Optimizing The Movement Strategies of "Ban Deng Dragon" with APO

Wenyuan Tian*, Zhiye Li

College of Mechanical Engineering, Yanshan University, Qinhuangdao, China, 066004

*Corresponding author: 15513737676@163.com

Abstract. This study investigates the challenges associated with collision avoidance and path optimization in the spiral coiling motion of the "Ban Deng Dragon" dance team. Current path planning methods, including the enhanced Jump Point Search, A*, and Ant Colony Optimization, still demonstrate limitations in computational efficiency, dynamic adaptability, and handling multiple constraints. A mathematical model of spiral motion, subject to boundary and collision constraints, was developed to determine the minimum pitch requirement. The APO algorithm, inspired by the adaptive flight and foraging behaviors of Arctic puffins, was then employed to iteratively optimize the spiral trajectory. Experimental results revealed that the APO algorithm achieved a minimum feasible pitch of 0.450338 m while ensuring collision avoidance, outperforming both the Genetic Algorithm and Simulated Annealing in terms of convergence speed and robustness. This study highlights the effectiveness of the APO algorithm in solving multi-constrained optimization problems, improving the precision of traditional cultural performances, and showcasing the potential of bio-inspired algorithms in dynamic systems.

Keywords: Arctic Puffin Optimization, Path Planning, Collision Avoidance, Spiral Coiling, Bio-inspired Algorithms.

1. Introduction

Recent advancements in path planning and collision detection, fueled by deep reinforcement learning and graph search algorithms, have notably enhanced decision-making efficiency and accuracy in complex environments. However, critical challenges remain, including multi-agent coordination, collision avoidance, and high-dimensional space precision detection. Recent studies have concentrated on enhancing path planning algorithms to tackle challenges such as high computational costs, inefficiency, and difficulty in handling complex environments. Wang Jiaxiang and his colleagues (2025) proposed an enhanced Jump Point Search algorithm, which reduced the number of expanded nodes, runtime, and turning points, though it still encounters difficulties in more complex environments and real-time applications [1]. Zhang Chenwei and his team (2025) introduced a dynamic weighting coefficient and incorporated the Tentacle Algorithm to enhance A*'s performance in fire scenarios, achieving a 60% reduction in search nodes, but the approach still faces high computational costs [2]. Wu Lei and his team (2025) enhanced Ant Colony Optimization by incorporating a potential field heuristic and a pheromone reward-punishment strategy, improving convergence and path quality but facing challenges with solution diversity and large-scale problems [3]. Tong Yunhao and his team (2025) further refined ACO by adjusting pheromone volatility and update criteria, reducing path length but still necessitating optimization for dynamic scenarios [4]. Finally, Li Chengjian and his colleagues (2025) applied Deep Reinforcement Learning to the Multi-Objective Traveling Salesman Problem, showing significant improvements in solution quality, yet still encountering challenges with large-scale, dynamic problems [5]. This study develops a pitch optimization model and employs the Arctic Puffin Optimization algorithm for path planning and collision detection tasks, demonstrating its superior convergence speed and robust performance.

The main contributions of this study are threefold: (1) establishing a mathematical model of spiral motion subject to boundary and collision constraints, and deriving the solution for the minimum pitch; (2) innovatively applying the Arctic Puffin Optimization Algorithm to path planning problems, thereby offering a novel approach for solving multi-constraint optimization problems; (3) conducting a comparative analysis between the Arctic Puffin Optimization Algorithm and conventional genetic algorithms as well as simulated annealing algorithms, thereby demonstrating its superior performance.

This article is organized as follows: Section 1 presents the introduction, outlining the research background, recent advancements, and key contributions. Section 2 provides the theoretical foundation, detailing the Arctic Puffin Optimization algorithm. Section 3 describes the experimental design and analysis, including the methodology and implementation procedures. Section 4 summarizes the experimental results and their implications. Section 5 concludes the study, emphasizing its significance and proposing future research directions.

2. Related Theories

Arctic puffins coordinate their flight patterns through formation or group flight, improving flight efficiency and facilitating cooperative hunting opportunities. Upon detecting abundant food resources, Arctic puffins swiftly adjust their flight direction and employ a diving predation strategy to capture prey effectively. On the water surface, they typically encircle fish schools through group cooperation, thereby significantly improving hunting efficiency. Additionally, they identify potential diving hotspots or food-rich areas by monitoring the behavior of group members. When food resources are depleted, Arctic puffins seek new sources by dynamically adjusting their underwater positions. When detecting potential threats, such as nearby predators, Arctic puffins swiftly relocate and signal group members to avoid danger.

Each Arctic puffin is seen as a representative of potential solutions in the optimization process. The generation process of population initialization can be described by the following formula:

$$\overrightarrow{X_i^t} = rand * (ub - lb) + lb, i = 1,2,3...N \tag{1}$$

In daily life, Arctic puffins must adapt flexibly between the sea and the air to meet their nutritional needs. When navigating in the air, Arctic puffins usually adopt two key strategies to deal with different situations.

During the air search phase, the location update equation associated with the strategy is expressed as follows:

$$\overrightarrow{Y_i^{t+1}} = \overrightarrow{X_i^t} + (\overrightarrow{X_i^t} - \overrightarrow{X_r^t}) * L(D) + R \tag{2}$$

$$R = round(0.5 * (0.05 + rand)) * a \tag{3}$$

$$a \sim Normal(0,1) \tag{4}$$

During the subduction predation stage, the position update equation associated with the strategy is expressed as follows:

$$\overrightarrow{Z_i^{t+1}} = \overrightarrow{Y_i^{t+1}} * S \tag{5}$$

$$S = \tan((rand - 0.5) * \pi) \tag{6}$$

To achieve optimal results across various scenarios, the algorithm merges the candidate positions generated in the two stages into a new solution. These solutions are subsequently ranked based on fitness, and the top N individuals are selected to form a new population. The corresponding equation is as follows:

$$\overrightarrow{P_i^{t+1}} = \overrightarrow{Y_i^{t+1}} \cup \overrightarrow{Z_i^{t+1}} \tag{7}$$

$$new = sort(\overrightarrow{P_i^{t+1}}) \tag{8}$$

$$\overrightarrow{X_i^{t+1}} = new(1:N) \tag{9}$$

While foraging underwater, Arctic puffins employ three distinct strategies to enhance their hunting efficiency.

During the foraging stage, the position update equation is expressed as follows:

$$\overrightarrow{W_i^{t+1}} = \begin{cases} \overrightarrow{X_{r1}^{t}} + F * L(D) * (\overrightarrow{X_{r2}^{t}} - \overrightarrow{X_{r3}^{t}}) & rand \geq 5 \\ \overrightarrow{X_{r1}^{t}} + F * (\overrightarrow{X_{r2}^{t}} - \overrightarrow{X_{r3}^{t}}) & rand < 5 \end{cases} \tag{10}$$

During the enhanced search phase, the position update equation is expressed as follows:

$$\overrightarrow{Y_i^{t+1}} = \overrightarrow{W_i^{t+1}} * (1 + f) \tag{11}$$

$$f = 0.1 * (rand - 1) * \frac{(T - t)}{T} \tag{12}$$

During the predator avoidance stage, the position update equation is expressed as follows:

$$\overrightarrow{Z_i^{t+1}} = \begin{cases} \overrightarrow{X_i^{t}} + F * L(D) * (\overrightarrow{X_{r1}^{t}} - \overrightarrow{X_{r2}^{t}}) & rand \geq 0.5 \\ \overrightarrow{X_i^{t}} + \beta * (\overrightarrow{X_{r1}^{t}} - \overrightarrow{X_{r2}^{t}}) & rand < 0.5 \end{cases} \tag{13}$$

The population merging operation is also applied in the above three stages as follows:

$$\overrightarrow{P_i^{t+1}} = \overrightarrow{W_i^{t+1}} \cup \overrightarrow{Y_i^{t+1}} \cup \overrightarrow{Z_i^{t+1}} \tag{14}$$

$$new = sort(\overrightarrow{P_i^{t+1}}) \tag{15}$$

$$\overrightarrow{X_i^{t+1}} = new(1:N) \tag{16}$$

In the APO algorithm, Arctic puffins initially fly frequently in the air to facilitate global search, while toward the end of the iteration, they dive more frequently to forage for food, facilitating local development. Based on these behavioral patterns, a behavior conversion factor B is introduced to enable a smooth transition from global search to local development. The expression is as follows [6] :

$$B = 2 * \log(1/rand) * (1 - t/T) \tag{17}$$

The flow chart of Arctic Puffin Optimization is shown in Figure 1.

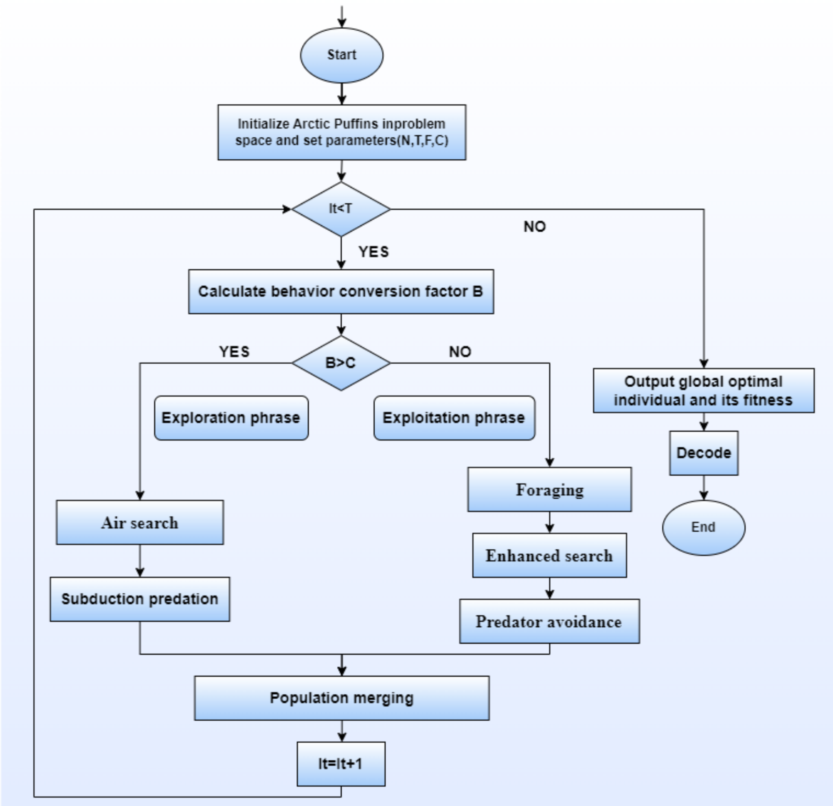

Figure 1. Arctic Puffin Optimization Flow Chart

3. Experments

This study develops a motion model for the dragon dance team during spiral coiling, with the goal of determining the minimum pitch required to avoid collisions and complete the coiling process. By utilizing the spiral polar coordinate equation and the iterative positional relationships between the benches, the coordinates of each handle and external corner point of the dragon dance team are calculated at each time step, and collisions are identified based on geometric conditions. By progressively reducing the pitch using the APO algorithm, the minimum feasible pitch is obtained, and the final position and time of the dragon head are determined. The results reveal that the collision at the minimum pitch occurs at the left rear corner of the dragon head bench, and the study effectively solves the optimization problem of the dragon dance team's entry path [7].

Derive the polar coordinate equation corresponding to the spiral of the dragon dance team:

$$\rho(\theta) = \frac{d}{2\pi}\theta \tag{18}$$

The position of the center of the front handle of the dragon head can be determined from the integral formula of the spiral length:

$$s = \int_{\theta_0}^{32\pi} \sqrt{(\rho^{'}(\theta))^2 + \rho^2(\theta)}d\theta \tag{19}$$

Using the transformation formulas between polar and Cartesian coordinates, the center coordinates of the front handle of the dragon head can be derived as:

$$\begin{cases} x_0 = \rho(\theta_0)\cos\theta_0 \\ y_0 = \rho(\theta_0)\sin\theta_0 \end{cases} \tag{20}$$

The positional relationship between the centers of the front and rear handles of the same bench is:

$$\rho_{rear} = \rho_{front} + \frac{d}{2\pi}(\theta_{rear} - \theta_{front}) \tag{21}$$

Based on the law of cosines:

$$\rho_{front}^2 + \rho_{rear}^2 - 2\rho_{front}\rho_{rear}(\theta_{rear} - \theta_{front}) = L^2 \tag{22}$$

Additionally, the central coordinates of the rear handles for each bench can be calculated. Derive the velocity update equation based on an analysis of positional relationships.
The tangent slopes of the spiral at the center positions of the front and rear handles are:

$$k_{front} = \frac{\sin\theta_{front} + \theta_{front}\cos\theta_{front}}{\cos\theta_{front} - \theta_{front}\sin\theta_{front}} \tag{23}$$

$$k_{rear} = \frac{\sin\theta_{rear} + \theta_{rear}\cos\theta_{rear}}{\cos\theta_{rear} - \theta_{rear}\sin\theta_{rear}} \tag{24}$$

The slope of the straight line connecting the center positions of the front and rear handles of the same bench is:

$$k = \frac{y_{front} - y_{rear}}{x_{front} - x_{rear}} \tag{25}$$

The iterative formula for calculating the correlation speed between the center positions of the front and rear handles of the same bench is as follows:

$$v_{front}\cos\alpha = v_{rear}\cos\beta \tag{26}$$

$$\alpha = \arctan\left|\frac{k_{front} - k}{1 + k_{front}k}\right| \tag{27}$$

$$\beta = \arctan\left|\frac{k_{rear} - k}{1 + k_{rear}k}\right| \tag{28}$$

To prevent collisions during the dragon dance team's coiling process, collision criteria need to be defined. Analysis reveals that potential collision locations include the four corner points on the outer side of the dragon head and the first section of the dragon body.

The equation for the straight line connecting the outer corner point at the front end of the dragon head and the center point of its front handle is:

$$l_1 : y - y_{front} = k'(x - x_{front}) \tag{29}$$

$$k' = \frac{\tan\gamma + k}{k\tan\gamma - 1} \tag{30}$$

The equation for the straight line parallel to the centerline of the front and rear handles on the outer side of the dragon head is:

$$l_2 : y = kx + b \tag{31}$$

$$\frac{\left|b - y_{front} + kx_{front}\right|}{\sqrt{1 + k^2}} = 15 \tag{32}$$

$$|b| > \left|y_{front} - kx_{rear}\right| \tag{33}$$

The coordinates of the outer corner point near the center of the front handle of the dragon head can be determined by combining the relevant factors:

$$(x', y') = \left(\frac{y_{front} - k' x_{front} - b}{k - k'}, \frac{k y_{front} - k k' x_{front} - k' b}{k - k'} \right) \tag{34}$$

Similarly, the position coordinates of the remaining three corner points can be calculated.

The equation for the straight line connecting the centers of the front and rear handles of the i-th bench is:

$$l_i : y - y_i = \frac{y_i - y_{i+1}}{x_i - x_{i+1}} (x - x_i) \tag{35}$$

The distance between any corner point Q_j and the straight line l_i is:

$$Q_{ij} = \frac{\left| \frac{y_i - y_{i+1}}{x_i - x_{i+1}} (x_{Q_j} - x_i) - y_{Q_j} + y_i \right|}{\sqrt{1 + \left(\frac{y_i - y_{i+1}}{x_i - x_{i+1}} \right)^2}} \tag{36}$$

Define the collision criteria:

$$\begin{cases} \forall i, j (i \in I, j = 1,2,3,4), Q_{ij} > 15 & \text{No collision was detected at time } t \\ \exists i, j (i \in I, j = 1,2,3,4), Q_{ij} < 15 & \text{A collision is detected at time } t \end{cases} \tag{37}$$

Definition of the APO algorithm fitness function:

$$Fitness(P) = P + \lambda_1 \cdot \max(0, |r - 4.5| - \varepsilon) + \lambda_2 \cdot CollisionCount \tag{38}$$

The proposed fitness function explicitly represents the primary optimization objective P . To incorporate position-error and collision penalties, the weighting coefficients λ_1 and λ_2 are introduced.

By integrating the defined objective function, decision variables, and constraints, a comprehensive pitch optimization model is developed. The primary objectives of the model are collision avoidance and pitch minimization during boundary-aligned turning space entry [8].

4. Results

This study adopts a systematic methodology involving experimental design and model construction, utilizing the Arctic Puffin Optimization algorithm for iterative parameter optimization. During model refinement, a behavioral transition factor, B, is introduced to facilitate global exploration during aerial transit phases and localized exploitation during diving predation phases. The optimization framework rigorously integrates collision avoidance constraints and U-turn spatial boundary limitations to determine the minimal feasible pitch configuration [9].

The numerical implementation utilizes MATLAB to solve the pitch optimization model, yielding the minimum feasible pitch configuration through computational iterations. After 100 iterations of the Arctic Puffin Optimization algorithm, the optimized minimum pitch value converges to 0.450338 m. Figure 2 illustrates the helical trajectory parameters, including the spiral centroid coordinates and U-turn spatial boundaries related to the optimized motion strategy.

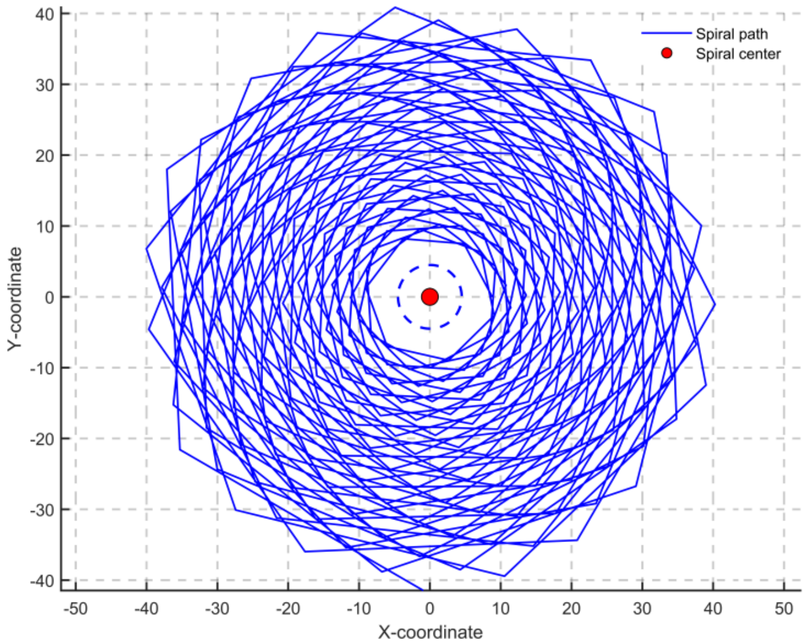

Figure 2. Minimum Pitch for Faucet Entry into Turning Space

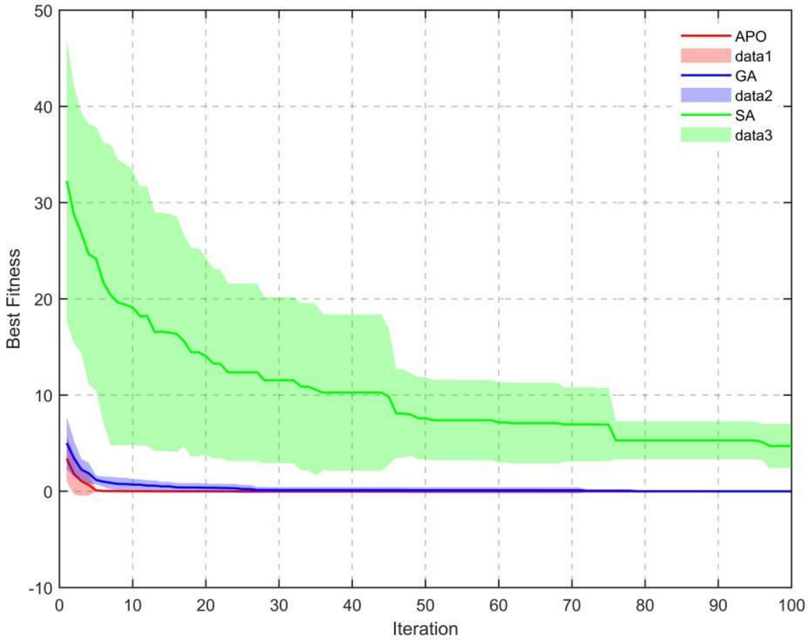

Figure 3. Algorithm Comparison (Mean±Std)

Figure 3. Comparative analysis of convergence performance: Average convergence trajectories and standard deviation error bands for the Arctic Puffin Optimization, Genetic Algorithm, and Simulated Annealing algorithms.

The comparative analysis demonstrates that the Arctic Puffin Optimization algorithm effectively addresses multi-constrained path optimization problems, exhibiting superior convergence speed and robustness compared to benchmarked methods.

5. Conclusions

In this paper, the Arctic Puffin Optimization algorithm is proposed to tackle the collision avoidance and path optimization challenges in the spiral coiling movement of the "Ban Deng Dragon" dance team. Inspired by Arctic puffins' adaptive flight and foraging strategies, APO dynamically integrates global exploration and localized exploitation, achieving a minimal feasible pitch of 0.450338 m while ensuring collision avoidance. Comparative analysis with the Genetic Algorithm and Simulated Annealing highlights APO's superior convergence speed and robustness in solving multi-constrained optimization problems. This work not only enhances the planning precision of traditional cultural performances but also demonstrates the broader applicability of bio-inspired algorithms in complex dynamic systems [10].

References

[1] Wang Jiaxiang, Zhang Sai, Zhang Wei. A Path Planning Method Based on Improved Jump Point Search Algorithm [J]. Software Guide, 2025, 24(1): 1-9.

[2] Zhang Chenwei, Huang Ping, Zhang Guoheng, et al. Research on Adaptive Path Planning Based on Improved A* Algorithm [J]. Journal of Electrical Engineering and Information Science, 2025, 26(2): 43-47.

[3] Wu Lei, Bing Zhigang, Liu Jia. Research on Intelligent Vehicle Path Planning Based on Improved Ant Colony Algorithm [J]. Automation & Instrumentation, 2025, 40(1): 72-76.

[4] Tong Yunhao, Xi Zhihong. Intelligent Path Planning Based on Ant Colony Algorithm [J]. Electronic Science & Technology, 2025, 38(1): 23-28.

[5] Li Chengjian, Song Shuyi, Su Yu, et al. Review of Multi-Objective Traveling Salesman Problem Based on Deep Reinforcement Learning [J]. Computer Engineering and Applications, 2025, 61(2): 1-10.

[6] Wang W C, Tian W C, Xu D M, et al. Arctic Puffin Optimization: A Bio-Inspired Metaheuristic Algorithm for Solving Engineering Design Optimization [J]. Advances in Engineering Software, 2024, 195: 103694.

[7] Liu Tianbao, Li Yang. An Improved Arctic Puffin Optimization Algorithm with Multi-Strategy [J]. Journal of Bohai University (Natural Science Edition), 2024, 45(3): 195-204.

[8] Sun Peng, Liu Chunhui, Shi Xiangdong, Zhang Hengheng, Zha Wenke. Research on Path Planning of Mobile Robot Based on Improved A* Algorithm [J]. Journal of Heilongjiang Institute of Technology, 2025, 40(3): 1-10.

[9] Yang Wenjuan, Zhang Ran, Zhang Xuhui, Tian Sihao, Wang Zeyao, Zheng Xili, Ren Zhiteng, Wan Jicheng, Du Yuyang, Zhang Hanbing. Research on the collision avoidance Path Planning Method for Mining and Anchoring Equipment in the Narrow and Restricted Space of Tunneling Laneways [J]. Coal Science and Technology, 2025, 53(1): 1-10.

[10] Li Yongzhen, Huang Xuegong, Zhang Zhian. Multi-target Path Planning Method Based on Fused Ant Colony-A* Algorithm [J]. Computing Technology and Automation, 2024, 43(4): 66-72.