Advances in Engineering Software 99 (2016) 121–136

Contents lists available at ScienceDirect

Advances in Engineering Software

journal homepage: www.elsevier.com/locate/advengsoft

Research paper

Grey wolf optimizer for unmanned combat aerial vehicle path planning

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ARTICLE INFO

Article history:
Received 2 February 2016
Revised 16 May 2016
Accepted 29 May 2016

Keywords:
Unmanned combat aerial vehicle
Path planning
Grey wolf optimizer

ABSTRACT

Unmanned combat aerial vehicle (UCAV) path planning is a fairly complicated global optimum problem, which aims to obtain an optimal or near-optimal flight route with the threats and constraints in the combat field well considered. A new meta-heuristic grey wolf optimizer (GWO) is proposed to solve the UCAV two-dimension path planning problem. Then, the UCAV can find the safe path by connecting the chosen nodes of the two-dimensional coordinates while avoiding the threats areas and costing minimum fuel. Conducted simulations show that the proposed method is more competent for the UCAV path planning scheme than other state-of-the-art evolutionary algorithms considering the quality, speed, and stability of final solutions.

1. Introduction

The development of automation and unmanned flight technology has become an irresistible trend in many countries. In fact, unmanned combat aerial vehicle (UCAV) has been of great importance to many military organizations throughout the world owing to its potential to perform dangerous, repetitive tasks in remote and hazardous environments [1]. Path planning and trajectory generation is one of the critical technologies in coordinated UCAV combating. The path planning aims to offer an optimal path from a starting point to a desired destination with the artificial threats and a variety of constraints considered in the combat field. For the UCAV path planning scheme, the optimality of a flight path can be calculated through minimizing the gross flight route, fuel consumption, and exposure to radar or artillery, and so on [2]. With the development of ground defense weapons, the difficulty of describing artificial threats is greatly increased. So, solving such problems requires effective optimization techniques and consideration of several difficulties included: constrained, local solutions, and expensive objective function.

Swarm Intelligence (SI) [3] techniques have become a reliable alternatives compared to conventional optimization techniques in several engineering fields because of their promising performances when solving different kinds of real world optimization problems: parameter estimation, feature selection, neural network training, knapsack problem, and so on. Although SI-based algorithms include many methods, two of the most popular algorithms in this field are particle swarm optimization (PSO) [4] and ant colony optimization (ACO) [5] that are inspired by the social behavior of birds and marking paths via pheromone by ants when searching for food. Some of the recent SI-based algorithms have been developed and proposed in the literature such as grey wolf optimizer (GWO) [6], whale optimization algorithm (WOA) [7], ant lion optimizer (ALO) [8], virus colony search (VCS) [9], dolphin echolocation (DE) [10], and big bang-big crunch (BB-BC) [11]. These algorithms have been successfully applied to a wide range of practical problems as well. Although these algorithms are popular, there is little application on UCAV path planning. The SI-based algorithms have the potential to solve various hard optimization problems. This is the current work, in which GWO will be analyzed in detail and employed to solve UCAV problems.

Up to now, series of algorithms have been proposed to solve the UCAV path planning problem. Some of the most popular in the literature are $A*$ search algorithm [12], evolutionary computation [13], genetic algorithm [14], particle swarm optimization [15], ant colony optimization [16], artificial bee colony [17,18], and differential evolution [19]. The recent evolutionary algorithms are biogeography-based optimization approach [20], firefly algorithm [21], cuckoo search [22], bat algorithm [23], flower pollination algorithm [24], intelligent water drops [25], and imperialist competitive algorithm [26]. However, those methods can be easily trapped into the local best, therefore would probably end up without finding a satisfying trajectory path. Moreover, there is a theorem here called No Free Lunch (NFL) [27] that has been logically proved that

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http://dx.doi.org/10.1016/j.advengsoft.2016.05.015
0965-9978/

there is no meta-heuristic best suited for solving all optimization problems. In other words, a particular meta-heuristic may show very promising results on a case, but the same algorithm may show poor performance on another. These reasons allow researcher to investigate of new algorithms in UCAV path planning problem.

Grey wolf optimizer (GWO) was originally presented by Mirjalili et al. [6] in 2014. It simulates hunting behavior and social leadership of grey wolves in nature. Some of the advantages of GWO are simplicity, flexibility, derivation-free mechanism, and local optima avoidance. Also, it is easy to implement; and it requires few control parameters to regulate. First, GWO is fairly simple. It is inspired by hunting behavior and social leadership of grey wolves in nature. The inspirations are related to animals' behaviors that are pretty easy to understand. Furthermore, the simplicity assists some scientists engaging in different research fields to learn the algorithm quickly and apply it to their problems. Second, flexibility refers to GWO applying in different problems without any special changes in the structure of the algorithm. GWO is easily applicable to different problems because it supposes problems as black boxes. Third, GWO has derivation-free mechanisms. In comparison with gradient-based optimization methods, GWO optimizes problems stochastically. During the process of optimization, there is no need to calculate the derivative of search spaces. This will be effectively used for real problems with expensive or unknown derivative information. Finally, local optima avoidance compared to conventional optimization techniques is high due to the stochastic nature of GWO. This leads to GWO highly suitable for solving highly nonlinear, multivariable, multimodal function optimization problems.

Recent studies have shown that GWO is able to provide competitive results compared to other well-known meta-heuristics. The GWO has been successfully applied to three classical engineering design problems and real optical engineering [6]. Sulaiman et al. [28] have used GWO for reactive power dispatch problem. Song et al. [29] have successfully applied GWO for surface wave analysis. Komaki et al. [30] have used GWO for two-stage assembly flow shop scheduling problem. Medjahed et al. [31] have used GWO for hyperspectral band selection. Emary et al. [32, 33] have applied GWO for attribute reduction and feature selection. Mirjalili [34] has surveyed the effectiveness of GWO in training multi-layer perceptions (MLP). Saremi et al. [35] proposed the use of evolutionary population dynamics (EPD) in the GWO to further enhance its performance. Song et al. [36] have successfully applied GWO for solving combined economic emission dispatch problems. Mirjalili et al. [37] proposed multi-objective grey wolf optimizer that is an essential in solving real problems.

However, in the field of two-dimensional path planning for UCAV, no application of GWO exists yet. In this paper, we use GWO to solve UCAV path planning problem. GWO is verified on three test cases with different dimensions and compared with other population-based optimization methods, such as CS [38], FPA [39], NBA [40], BSA [41], ABC [42], and GGSA [43]. The rest of the paper is structured as follows.

Section 2 describes the mathematical model in UCAV path planning problem. Section 3 discusses the principles of GWO. The experimental results are conducted in Section 4. Finally, Section 5 concludes the study and advises some directions for future studies.

2. Mathematical model for UCAV path planning

As a key component of mission planning system [44], UCAV path planning is a new low altitude penetration technology to achieve the purpose of terrain following and terrain avoidance and flight with evading threat. The goal for path planning is to find an optimal or near-optimal flight path for UCAV to break through the enemy threat environments, and self-survive with the perfect completion of mission. In this paper, we use the mathematical model for UCAV path planning described as follows [17,23].

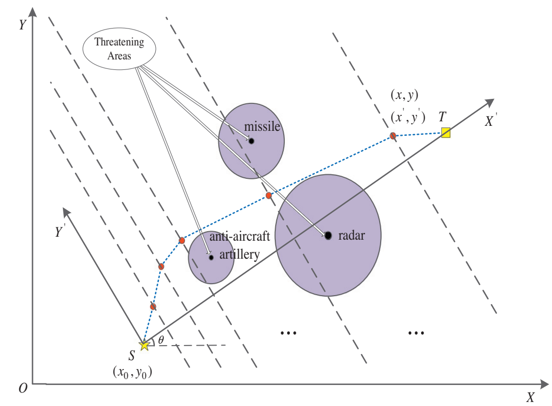

Fig. 1. UCAV battle field model. (For interpretation of the references to colour in the text, the reader is referred to the web version of this article.).

2.1. Threat resource model in UCAV path planning

In this model, S and T are defined as the starting point and the target point (see Fig. 1), respectively. There are some installations in the combat field, for instance, radars, missiles, and artilleries. The effects of such installations are presented by circles in the combat field of different radiuses and threat weights [18]. If part of its path falls in a circle, an UCAV will be vulnerable to the threat with a certain probability proportional to the distance away from the threat center. Moreover, when the fight path is outside a circle, it will not be attacked. The UCAV flight mission is to calculate an optimal path from S to T. Meanwhile all the given threat regions in the combat field and the fuel consumption should be considered.

To make this problem more specific, we draw a segment ST connecting the starting point S and the target point T. Then, ST is divided into D equal portions and vertical coordinate Y' is optimized on the vertical line for each node to get a group of points composed by vertical coordinate of D points. Obviously, it is easy to get the horizontal abscissas of these points. We can get a path from start point to end point through connecting these points (see the red circle in Fig. 1) together, so that the route planning problem is transformed into a D-dimensional function optimization problem.

In Fig. 1, the original coordinate system is transformed into new coordinate whose horizontal axis is the connection line from the starting point to the target point according to the transformation formula shown in Eq. (1), where the point (x, y) is coordinate in the original coordinate system O_{XY}, the point (x', y') is coordinate in the new rotating coordinate system $O_{X'Y'}$, θ is the rotation angle of the coordinate system.

$$\theta = \arcsin \frac{y_2 - y_1}{\left|\overrightarrow{AB}\right|}$$

$$\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x' \\ y' \end{bmatrix} + \begin{bmatrix} x_1 \\ y_2 \end{bmatrix} \tag{1}$$

2.2. Performance evaluation

Regarding the evaluation of one candidate flight path, the threat cost J_t and the fuel cost J_f are taken into consideration as follows [17]:

$$J = \lambda \cdot J_t + (1 - \lambda) \cdot J_f$$