

UNMANNED AERIAL VEHICLE PATH PLANNING BASED ON TLBO ALGORITHM

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Abstract- Path planning of unmanned aerial vehicle (UAV) is an optimal problem in the complex combat field environment. Teaching-Learning-Based Optimization (TLBO) algorithm is presented under the inspiration of the teaching-learning behavior in a classroom. In this paper, this algorithm is applied to design a path by the search angle and distance, by which a better path at higher convergence speed and shorter route can be found. Finally experimental comparison results show that TLBO algorithm is a feasible and effective method for UAV path planning.

Index terms: Unmanned Aerial Vehicle (UAV), Path planning, Teaching-Learning-Based Optimization (TLBO), Optimization problem.

I. INTRODUCTION

Path planning for unmanned aerial vehicle (UAV) is to find a space path which can reach terrain following, terrain avoidance and threat avoidance. It is a key component for mission planning system, and is aims to figure out a optimal or suboptimal flight route from the starting point to the target under specific constraint conditions. Research on UAV directly affect battle effectiveness of the air service, therefore is important to safeness and energy of a country. Along with planned path, UAV can penetrate threats of enemy, complete its missions successfully along with the minimal danger rate in enemy's air defense area and assure their safety [1]. An ideal path planning includes several requirements: optimality, completeness and computational complexity.

The path planning is a typical large scale optimization problem. In recent years, artificial intelligence algorithms are paid much attention, more and more algorithms has been proposed for solving this complicated optimization problem, such as Evolutionary Computation, Particle Swarm Optimization (PSO) [2,3], ACO-DE algorithm [4], Modified Ant Optimization Algorithm[5], and artificial fish swarm optimization method [6,7]. However, some of algorithms can be trapped into local optima easily, hence would end up probably. So a satisfied path can't be found.

Teaching-Learning-Based Optimization (TLBO) is a novel algorithm based on swarm intelligence. It was firstly proposed by Rao et al [8, 9], under the inspiration of teaching-learning phenomenon of a classroom to solve multi-dimensional, linear and nonlinear problem. The effectiveness of the TLBO algorithm has been compared with the other population intelligence optimization algorithms based on the best solution, average solution, convergence rate and computational complexity. The result of TLBO algorithm is better performance, algorithm-specific parameter-less, effective and efficient to solve optimization problems.

However, using TLBO algorithm find flight route of UAV is rarely. Due to this algorithm can find the shortest flight route through learn from teacher and interact with themselves, and in teacher phase and learner phase, it conducts global search and local search, and avoid local best solutions efficiently. So the presented paper is designed for finding the flight route based on the

advantages of TLBO algorithm. Experimental results showed an ideal flight route can be quickly found by using TLBO algorithm.

This paper is organized as follows. Threat resources modeling and objective function for UAV is given in Section 2. Subsequently, the principle and implementation procedure of TLBO to UAV path planning are presented in Section 3. In Section 4, comparison experiments are given. Conclusions are presented in final Section.

II. PROBLEM DESCRIPTION

a. Environment and path planning

In UAV optimal planning, modeling of the threat sources is the key component. We can depict the typical UAV combating field model in three-dimensional space with Fig.1 [10,11].

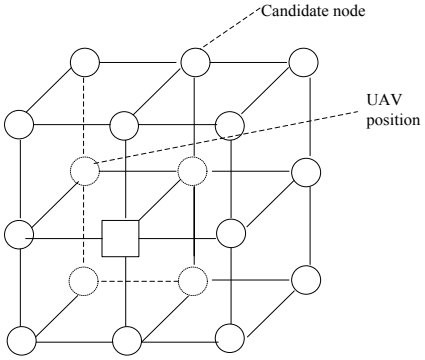


Fig.1. Typical UAV combating field model in three-dimensional space

The task region of UAV can be divided into two-dimensional mesh to simplify the UAV planning problem, obtain a two-dimensional network diagram connecting the starting point and target point, which is given in Fig.2.

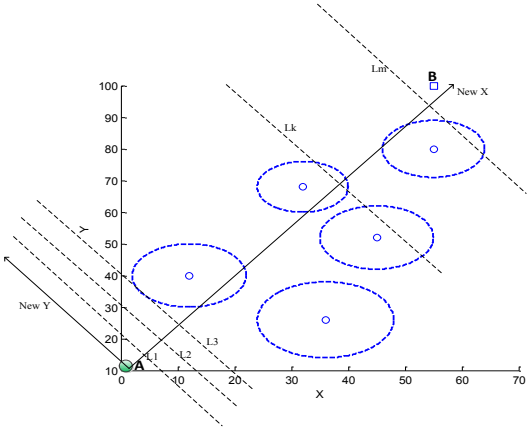


Fig.2. Typical UAV battle field model

From above picture, assume that the distance from node A to node B is the flight task for the UAV. There are some threatening areas in the mission region, which are presented by points, such as missiles, radar, and artillery. The cycle centered on these points represents the range of threats [12,13,14,15]. Let OA be the x axis, the vertical line to OA be y axis, then contrarotate original x axis to parallel segment AB. we can obtain new x axis and y axis, thus a new coordinate system is established. The new X axis is divided into ($m+$) equal portions. Then, the new Y axis is divided into ($n-$) sub-sections equally. There are m vertical lines between node A and node B, which can denote as $L_1, L_2, ..., L_k, ..., L_m$. The m vertical lines and the n horizontal lines cross-constitute $m*$ nodes. Named these node $L_1(x_1, y_1)$, $L_2(x_2, y_1)$,..., $L_m(x_m, y_1)$,..., $L_1(x_1, y_n)$, ..., $L_m(x_m, y_n)$, where $L_i(x_i, y_i)$ is the i-th node in the vertical line L_i. Then form a path from the starting point A to the target node B, which can be depicted as follows:

$$Path = \quad \cdots \quad \cdots \quad B \tag{1}$$

b. The objective function of route optimization

Now, analyze the performance index of the UAV path planning. The performance indicators of the UAV path mainly include safe performance (i.e. threat cost is minimum) and fuel performance (i.e. fuel consumption cost is minimum) when complete given task. In this paper, we are mainly considered threat cost and the fuel consumption cost. The calculating formulas of which are described as follows:

$$J_t = \int_0^L \tag{2}$$

$$J_f = \int_0^L \tag{3}$$

Where L is the total length of the generated path, ω is threat cost of each point on the route, and ω_j is fuel cost. ω , ω_j are changing along with‘ l’ .

In order to simplify the computation, each edge is divided 5 segment, the threat price is calculated by choosing five points along each edge, as shown in Fig.3.

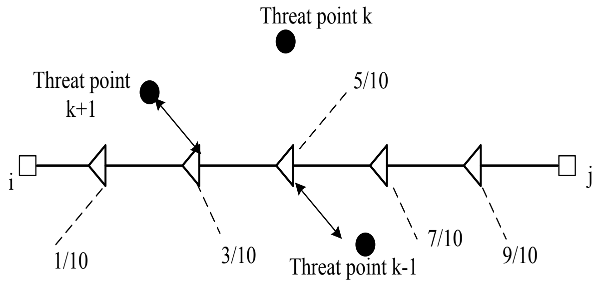


Fig.3. Calculation of threat cost

When UAV flight along with path L_{ij}, total threat cost caused by n threat sources is defined by following equation:

$$\omega_{t,ij} = \int_0^{L_{ij}} \sum_{k=} \quad dl \tag{4}$$

If threat node within radius of threat range, the threat cost is given by the following equation (5):

$$\omega_{t,ij} = \frac{L^5}{5} \sum_{k=} \quad d_{0.1,k} \quad d_{0.3,k} + \frac{1}{d_{0.5,k}} + \frac{1}{d_{0.7,k}} + \frac{1}{d_{0.9,k}} \tag{5}$$

where L_{ij} is the length of connecting node i and node j, $d_{0.1,k}$ is the distance from the 1/10 point on the i th edge to the k th threat, k is the number of the radars, the artilleries, the missiles and /or other threats, t_k is threat level of threat sources.

In addition, due to consume fuel cost relate to flight path, thus considered as $\omega_f =$ simply, consume fuel cost of each edge $\omega_{f,ij} =$.

Path planning evaluation model is established in order to minimize price of the UAV while completing the task. The total price comes from a sum of the threat and fuel costs by the equation (6):

$$\min J = \quad + \quad - \tag{6}$$

Where J is path price, and $k \in$ is weighing coefficient of safe performance and consume fuel performance. Which gives the designer certain flexibility to dispose relations between the threat degree and the fuel consumption. When k is more approaching 1, a shorter path is needed to be planned, and less attention is paid to the radars exposed threat. Otherwise, when k is more

approaching 0, it is required avoiding the threat as far as possible on the cost of sacrifice the path length. The optimized path is founded only when function J reaches its minimal value.

If task must attach importance to safe when flying, k should choose a larger value, if task must value the rapid of the airplane ,minor value endue to k . The best path is founded only when J reaches its minimal value. The TLBO algorithm is explained in detail in the next section.

III. TLBO ALGORITHM FOR UAV PROBLEMS

a. Principles of the TLBO algorithm

Nature inspired population based algorithms is a delve field which simulates different natural phenomena to solve different problems. In this paper, in order to solve path planning of unmanned aerial vehicle problems, a new evolutionary algorithm is used. This algorithm is called teaching-learning-based optimization (TLBO) algorithm which was first proposed by Rao et al.. This algorithm has been shown perform well on many optimization problems such as single-objective benchmark problems and real life application problems et al. [16,17,18,19]. Although, TLBO exists poorer performance for multimodal problem and large scale high-dimension problem [20,21]. TLBO is inspired from the philosophy of teaching and learning in a class. The TLBO method is based on the effect of the influence of a teacher on the output of learners in a class which is considered in terms of results or grades.

In a classroom, many learners are considered as the population, different subjects offered to learners are considered as different design variables for the TLBO. A teacher is considered as the most knowledge person, thus the best learner is considered as a teacher, learners acquire knowledge from a teacher (i.e., Teacher Phase), which imparts knowledge directly to his students, and then acquire from other learners (i.e., Learner Phase). That is to say, how much knowledge is transferred to a student does not only influenced on by his/her teacher but on interactions among students through learning. So learning results of learners is analogous to the ‘fitness’. But the quality of a teacher affects the results or grades of learners. It is obvious that a good teacher trains learners such that they can have better results in terms of their results or grades. The quality of the learners is judged from the mean value of the population.

In TLBO, there are two vital components. The first component consists of "Teacher Phase" and the second component consists of "Learner Phase". The "Teacher Phase" means learning from the teacher and the "Learner Phase" means learning through the interaction between learners.

Teacher Phase simulates the learning of the students (i.e., learners) by the teacher. During this phase, a teacher possess knowledge brings his/her learners up to his/her level in terms of knowledge. It is not possible a teacher can only move the mean of a class up to some extent depending on the capability of the class in practice. This follows a random process depending on many factors.

Let M be the mean and T be the teacher at any iteration. T will try to move mean M toward its own level, so now the new mean will be T designated as M_{new}. The solution is updated according to the difference between the existing and the new mean given by

$$Difference_Mean = \quad \times \qquad - \quad \times \tag{7}$$

Where T_F is a teaching factor that decides the value of mean to be changed, and r is a random vector which each element is a random number in the range [0, 1]. The value of T_F can be either 1 or 2, which is a heuristic step and decided randomly with equal probability as

$$T_F = \qquad + \tag{8}$$

This difference modifies the existing solution according to the following expression:

$$newX = \quad + \qquad ıce_Mean \tag{9}$$

Where $newX$ is the updated value of X, accept $newX$ if it gives a better function value. All the accepted function values are maintained at the end of the teacher phase, and these values become the input to the learner phase.

Learner Phase simulates the learning of the students (i.e., learners) through interaction among themselves. Learners enrich their knowledge by two different means: one through input from the teacher and other through interaction between themselves. A learner interacts randomly with other learners with the help of group discussions, presentations and formal communications, etc. A learner learns something new if the other learners have more knowledge than him or her. Learner modification is expressed as:

for each learner X_i of the class

Randomly select one learner X_k, such that $k \neq$

if f(X_i) <

$newX_i =$ + ×

else

$newX_i =$ + ×

endif

Accept new$X$ if it gives a better function value

endfor

b. The step of TLBO approach for UAV problems

Based on the above analysis, the TLBO algorithm for UAV path planning is described as follows:

Step 1: According to the environmental modeling above, initialize the detailed information about the UAV mission, as well as the threaten information including the coordinates of threat centers, threat radius and threat levels.

Step 2: Initialize the parameters of teaching-learning-based optimization algorithm. Such as numbers of learners, the number of dimensions.

Step 3: According to the parameters of the learners, calculate the threat cost of each path formed by relative parameters based on formulas (2)-(6). The smaller the threat cost is, the better performance the path maintains.

Step 4: In teacher phase, identify the best solution (teacher), modify solution based on best solution (9), to find new solutions, and update their value if the new threat cost is lower than the original value.

Step 5: Select any two different individuals, according to learner phase, obtain new solutions, and update the value if the new threat cost is lower than the original value.

Step 6: Store the lowest threat cost value.

Step 7: If termination criteria is satisfied, stop the algorithm, and output the optimal path, otherwise go to Step 3.

The flow chart for TLBO for UAV problems is given in Fig.4.

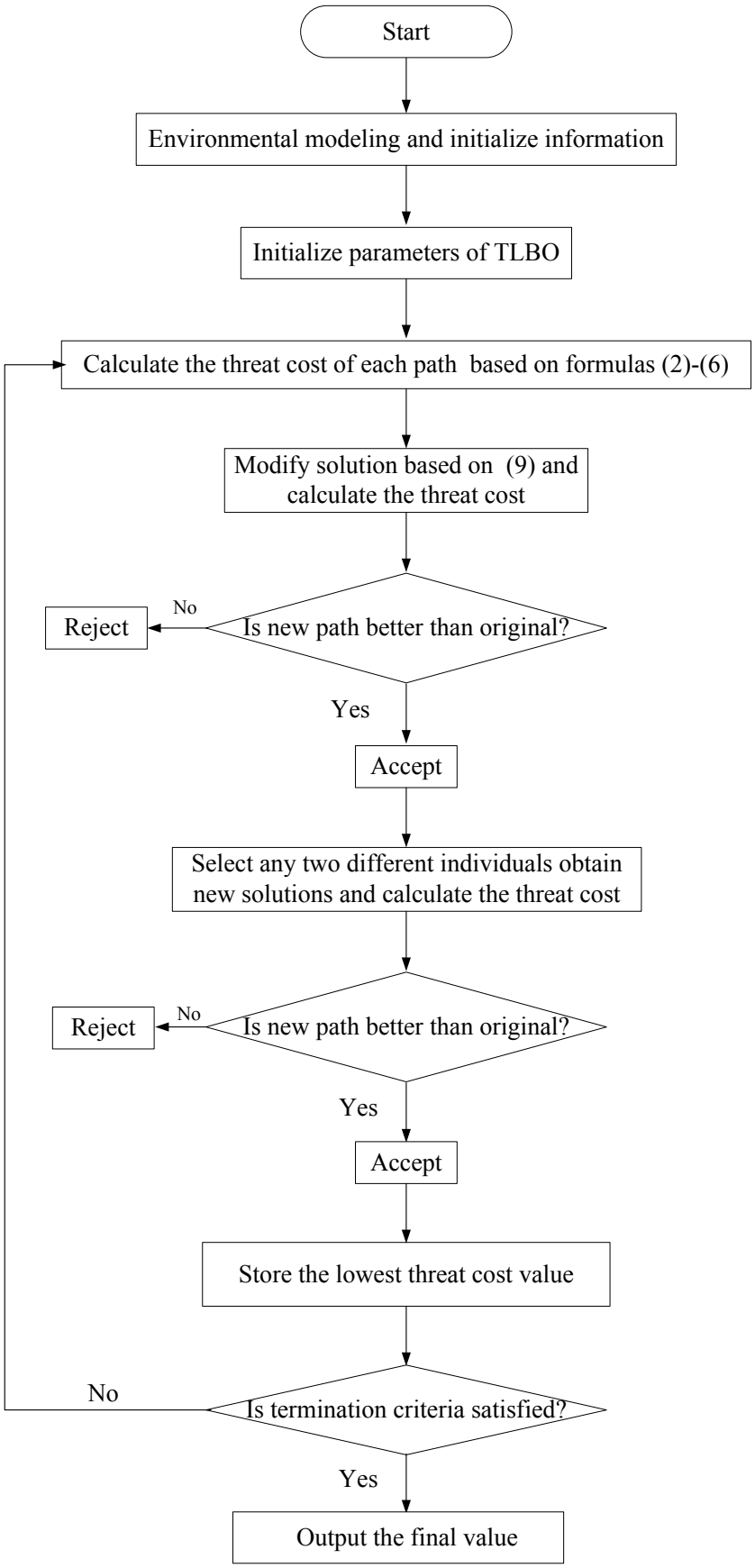

Start
Environmental modeling and initialize information
Initialize parameters of TLBO
Calculate the threat cost of each path based on formulas (2)-(6)
Modify solution based on (9) and calculate the threat cost
Is new path better than original?
No
Reject
Yes
Accept
Select any two different individuals obtain new solutions and calculate the threat cost
Is new path better than original?
No
Reject
Yes
Accept
Store the lowest threat cost value
Is termination criteria satisfied?
No
Yes
Output the final value

Fig.4. Flow chart showing the working of TLBO for UAV problems

IV. EXPERIMENTAL STUDIES

a. Experiment 1

In this experiment, TIBO algorithm is benchmarked by using the Peak Function [22] (see Fig.5) as:

$$Y = \qquad (10)$$

The optimization problem is defined as follows:

$$Minimize \;\; F(x) = \sum_{i=} \qquad - \qquad -$$

The optimization parameters are defined for this peak function as follows:

- Population size $(M) =$,
- Number of iteration $(maxcycle) =$,
- Number of dimension $(D) =$,
- Limits of design variables $(lu(1, j) \leq \quad \leq \qquad = - \quad \leq \quad \leq \quad .$

In this problem, 15 population individuals are divided into two stages to find the minima. The population positions in spread of the individuals after 3rd, 4th, 7th, 8th, 11th, and 12th iterations are respectively shown in Fig.6 (a)-(f). The population individuals are shown by • marks and the optimal position is shown by * mark.

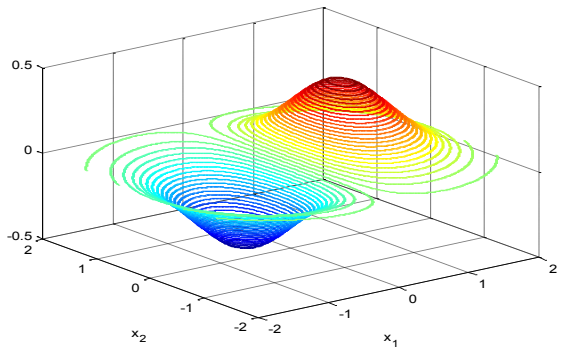


Fig.5. 3-D contours of the Peak Function

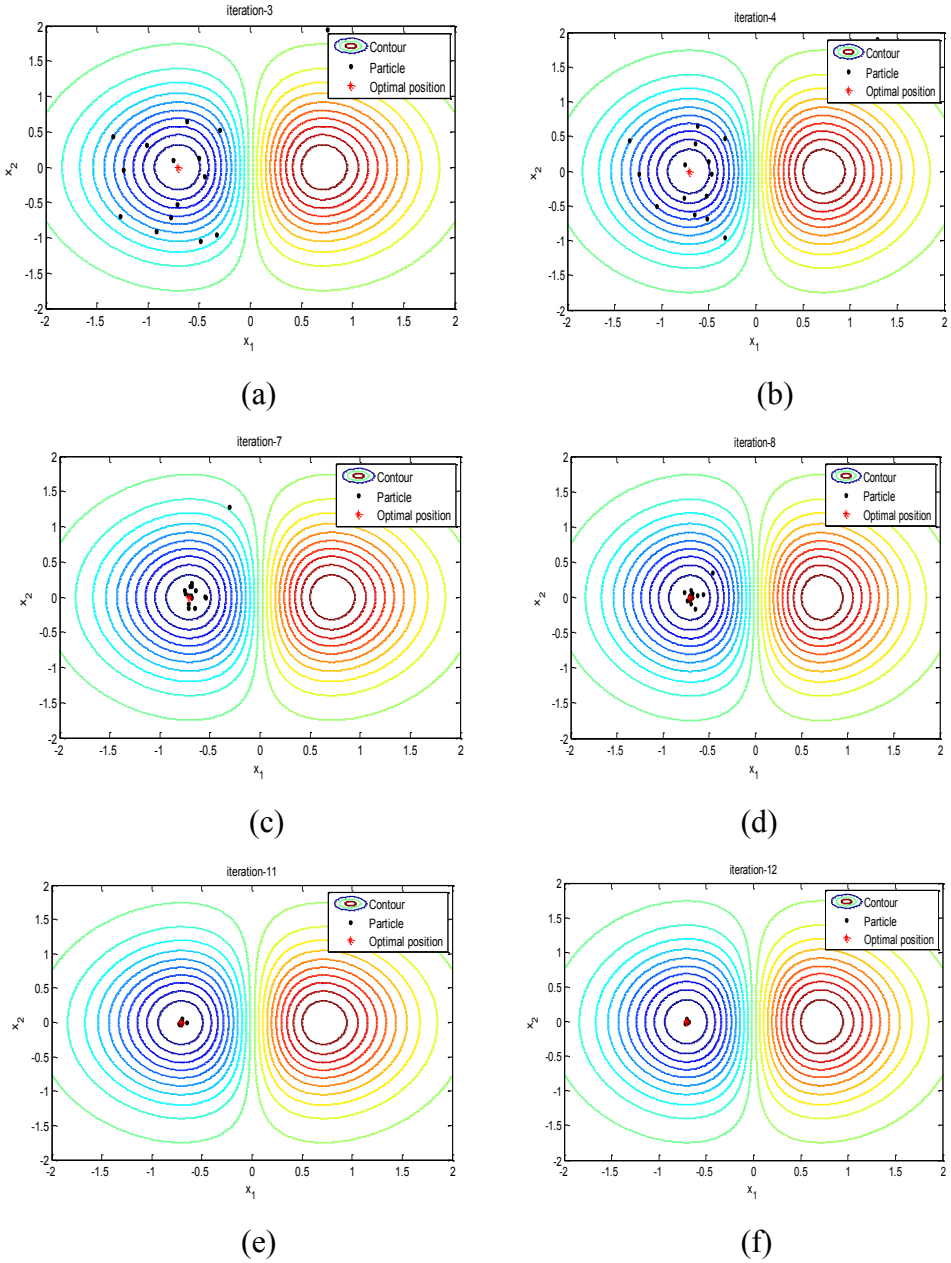


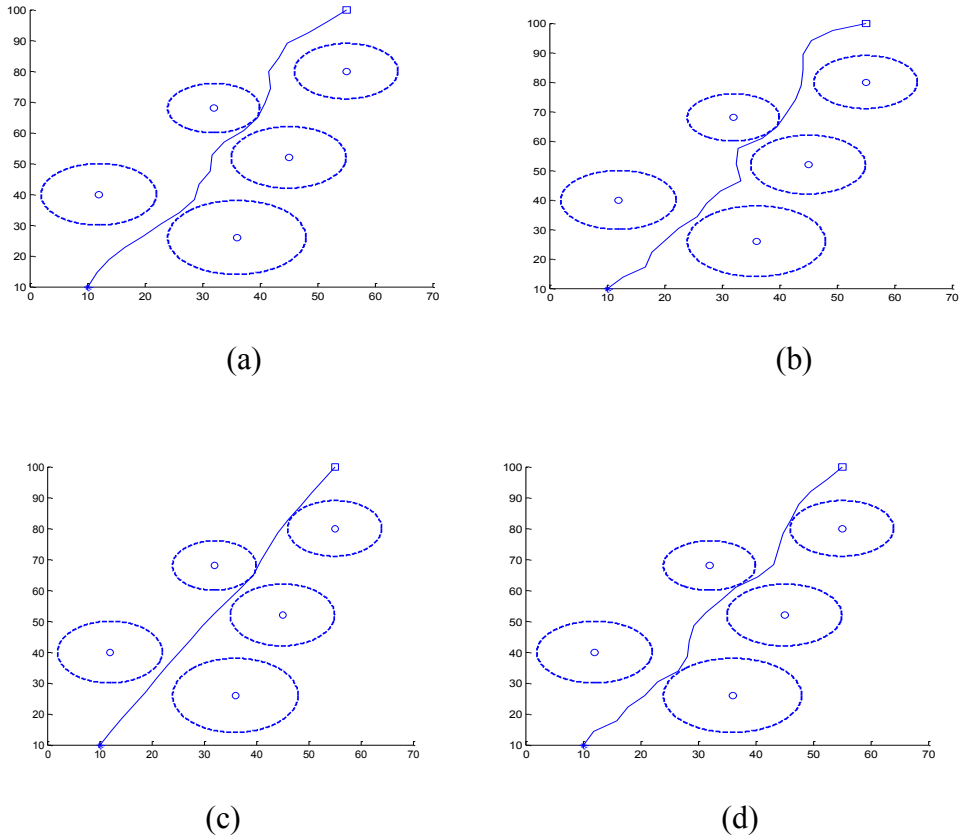
Fig.6. The positions of the population individuals and the optimal after (a) iteration-3, (b) iteration-4,(c) iteration-7, (d) iteration-8,(e) iteration-11, and (f) iteration-12.

As it is shown, the positions of the population individuals go toward the global minimum with increasing the iteration. As is shown in Fig.6 (a)-(f), it can be concluded that the algorithm make sure convergence.

b. Experiment 2

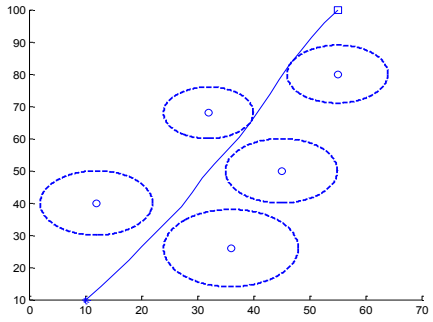
Suppose that UAV flight from start point (10, 10) to end point (55,100). In the flight course, there exist five threat areas, all of coordinates are (45, 50), (12, 40), (32, 68), (36, 26), (55, 80), respectively. Corresponding threat radius are 10,10,8,12,9. Threat level is 2, 10, 1, 2, 3, respectively. Y-axis is equable divided into 100 parts. X-axis is 70 parts. Supposed that the population size M was set 15, the dimension is 20, maximum iteration is 200, k was set 0.5.

All experiments are carried out on the same machine with Intel Core i5-3210 CPU 2.50GHz, 4GB memory, a hard drive of 750 GB and windows7 with MATLAB R2010a. In order to keep uniformity, the parameters about these algorithms have been dealt with, such as the population size of ABC was set 15, whilst the population size of PSO was set 30, DE was set 30, etc. Results compared with different algorithms are shown in Fig.7. Meanwhile, we give the evolution curves of different algorithms in Fig.8.



(a) (b)

(c) (d)



(e)

Fig.7. The path planning result using (a) ABC algorithm, (b) PSO algorithm,(c) DE algorithm,(d) GSO algorithm, and (e) TLBO algorithm.

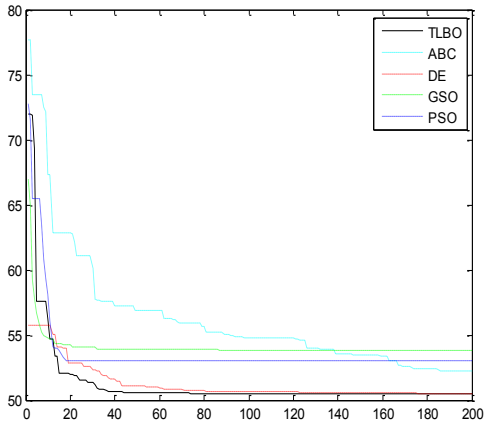


Fig.8.Convergence curve for different evaluation algorithm

To future prove the performance of TLBO algorithm. An algorithm is tested for 20 independent times, to obtain the average cost of the best path, the comparative experimental results are shown in the following table 1.

Table 1 Comparison of results for the average cost for ABC, PSO, DE, GSO and TLBO.

Algorithms	ABC	PSO	DE	GSO	TLBO
Average cost	52.5088	56.0034	50.5431	53.3559	50.7020

It is clear that the TLBO algorithms works very well because the TLBO was ranked the first in Table 1, in Fig.8 was ranked the second, among 5 algorithms. The other four algorithms converge rapidly, and curves stable without oscillation in the later stage of evolution except ABC

algorithm. PSO method is easy to trap in local optima and difficult to achieve the global optimal, GSO algorithm required much fewer iteration times than the other four algorithms, DE could find a better path easily, TLBO method could find feasible and optimal path for the UAV very quickly, the effectiveness is better than ABC, PSO, and GSO. It can effectively solve the path planning of UAV in complicated combating environments.

V. CONCLUSIONS

This paper discusses the problem that the Path of unmanned aerial vehicle is planned with the teaching-learning-based optimization algorithm. The results of the simulation show that the optimized solution is better obtained through the teaching- learning-based optimization algorithm. That is to say, the UAV can find the safe path while avoiding the threats area and costing the minimum fuel at higher convergence speed. The study of the teaching-learning-based optimization algorithm start just now, and there exists many questions waiting for solving. For example, the results obtained from TLBO method is inferior compared with DE algorithm, to solve multi-dimension complex problem exists poorer performance in global search, easily trapped in local search, it's performance is poorly for solving multimodal problem. Thus, our future work is how to modify TLBO algorithm, so as to find optimal path in the conditions less fuel consumption and higher safe index, and we should focus on application of TLBO method in UAV path planning in real world.

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