

Robust Converged UAV Path Planning Using Q-learning Based Sheep Flock Optimization Algorithm with Cauchy Operator

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An unmanned aerial vehicle (UAV) works without the aid of a human pilot and is widely used in commercial, agricultural, military, and other industrial-related applications nowadays [1]. However, determining the efficient path is one of the most challenging tasks in UAVs [1]-[3]. Recently, many techniques have been introduced in UAV path planning, which is a complex optimization problem dealing with flight length, altitude cost, and other constraints. In this research, a novel path-planning algorithm entitled Q learning based multi-objective sheep flock optimization algorithm with Cauchy operator (Q-MOSFO-CA) is proposed to find the optimum path. The sheep flock optimization algorithm (SFOA) is an evolutionary technique to provide the global optimal solution. But it takes too many iterations to converge while determining the path efficiently. Hence, the Cauchy operator has been introduced to eliminate unwanted collisions among the UAVs. Furthermore, Q-learning-based mode selection logic is introduced to balance global search with local search in the evolution process. The performance measures, such as route distance, fitness value, constraint cost, and altitude with varying iterations are analyzed and compared with the existing method. The performance analysis proves the efficacy of the proposed method.

The Q-learning is one of the most commonly used procedures in reinforcement learning (RL) [2]-[3], in which the agent learns trial an error manner, and rewards are obtained while interacting with the environment. It can also learn how the action is chosen by constructing the largest reward value via rewarding or punishing. The multi-objective (MO) optimization model can be formulated as a constrained path-planning problem as follows:

$$\min F = (A, B), \quad A = A_f + A_g \text{ and } B = B_1 + B_2 + B_3 + B_4 \quad (1)$$

Here, A represents the sum of flight cost A_f and the length cost A_g , B represents the sum of constraint cost and the threat constraints indicated as B_1 , terrain constraint represented as B_2 , B_3 indicates the turning constraint and gliding constraint represented as B_4 . For the altitude cost with a low flying range, the mathematical formulation for A_f is represented as, $A_f = \int_{path} G_r dl$, where G_r is represented as $\begin{cases} 0 & \text{if } j_n < 0 \\ j_r & \text{otherwise} \end{cases}$, j_r depicts the waypoint height at the range r .

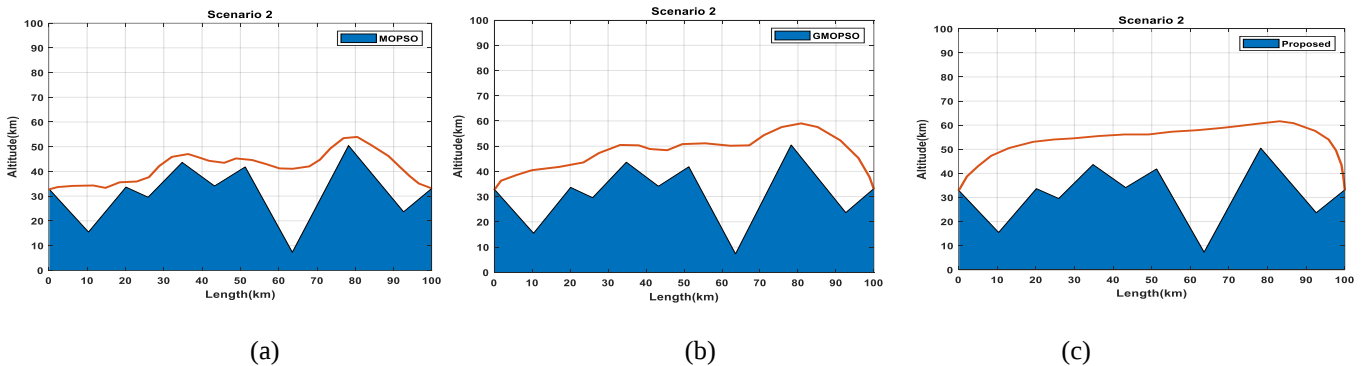


Figure 1. Comparison of Altitude and length based on the best path, (a) MOPSO (b) GMOPSO (c) proposed Q-MOSFO-CA

References

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