp. 5829-5839, October 2017.
- [23] H. and J. H, "Genetic algorithms and the optimal allocation of trials," *SIAM Journal on Computing*, vol. 2, no. 2, pp. 88-105, August 1973.
- [24] A. Bakdi, A. Hentout, H. Boutamai, A. Maoud and B. Bouzouia, "Optimal path planning and execution for mobile robots using genetic algorithm and adaptive fuzzy-logic control," *Robotics and Autonomous Systems*, vol. 89, pp. 95-109, March 2017.
- [25] C.-C. Shih, C.-C. Shih, T.-S. Pan, J.-S. Pan and C.-Y. Chen, "A genetic-based effective approach to path-planning of autonomous underwater glider with upstream-current avoidance in variable oceans," *Soft Computing*, vol. 21, no. 18, pp. 5369-5386, September 2017.
- [26] B. K. Patlea, D. R. K. Parhi, A. Jagadeesh, S. K. Kashyap, "Matrix-Binary Codes based Genetic Algorithm for path planning of mobile robot," *Computers & Electrical Engineering*, vol. 67, pp. 708-728, April 2018.
- [27] M. Elhoseny, A. Tharwat, and A. E. Hassanien, "Bezier curve based path planning in a dynamic field using modified genetic algorithm," *Journal of Computational Science*, vol. 25, pp. 339-350, March 2018.
- [28] J. Xin, J. Zhong, F. Yang, Y. Cui and J. Sheng, "An Improved Genetic Algorithm for Path-Planning of Unmanned Surface Vehicle," *Sensors*, vol. 19, pp. 2640, June 2019.
- [29] Price and Kenneth V, "Differential evolution: a fast and simple numerical optimizer," *Proceedings of North American Fuzzy Information Processing*, pp. 524-527, June 1996.
- [30] M. Nazarahari, E. Khanmirza, and S. Doostie, "Multi-objective multi-robot path planning in continuous environment using an enhanced genetic algorithm," *Expert Systems with Applications*, vol. 115, pp. 106-120, January 2019.
- [31] Z. Sun, J. Wu, J. Yang, Y. Huang, C. Li and D. Li, "Path planning for GEO-UAV bistatic SAR using constrained adaptive multiobjective differential evolution," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 54, no. 11, pp. 6444-6457, November 2016.
- [32] A. Zamuda and J. D. H. Sosa, "Success history applied to expert system for underwater glider path planning using differential evolution," *Expert Systems with Applications*, vol. 119, pp. 155-170, April 2019.
- [33] H. Qu, S. X. Yang, A.R. Willms, and Z.Yi, "Real-time robotpath planning based on a modified pulse-coupled neural network model," *IEEE Transactions on Neural Networks*, vol. 20, no. 11, pp. 1724-1739, November 2009.
- [34] S. X. Yang and M. Meng, "An efficient neural network approach to dynamic robot motion planning," *Neural Networks*, vol. 13, no. 2, pp. 143-148, March 2000.
- [35] S. X. Yang and M. Meng, "Neural network approaches to dynamic collision-free trajectory," *IEEE Transactions on Systems, Man and Cybernetics*, vol. 3, no. 3, pp. 302-318, June 2001.
- [36] S. X. Yang and M.Q.-H.Meng, "Real-time collision-freemotion planning of a mobile robot using a neural dynamics-based approach," *IEEE Transactions on Neural Networks*, vol. 14, no. 6, pp. 1541-1552, November 2003.
- [37] A. L. Hodgkin and A. F. Huxley, "A quantitative description of membrane current and its application to conduction and excitation in nerve," *The Journal of Physiology*, vol. 117, no. 4, pp. 500-544, August 1952.
- [38] S. Grossberg, "Contour enhancement, short term memory, and constancies in reverberating neural networks," *Studies in Applied Mathematics*, vol. 52, no. 3, pp. 213-257, September 1973.
- [39] J. Ni, L. Wu, P. Shi, and S. X. Yang, "A dynamic bioinspired neural network based real-time path planning method for autonomous underwater vehicles," *Computational intelligence and neuroscience*, vol. 2017, February 2017.
- [40] J. Ni, Z. Zhang, B. Su, X. Fan, and W. Liang, "A bio-inspired neural network based PSO method for robot path planning," *IEEE 13th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery (ICNC-FSKD)*, pp. 234-238, July 2017.
- [41] X. Cao, H. Sun, and G. E. Jan, "Multi-AUV cooperative target search and tracking in unknown underwater environment," *Ocean Engineering*, vol. 150, pp. 1-11, December 2018.
- [42] C. Luo, S. X. Yang, X. Li, and M. Q. H. Meng, "Neural-dynamics-driven complete area coverage navigation through cooperation of multiple mobile robots," *IEEE Transactions on Industrial Electronics*, vol. 64, no. 1, pp. 750-760, January 2016.