Path planning for multi-copter UAVs using tutorial training and self learning inspired teaching-learning-based optimization

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ABSTRACT

Route preparation for drones is a complex method to achieve an optimal path and meet constraints following specific tasks. This paper addresses the problem of a planning method for a multi-copter unmanned aerial vehicle (UAV) to examine ground surfaces. A multi-objective route planning algorithm, named the tutorial training and self learning inspired teaching learning-based optimization (TS-TLBO), is then introduced to create a feasible and flyable path while avoiding obstacles. Here, we firstly select a joint cost function that includes different constraints to improve operational safety, at the same time, to meet task requirements. The path-tracking scheme is then applied in the quadcopter to verify the proposed approach. Experiment results show the workability of our proposed path planning process.

Keywords: Path planning; Teaching learning-based optimization; Optacle avoidance; UAV; Drone; Multi-copter.

1. INTRODUCTION

Drones, a type of unmanned aerial vehicles (UAVs), are flying machines without any human pilot onboard. They have contributed in various fields, from military to civil applications [1]. Studies of drones today have been widening in the practical world together with the accelerated expansion of communication, computer and sensor technology. Among those studies, route planning plays an essential role in drones to move freely in complicated environments with a number of constraints in productive manners [2].

Route or path planning is the process of creating a path for drones to increase the success of the mission assigned. The resulting route should guarantee safety for guidance and efficiency of sensor usability. Studies on this topic, thus, have been blown up with a variety of algorithms published, such as A*, D*, Fast Marching Square, Probabilistic Roadmap Method, and machine learning-based algorithms. Those can provide flyable and robust paths with collision avoidance capability. However, the path is demanded to satisfy some requirements like smoothness and optimization while large training data requirements are not always available. Therefore, route planning is still an exciting problem, particularly in practical fields [3].

Among optimization research for the path planning problem, nature-inspired algorithms, i.e., Genetic Algorithm (GA), Ant Colony Optimization (ACO), and Particle Swarm Optimization (PSO), have been confirmed by the creation of great performances [4-6]. They, however, contain some drawbacks, i.e., heavy computation and premature convergence (GA) [5], low convergence speed (ACO) [6], and vulnerability to the optimization execution in case of coefficients' wrong selection (PSO) [4].

Teaching learning-based optimization (TLBO) is recommended thanks to its simple structure and implementation. The structure with fewer modified parameters will minimize parameter selection challenges, while easy implementation will be meaningful in real optimization situations. TLBO has been approved in practical applications that require path length minimizing at a shorter time convergence. TLBO was applied for UAV path planning, with distance minimization and collision avoidance, in [7, 8]. However, the UAV is also required to complete other mission conditions in flight, such as keeping a range to a surface or the ground in examination tasks. Furthermore, those research results have not been demonstrated in practical situations.

This paper introduces a flight route planning algorithm for multi-copter UAVs to carry out their assigned tasks in real and practical complicated environments. A multi-objective optimization algorithm using tutorial training and self-learning inspired TLBO (TS-TLBO) will be investigated to create a desired path. Therein, extra constraints are added to promote collision avoidance and mission completion capability. A 3D model of the entire monitoring space will be modeled by employing a satellite map. The benefits of this work are not only a simple implementation but also an optimized path generation. Simulation and experiment results were conducted and compared with other approaches for evaluation and confirmation of the proposed method.

The paper is organized as follows. Section 2 presents the development of the route planning algorithm using multi-objective TS-TLBO (MOTS-TLBO). Section 3 describes the implementation of trajectory planning for UAVs. Simulation and experimental results are introduced in Section 4. The paper ends with a conclusion and recommendation for future work.

2. MULTI-OBJECTIVE TS-TLBO PATH PLANNING ALGORITHM

Different constraints must be satisfied in the path generation problem for the drone's desired movement to increase its maneuverability and safety while maintaining mission efficiency. In this research, constraints are merged into a single function to produce a feasible and flyable path in a 3D operating space. The multi-objective optimization solution based on the teaching-learning algorithm is described as the following.

2.1. Teaching learning-based Optimization

Teaching learning-based optimization [9] has been constructed based on teaching and learning activities inside a typical classroom. The algorithm simulates two critical fashions of learning, i.e., through the teacher (teacher phase) and interrelations among the students (learner phase). In the "Teacher phase", the teacher is acknowledged as the most intelligent person, such that she or he can lead all students with her or his knowledge. The students inherit the teacher's knowledge to increase their grades. On the other hand, the student’s grades can also develop through interconnection studying activities in the "Learner phase". The process of TLBO is briefly presented below.

2.1.1. Teacher phase

During the first stage, all learners in the class are encouraged to reach their teacher's knowledge. At the same time, the learners also try to study from teachers to raise their own grades. Hence, a learner's success consists of two principal contributors, i.e., the teacher and his/her ability. The learner's performance, which is an average of his/her grade, can be represented by a random solution. Mathematically, this solution is expressed as:

$$P_{i,j}^{new} = P_{i,j}^{old} + r_{ij}\left(T_j - T_F M_j\right) \tag{1}$$

where T is the selected teacher from the best solution, and M is the mean of the class grade; $P_{i,j}^{old}$ and $P_{i,j}^{new}$, $(i = 1, 2, \ldots, N,\ j = 1, 2, \ldots, S)$ denotes the old and the new solution, respectively, N is the population size (the number of students), S is the number of subjects (the design variables); r_{ij} is a randomly selected number from 0 to 1, and T_F is an arbitrary number, either 1 or 2, with an equal probability.

As illustrated in (1), T encourages M to approach his/her level. The adjusted process depends on the difference between the previous and the current value of M. Here, the new solution value ($P_{i,j}^{new}$) is updated if and only if its new solution is better than its previous one ($P_{i,j}^{old}$).

2.1.2. Learner phase

In this second stage, the learners study from each other in different studying actions, e.g., presentations, pair or group studies, and discussions; thus, they improve their grades among themselves. Stochastically, two learners numbered m and $n, \forall m \neq n \neq i$ are chosen in the class, so the solution can be adjusted as follows:

$$\begin{cases} P_{i,j}^{new} = P_{i,j}^{old} + r_{ij}\left(P_{i,j}^{old} - P_{k,j}^{old}\right), \forall i \neq k & \text{if } f\left(P_i\right) < f\left(P_k\right) \\ P_{i,j}^{new} = P_{i,j}^{old} + r_{ij}\left(P_{k,j}^{old} - P_{i,j}^{old}\right), \forall i \neq k & \text{otherwise} \end{cases} \tag{2}$$

The adjustment process will follow similarly to the teacher stage law, in which P_i^{new} will be allowed to change if and only if its value is better than the one in the last iteration.

2.2. TS-TLBO Algorithm

The TS-TLBO [10] was a development of TLBO to increase its exploration and exploitation capability by using two search functions, i.e., tutorial training and self-learning. In TS-TLBO, the students have chances to improve their grades by accompanying teachers in other teaching-studying activities to improve knowledge or to solve related problems. The tutorial training, hence, is incorporated into the teacher phase of TLBO and is represented below,

$$\begin{cases} P_{i,j}^{new} = P_{i,j}^{old} + r_{ij}\left(T_j - T_F M_j\right) + r_{ij}\left(P_{i,j}^{old} - P_{k,j}^{old}\right) & \text{if } f\left(P_i\right) < f\left(P_k\right) \\ P_{i,j}^{new} = P_{i,j}^{old} + r_{ij}\left(T_j - T_F M_j\right) + r_{ij}\left(P_{k,j}^{old} - P_{k,j}^{old}\right) & \text{if } f\left(P_k\right) < f\left(P_k\right) \end{cases} \tag{3}$$

where $r_{ij}\left(P_{i,j}^{old} - P_{k,j}^{old}\right)$ and $r_{ij}\left(P_{k,j}^{old} - P_{k,j}^{old}\right)$ displays studying through tutorial training.

Students' grades also improved by their self-learning, which is incorporated into the learner phase of TLBO as,

$$\begin{cases} P_{i,j}^{new} = P_{i,j}^{old} + r_{ij}\left(P_{i,j}^{old} - P_{k,j}^{old}\right) + r_{ij}\left(T_j - E_F P_{i,j}^{old}\right), \forall i \neq k & \text{if } f\left(P_i\right) < f\left(P_k\right) \\ P_{i,j}^{new} = P_{i,j}^{old} + r_{ij}\left(P_{k,j}^{old} - P_{k,j}^{old}\right) + r_{ij}\left(T_j - E_F P_{i,j}^{old}\right), \forall i \neq k & \text{otherwise,} \end{cases} \tag{4}$$

where E_F is an arbitrary exploration factor, $E_F = round(1 + r_i)$.

2.3. Multi-objective Cost Function

Selecting an appropriate objective function for the path planning optimization problem is crucial to obtain the optimal result. The two major factors are path length and collision avoidance. The former helps to minimize the flying distance, and the latter provides a safe path for UAVs. Depending on a specific mission, more constraints can be added to improve safety and mission efficiency. In the case of UAVs, potential constraints may include altitude, heading, and flight path angle. In comparison with other flying machines, multi-copters are flexible enough to perform any sharp turns at any angle and at any time, so that the restrictions on path curves can be released. The overall cost function is now represented in the following form [11]:

$$J\left(T_i\right)=\sum_{n=1}^{3}\beta_n J_n\left(T_i\right) \tag{5}$$

where T_i, $i = 1$ to *number_of_Iteration*, is the resulting path at the i^{th} iteration; β_n is the weighting factor depicting the collision intensity; $J_n\left(T_i\right)$, $n = 1,2,3$ are the individual costs related to the path length, obstacle violation, and flying altitude, respectively.

In this work, T_i is a combination of *M* segments. Each segment *m* is performed in 3D space by its middle point coordinates $T_m=\left\{x_m, y_m, z_m\right\}$. Hence, we have the path length cost:

$$J_1\left(T_i\right)=\sum_{m=1}^{M}\left\|T_m-T_{m-1}\right\|, \tag{6}$$

where $\left\|T_m-T_{m-1}\right\|$ is the distance between a node T_m and its adjacent node T_{m-1}.

We denote *K* as the total obstacles in the operation space. Each obstacle is represented in a cylinder $O_k\left(C_k, r_k, h_k\right)$. C_k is the coordinate of the k^{th} obstacle located on the Earth's surface. r_k and h_k are the obstacle's radius and height, respectively. The collision distance d_k^c to the k^{th} cylinder is determined from C_k to its outer surface at the flying height z_l. We have $d_k^c=0$ if the drone is flying higher than the obstacle's height ($z_l > h_k$). The drone's safe region can be represented by a sphere with a radius r_Q from its center of gravity. At a flight height z_l, the range to obstacle *k* is then compared with the safe distance to define the violation function:

$$V_m\left(k\right)=\sum_{k=1}^{K}\max\left(1-\frac{d_{m,k}}{r_{m,k}^s}, 0\right), \tag{7}$$

where $d_{m,k}$ and $r_{m,k}^s$ are the current and safe distances from the m^{th} segment to the k^{th} obstacle, $r_{m,k}^s=d_k^c+r_Q$. This function guarantees that $d_{m,k}$ is always greater than $r_{m,k}^s$.

Finally, we derive the violation cost of a whole generated path to all obstacles:

$$J_2\left(T_i\right)=\frac{1}{M.K}\sum_{m=1}^{M}\sum_{k=1}^{K}V_m\left(k\right) \tag{8}$$

The flying altitude constraint plays an essential role in protecting the UAV from crashing on the ground and keeping the UAV operating in a specific range of height, predefined by minimum and maximum restrictions, *i.e.*, $z_{\min}$ and $z_{\max}$, respectively. The following expression can present the sub-cost function for this constraint:

$$J_3\left(T_i\right)=\sum_{m=1}^{M} dz_{i,m}$$
$$dz_{i,m}=\begin{cases} z_{i,m}-z_{\max}, & if\ z_{i,m}>z_{\max} \\ 0, & if\ z_{\max}\geq z_{i,m}\geq z_{\min} \\ z_{\min}-z_{i,m}, & if\ z_{\min}>z_{i,m}>0 \\ \infty, & if\ 0\geq z_{i,m} \end{cases} \tag{9}$$

A negative value of $dz_{i,m}$ leads the drone to crash the terrain; thus, $dz_{i,m}$ must always be greater than 0, as shown in the last inequality of (7), to guarantee safe operations.

3. PATH PLANNING IMPLEMENTATION

We begin the implementation process with an agreement that digital maps, or satellite maps in particular, are available and up-to-date for data acquisition. To implement our algorithm, we first select the working space according to the drone's mission. We will have the entire map of the working space after completing the identification process.

Next, based on the collected information, we can generate an optimal path for the multi-copter by incorporating the cost function into the path planning process. This algorithm can be described as the following steps:

(1) Measure all parameters related to the multi-copter safe operation;

(2) Prepare the working space and parameters of obstacles. The working space should be limited within an area defined in 3D, i.e., bound of horizontal and height, based on the drone's task and flying ability. Then, we identify all obstacles inside this space;

(3) Pick proper parameters for TS-TLBO, such as *number_of_population*, *number_of_iteration*, mean of the class grade (*M*) and *Violation_cost*;

(4) Initialize a random path by connecting the departure and the destination;

(5) Start the path planning process by running TS-TLBO repeatedly. We first compute the mean of the class grade. Then, we run the teacher’s, followed by the learner's phases using (3) and (4);

(6) At each step, evaluation of the objective function values (5) is performed;

(7) Update the best solution and *Violation_cost* using equations (5-9);

(8) The optimized path T_n^* for the multi-copter is finally archived when we complete all iterations with the number set in step (2). T_n^* can now be used by the drone's onboard controller for trajectory tracking in the real and practical mission execution process.

4. EXPERIMENT RESULTS

This section presents experiments that have been executed to demonstrate the performance of the proposed planning algorithm.

4.1. Experimental setup

In this experimental scenario, the multi-copter is assigned a mission of surface monitoring. We employ Mission Planner with the Google Satellite Map (GST) for data acquisition of the working space, as shown in figure 1. The GST is selected because it provides many benefits for monitoring purposes, such as imagery, aerial photography, maps and view, almost in real-time or regularly updated. The monitoring space is limited in a rectangular prism limited by the coordinates "12.233106, 109.114506, 0m" and "12.233563, 109.115220, 20m". The departure and destination positions are "12.233194, 109.114557" and "12.233411, 109.115187", respectively. In this region, we detected a vast number of obstacles with different radii.

We use in this work the 3DR Solo quadcopter with retrofitted devices shown in figure 2. A Hero 4 camera is attached to a 3D gimbal for data acquisition. The Solo is capable of exchanging signals to and from the ground station thanks to the built-in MAVLink (Micro Air Vehicle Link) telemetry protocol and an added Internet-of-Things (IoT) board with a Wi-Fi router. The MAVLink is used to connect the onboard and downstream devices. The Wi-Fi network helps to upload monitoring data directly to the internet.

In the path planning algorithm, the population and iteration number are respectively selected as 100 and 150. The relative elevation range of the quadcopter is limited [3, 7] m.

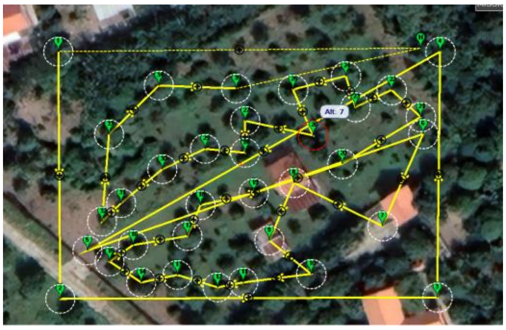

Figure 1. *Working space acquisition.*

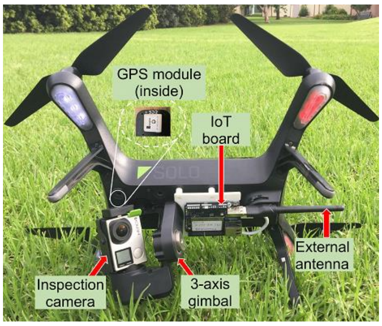

Figure 2. *3DR Solo quadcopter retrofitted.*

The path planning program is run in the DELL LATITUDE E6510 I7-720QM laptop with the following parameters: CPU: Intel® Core™ i7-720QM Processor 1.6GHz (4M Cache, Turbo Boost 3.2 GHz), RAM: 4GB DDR3 1333Mhz, and hard disk HDD 250GB.

4.2. Results

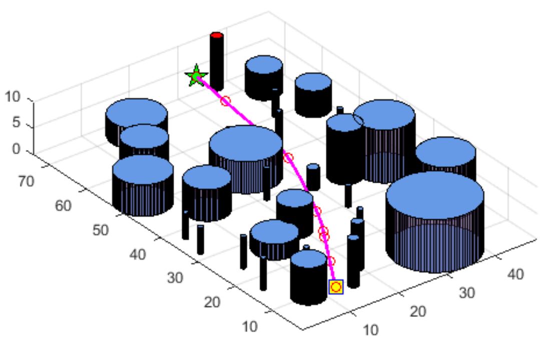

Figure 3. *3D-path generation using TS-TLBO.*

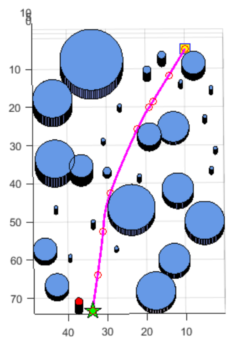

Figure 4. *Generated path on Earth's surface.*

The implementation of the path planning algorithm has been conducted for the abovementioned monitoring scenario. Figures 3 and 4 show our algorithm's capability to find the shortest path with collision avoidance within the altitude limitation simultaneously. The result shown in this paper is an average of the corresponding parameters after 30 algorithm executions.

To perform the convergence of TS-TLBO, we made a comparison with the well-known GA, ACO, TLBO, and the enhanced teaching-learning-based optimization (MSTLBO) [12] planning algorithms, as illustrated in figure 5. The best cost values and convergence iterations of TS-TLBO are 73.74 and 70, compared to those in GA (75.39, 116), ACO (75.24, 82), TLBO (74.30, 62), and MSTLBO (73.93, 75). Thus, TS-TLBO is better in terms of cost-effectiveness, with smaller running iterations.

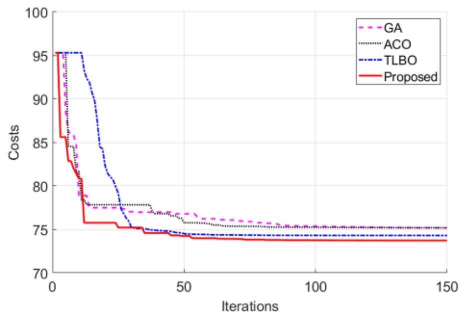

Figure 5. *Convergence comparison.*

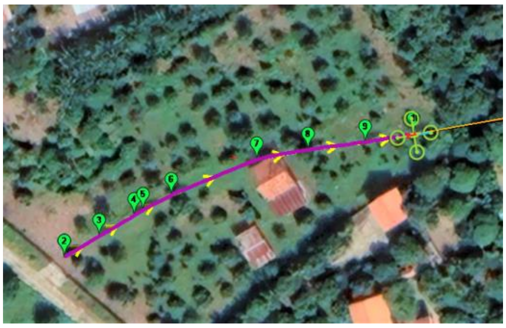

Figure 6. *Field-test experiments.*

The 3D-generated path (T_n^*) has been uploaded to the 3DR Solo's onboard controller for trajectory tracking. The experimental result in figure 6 illustrates that the copter can perform obstacle avoidance during the monitoring task. The overlap of the actual execution path (purple) on the generated path (yellow) also indicates the feasibility and reasonable smoothness of both planned and flown routes.

5. CONCLUSIONS

This paper has introduced a new approach for a multi-copter UAV's route planning algorithm in surface monitoring applications. The tutorial training and self learning inspired teaching-learning-based optimization is used to provide command routes for the drone. To improve operational safety and mission efficiency, the TS-TLBO then incorporated different constraints to make it a multi-objective optimization algorithm for the path planning process. The study also offered satellite maps and IoT-based communication for the enhancement of autonomy level and online data analysis. Implementation and field tests verified the route planning algorithm with an excellent performance in dealing with distinctive constraints.

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TÓM TẮT

Thiết lập đường bay cho trực thăng nhiều cánh không người lái ứng dụng giải thuật TS-TLBO

Thiết lập đường bay cho máy bay không người lái (UAV) là một quy trình phức tạp để tạo ra quỹ đạo tối ưu và đồng thời đáp ứng các ràng buộc quy định cho nhiệm vụ cụ thể. Bài báo này đề xuất thuật toán lập quỹ đạo bay tối ưu đa nhiệm bằng phương pháp sử dụng giải thuật Tutorial Training and Self Learning Inspired Teaching-Learning-based Optimization (TS-TLBO) để tạo ra đường bay khả thi và an toàn. Thuật toán này được áp dụng cho loại UAV trực thăng nhiều cánh trong ứng dụng khảo bề mặt hạ tầng. Ở đây, trước tiên chúng tôi giới thiệu một hàm chi phí chung bao gồm nhiều hàm ràng buộc khác nhau để nâng cao độ an toàn và đồng thời đáp ứng yêu cầu nhiệm vụ. Sau đó, đường bay tối ưu tạo ra được áp dụng trên một dạng quadcopter để xác minh giải thuật. Kết quả thử nghiệm cho thấy tính khả thi của thuật toán lập thiết đường bay đề xuất.

Từ khóa: Thiết lập quỹ đạo; Tối ưu dạy-học; Chướng ngại; Máy bay không người lái; Trực thăng bốn cánh.