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Comparing Multi-Objective Approaches for Air Route Planning in Hostile Environments

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Abstract. Route planning for aircraft that should fly in hostile environments can be regarded as a multi-objective optimization problem, where the route should enable the aircraft to accomplish its mission tasks with a minimum risk exposure and minimum fuel consumption. This work compares different approaches for multi-objective route planning that have been suggested in the literature regarding their formulation of objectives as well as how they handle the decision maker's preferences. It is concluded that most route planners minimize threat exposure and route length, but can also include altitude and flight dynamics constraints. Preferences regarding the objectives can be included in the route planning algorithms with weights or priorities. An alternative approach is that the route planner suggests a number of routes and thereafter lets the decision maker select the best one.

Keywords: Multi-objective optimization, route planning, path planning, aircraft, uav.

1 Introduction

Flying an air mission within hostile environment is a complex task, since several factors need to be considered such as performing the mission tasks and avoiding the enemy's defense systems. Schulte [16] has described three classes of goals for air missions: *flight safety*, *mission accomplishment* and *combat survival*. Flight safety includes all aspects of flying the aircraft, such as navigation, avoiding ground collision and monitoring the fuel level. Combat survival implies that the aircraft should avoid getting hit by enemy fire. Mission accomplishment means that the aircraft should perform the mission tasks, e.g., patrolling an area, locating a target or gathering information about a region of interest. When flying within hostile territory, it is often necessary to accept some risk in order to accomplish the mission tasks. On the other hand, an aircraft must be unharmed when performing the tasks and unnecessary risks should therefore be avoided. The goals in Schulte's model are therefore both interrelated and often conflicting. It is therefore motivated to develop decision support systems that aid the pilots to plan where to fly. A large number of route planning algorithms have been suggested in the literature for supporting the planning process for missions executed by manned aircraft or unmanned aerial vehicles (UAVs). The use of computer generated forces (CGFs) within training simulators has also contributed to the need of route planning algorithms.

The route planning problem is often formulated as an optimization problem, where the aim is to find the route with the lowest cost. It can generally be formulated as:

$$\min_{\mathbf{x}\in X} \mathbf{C}(\mathbf{x}) = ((C_1(\mathbf{x}), C_2(\mathbf{x}), \ldots, C_k(\mathbf{x}))\,. \tag{1}$$

The vector $\mathbf{x} = (x_1, x_2, \ldots x_N)$, sometimes referred to as the decision variable, denotes the route that the aircraft should fly. There are many different ways to represent a route, such as a sequence of control signals for the aircraft, see e.g., [12], a number of waypoints that the aircraft should pass, see e.g. [6], cubic spline trajectories, see e.g., [3] or a selection of edges within a network, see e.g., [23]. In general, the dimension of $\mathbf{x}$ is high, since many control signals or waypoints are needed in order to describe the route or a trajectory in 3D-space. This implies that the set X, which represent all possible routes, in general is large, which makes it infeasible to evaluate and compare all possible routes.

$C_k(\mathbf{x})$ describes a cost function for objective k, which depends on the route $\mathbf{x}$. For example, the objective of flying a short route can be associated with a cost function that is proportional to the route length. There might also be a number of conditions that the route must fulfill in order to be feasible. These conditions are generally formulated as constraints, for instance that all points of the route should be located above the terrain level. Ideally, a route that fulfills all constraints and minimizes all cost functions is the best route. However, usually no such a route exists, since the objectives are conflicting. The decision maker, i.e., the pilot or the UAV operator, therefore wants a route that corresponds to his/her preferences regarding the importance of the different objectives.

1.1 Aim of the Work and Related Literature

The literature regarding multi-objective air route planning in hostile environments have modeled the objectives in several different ways and used different approaches for preference handling. The aim of this work is to compare these approaches and analyze their advantages and disadvantages. A review of multi-objective approaches for general engineering applications have previously been presented by Marler & Arora [10]. Jozefowiez et al. [8] presented a literature review regarding multi-objective vehicle routing problems, where tours within a network should be generated to allow a fleet of vehicles to visit a number of costumers. Even though there are similarities between vehicle routing problems and route planning, there are also important differences such as that the aircraft is not limited to fly in a road network. Furthermore, the risks associated with flying in hostile environments are usually not applicable in vehicle routing problems. It is therefore motivated to analyze the multi-objective approaches with respect to the characteristics of air route planning. Section 2 classifies and describes the cost functions for the different objectives and constraints that have been used in the air route planning literature. Section 3 reviews different approaches for combining the cost function and how they take the decision maker's preferences into account. The results from the literature review is discussed in Section 4 and the conclusions and suggestions for future work are presented in Section 5.

It should be noted that this work does not review the optimization algorithms that are used for finding solutions to equation (1) are not included in this review. Instead, classical and heuristic approaches for single-objective route planning have been reviewed for instance in [11, 14]. Furthermore, Besada-Portas et al. [2] compared the statistical performance of several evolutionary algorithms for multi-objective UAV route planners, such as genetic algorithms, particle swarm optimization and differential evolution.

2 Objectives and Constraints

The cost functions $C_k(\mathbf{x})$ in equation (1) represent the objectives that the route planner should regard. There are often several different ways to model a cost function for a particular objective or constraint. This section reviews the the cost functions for the objectives and constraints have been described in the multi-objective route planning literature.

2.1 Threat Avoidance and Risk Minimization

Route planning within hostile environments usually include at least one objective associated with threat exposure or risk of getting detected or hit by the enemy. One approach is to model the enemies locations as danger zones or threat areas. The cost function then penalizes routes that enter these kinds of zones. Roberge et al. [15] used a cost function that calculated the intersection of the route and the danger zones. Foo et al. [7] described a threat cost proportional to the distance between the route and the center of the threat area. Li et al. [9] used a similar cost function, but also included a threat level for each area, which was assessed using fuzzy logic techniques.

The fact that the enemy's air defense systems often use radar in order to detect and track aircraft has inspired many references. Tulum et al. [18] calculated the time during which the aircraft would be visible for enemy radar stations depending on the terrain and the aircraft's radar cross section. Zhang et al. [20] used a threat cost function inspired by the radar equation:

$$C_{threat} = \sum_i \sum_j \frac{1}{d_{ij}^4}, \tag{2}$$

where d_{ij} is the shortest distance between the path segment j and threat radar i. Similar cost functions that include d^{-4} have been used by e.g., [23, 19, 12, 22, 21, 1].

Another approach is to minimize the risk associated with flying the route, as was done by Pfeiffer et al. [13]. Dogan [5] used a threat map where each position on the map described the risk exposure for the aircraft with respect to the threats in the environment. Besada-Portas et al. [3] included two objectives regarding threats; minimimum probability of getting killed and minimum probability of detection. These probabilities were calculated based on a model of the enemy's air defense units. Erlandsson [6] argued that the risk of getting hit depends on the risk that the aircraft is already detected and proposed a survivability model that took these dependencies into account.

2.2 Route Length and Fuel Consumption

The objectives of either short route length or short time in air are used in many references, see e.g., [22, 9, 21, 1, 13]. Roberge et al. [15] defined a cost function with:

$$C_{length} = 1 - \left(\frac{L_{P1P2}}{L_{traj}} \right), \tag{3}$$

where L_{traj} is the length or the route (trajectory) and L_{P1P2} is the length of straight path between the start point and the end point. The cost increases with route length and is also bounded within the interval $[0, 1]$. This is advantageous when several cost functions should be aggregated into a single cost function for instance as a weighted cost, see further 3.1.

There are several reasons for minimizing the route length and the time in air. A shorter route decreases the risk that the aircraft will get hit by unknown threats. It also shortens the time until the aircraft will be available for new missions. Furthermore, the route length is related to the fuel consumption and several references argue that the route length represents the fuel cost [20, 19, 1]. However, the are many factors that influences the amount of fuel that the aircraft consumes and more realistic models might be needed. Tulum et al. [18] calculated the fuel consumption based on the vehicle's engine characteristics and took mass, altitude, climb rate and velocity into account.

The route length can also be expressed as a constraints, where the route should be shorter than the maximum allowed route length, L_{max}. Roberge et al. [15] and Zheng et al. [21] include route length as both an objective and a constraint. Hence, the route length must not exceed L_{max} in order to be feasible, but the route should also be as short as possible. Besada-Portas et al. [3] minimized the route length and also defined a constraint of fuel consumption based on fuel model including altitude, bank angle and flight profile.

2.3 Terrain, Map and Flight Dynamics

A number of objectives and constraints have been formulated regarding the terrain and the aircraft's flight dynamics. Roberge et al. [15] included the objective to minimize the altitude by

$$C_{altitude} = \frac{A_{traj} - Z_{min}}{Z_{max} - Z_{min}}, \tag{4}$$

where A_{traj} is the average altitude for the route. Z_{min} and Z_{max} represent the altitudes at the highest and lowest points in the terrain. Besada-Portas et al. [3]

included the objective to minimize the flight altitude in a similar way, with the motivation that flying at a low altitude will make it more difficult for enemy's radar systems to detect the aircraft. Similar objectives regarding minimizing the altitude have been formulated in [12, 21]. This objective was in all references combined with a constraint regarding minimum allowed flight height in order to avoid ground collisions. Besada-Portas et al. [3] also included several constraints associated with the map, such as flying inside the map limits and avoiding flight prohibited zones.

Zhang et al. [20] included the objective to minimize the sum of turn angles. Furthermore, a number of flight dynamics constraints have been combined in order to plan routes that the aircraft will be able to fly. These constraints include maximum turning angle, maximum climbing/divining angle, minimum segment length and maximum power consumption [21, 15, 12, 3].

2.4 Other Kinds of Objectives

The route planning literature also shows examples of other kinds of objectives and constraints that do not fit within the classes described above. Bao et al. [1] studied route planning for reconnaissance missions and included the objective to maximize the mission effectiveness, which they modeled as the length of the path during which the UAV could observe a target. Erlandsson [6] argued that the aircraft should be unharmed in order to perform the mission task and modeled the probability of mission success including the probability of reaching the target area unharmed.

Zheng et al. [21] developed a route planner for a group of UAV. They included a constraint that the routes should enable the UAVs to simultaneously arriving at the goal locations. Furthermore, they also prevented collisions between the UAVs by including a constraint that the routes should not coincide. The same constraint was also used by Besada-Portas et al. [3].

Peng et al. [12] designed a route planning algorithm for on-line re-planning of routes. They included an error cost function that described the deviation of the new route from the reference route. The rationale was that the re-planned route should not differ more than necessary from the original route.

2.5 Implicitly Expressed Objectives

The aircraft flies the route in order to perform a mission task. At first, it might seem surprising that only a few of the references included objectives or constraints regarding mission accomplishment, see Section 2.4. However, the destination of the route is often a target point and the mission task is simply to reach this position unharmed. In this sense, the mission accomplishment objective is implicitly included in the route planner as a constraint that the route must end in the target point.

Constraints regarding flight dynamics can be also be included in the route planning algorithm in an implicit way. For instance, Tulum et al. [18] suggested a route planner based on A*. The aircraft's minimum turn angle and turn radius were taken into account in the search process, such that inappropriate routes were not considered. A similar approach was used in the ant colony optimization route planner by Zhang et al. [20]. The simulated ants were not allowed to select paths that violated the maximum turning constraint.

Zhou et al. [23] and Zhenhua et al. [22] formulated the route planning problem as finding a path through a Voronoi diagram based on the threats' positions. When the route follows the edges in the Voronoi diagram, the aircraft flies as far away from the threats as possible. The use of Voronoi diagram therefore implicitly expresses the objective of minimizing threat exposure. However, both of these references also included minimizing threat exposure as an explicitly expressed objective.

3 Preference Handling

There are two different ways to handle the decision maker's preferences in multi-objective optimization; a priori approaches and a posterior approaches [10, 8]. A priori approaches require that the decision maker expresses preferences regarding the objectives before potential solutions are identified. A posteriori approaches, on the other hand, generate a number of solutions. The decision maker thereafter selects the solution that best corresponds to his/her preferences.

3.1 A Priori Approaches

In a priori approaches, the decision maker has to express preferences regarding the importance of the objectives, for instance by giving them different weights. This information is used for transforming the problem into a single-objective optimization problem by formulating a new cost function that aggregates the cost functions regarding the individual objectives.

The most common method to handle multi-objective optimization problems according to Marler & Arora [10], is to aggregate the objectives as a weighted sum of the cost function, i.e.:

$$C_{tot} = \sum_k w_k \cdot C_k. \tag{5}$$

The weight parameter w_k represents the preference regarding objective k. It is common to normalize the objective costs, for instance in the interval $[0, 1]$, in order to ease the selection of the weight parameters.

This approach has been used for route planning with the objectives of minimizing threat exposure and fuel consumption, see e.g., [19, 18, 9]. They used the cost function:

$$C_{tot} = w \cdot C_{threat} + (1 - w) \cdot C_{fuel}, \tag{6}$$

where the weight $w \leq 1$. In this case, the decision maker only need to specify a single parameter, w. The weighted sum has also been used for including additional objectives such as minimize the sum of turn angles [20] or minimize flight altitude and deviation between new route and original route [12].

The weighted sum approach has also been used to incorporate constraints into the route planning. Roberge et al. [15] used a cost function with seven factors:

$$C_{cost} = C_{length} + C_{altitude} + C_{threat} + C_{power} + C_{collision} + C_{fuel} + C_{smooth}. \quad (7)$$

The three first terms represent objectives and each cost function is defined in the interval $[0, 1]$. The four last terms are defined such that the cost equals 0, if the constraint is fulfilled and in the interval $[3, 4]$ otherwise. This implies that the costs for feasible routes are smaller than the costs for infeasible routes. A similar approach was used by Sun et al. [17], who also defined the cost function as a sum with the property that infeasible routes had higher costs than feasible routes. Zheng et al. [21] and Peng et al. [12] used two different weighted sums of cost functions, one for feasible routes and another cost function for infeasible routes that described how much the route violated the constraints. Their approaches also ensured that feasible routes were preferred over infeasible routes.

Bao et al. [1] developed a route planner for reconnaissance missions that should maximize the mission effectiveness as well as minimize the route length and the threat exposure. The route planner maximized the function F, defined as:

$$F = \frac{V_{eff}}{w \cdot C_{threat} + (1 - w) \cdot C_{length}}, \quad (8)$$

where V_{eff} described the mission effectiveness, C_{threat} described the threat cost and C_{length} described the length cost. The variable w expressed the relative importance between threat and route length.

Erlandsson [6] assigned costs representing the decision maker's preferences regarding states and transitions in a stochastic model, where the states represented the fulfillment of the mission task and the aircraft's relation to the threats. The route planner aimed at find the route that minimized the expected value of the cost.

3.2 A posteriori approaches

A posteriori approaches generate a number of solutions. The idea is that the decision maker should select the preferable route from this set solutions. These methods are also referred to as generate-first-choose-later approaches [10].

Foo et al. [7] used a weighted sum cost function with:

$$C_{tot} = w_1 \cdot C_{threat} + w_2 \cdot C_{length}. \quad (9)$$

Their route planner generated solutions for three different sets of values for the weights w_1 and w_2. The pilot then had three different routes to choose between.

Pfeiffer et al. [13] formulated a bi-criteria optimization problem for minimizing flying time and risk exposure. They minimized the flying time with the constraint of keeping the risk below a threshold ϵ_1 and minimized the risk while keeping the flying time below a threshold ϵ_2. By solving these two problems for different values of ϵ_1 and ϵ_2, a set of routes were generated.

There are also methods that aim at approximating the entire set of Pareto optimal solutions. Loosely speaking, a solution is said to be Pareto optimal if there does not exist any other solution that is at least as good regarding all objectives and better regarding at least one objective. Zhenhua et al. [22] used a multi-objective ant colony systems algorithm for calculating the Pareto optimal solutions regarding the objectives of minimizing route length and threat exposure. Besada-Portas et al. [3] combined in total four objectives and seven constraints and also assigned priorities to each objective and constraint. The constraints all got the highest priority, since they must be fulfilled for the route to be feasible. The objectives were divided into two groups, where the objectives regarding route length and kill probability were associated with the second highest priority and flight altitude and detection probability got the lowest priority level. The route planner calculated the Pareto optimal routes for each priority level.

4 Discussion

The literature review has shown that the multi-objective route planning in hostile environments has been handled in a number of different ways. Almost all of the identified references combined the objectives of low threat exposure and short route length. The cost function associated with threat exposure has been formulated in several different ways, such as time within danger zone, distance to the threats' radar or probability of getting detected or hit. A few references included additional objectives such as minimize the flight altitude or maximize the mission effectiveness. However, none of the references identified in the literature included more than four objectives.

Many route planner complemented the objectives with constraints in order to generate feasible routes. The constraints are often associated with the flight safety class in Schulte's goal model [16], such as limitations in route length depending on the available amount of fuel or flying above the terrain in order to avoid ground collisions. There are also constraints associated with the limitations of the aircraft's dynamics in order to ensure that the routes will be possible to fly. The desire to generate flyable routes is typically important for UAV route planning, when the aircraft is assumed to more or less automatically follow the route. In training simulators with computer generated flying opponents, the constraints can be included to ensure that the opponents behave in realistic ways. When the route planning algorithm is intended to support manned aircraft, these kinds of constraints may sometimes be omitted, since the pilots use the pre-planned routes merely as a guideline of where to fly. They do not strictly follow the routes and can adjust them according the performance of the aircraft.

The literature shows that the same goal can be included as both an objective and a constraint. For example, the objective of minimizing the flight altitude was combined with the constraint of flying above a minimum height level, see e.g., [3]. In this case, the constraint ensures that the desire to minimize the flight altitude does not lead to a ground collision. The objective to minimize route length was combined with a constraint that the route length may not exceed the threshold L_{max}, see e.g., [15]. In this case, the objective and constraint are correlated. In a single-objective route planner, this constraint would be unnecessary, since the algorithm should find the shortest route regardless of the constraint. However, in multi-objective problems, the shortest route might not been found even though short route length is one of the objectives. The constraint therefore ensures that the route length is limited.

The literature review identified several ways to implicitly include objectives and constraints into the route planning algorithm, such as using the constraint for limiting the search within the A^*-algorithm or generate Voronoi diagrams for avoiding the threats. These examples show that it can be beneficial to consider the objectives when selecting the optimization method.

The most common approach to include the decision maker's preferences, found in the literature review, was to use an aggregated cost function with the a weighted sum of the individual cost functions. The main advantages with this approach is that single-objective optimization algorithms can be applied and that inclusion of any number of objectives is straightforward. However, it might be difficult for the decision maker to comprehend the weight parameters and assign them in an appropriate way. The decision maker has to compare objectives that are expressed in different dimensions, for instance fuel consumption versus risk of getting hit. The weight assignment is in particular problematic in situations with many objectives. The multi-objective route planners found in the literature usually only included two or three objectives. It might therefore be possible that the decision maker's can easily learn how to set the weights.

It is common to combine objectives and constraints and one reference included as many as seven constraints, see [3]. The constraints can be handled independently of each other, since all of them must be fulfilled in order for the route to be feasible. The decision maker therefore does not have express preferences between the constraints. A potential disadvantage with using constraints is that the route planner will not aim at improving an objective beyond the constraint threshold. For instance, if there is a constraint that the route length should be shorter than L_{max}, the route planner will not suggest routes that are shorter than this, even if it would be possible. This might not be a problem for natural constraints, such as limitations regarding the aircraft's dynamics. For instance, the turns in the route might not be important as long as the aircraft has the maneuverability to perform the turns. In the case with route length, it can be included as both a constraint and objective as discussed above. The use of objectives and constraints in this case can be seen as a way of expressing priorities, since constraints have a higher priority than objectives.

The use of a posteriori approaches is less common than the a priori approaches. Nevertheless, several references suggested route planners that suggested several routes. The main advantage with these approaches is that the decision maker can focus on selecting routes instead of selecting weights. Furthermore, when flying in hostile environments, it can be suitable to have a few alternative plans in case the situation changes and the main plan is no longer suitable. Marler & Arora [10] pointed out that a challenge with a posteriori approaches is that the solutions must be presented in graphical or tabular form in such a way that the decision maker is able to select the preferred solution. However, since the literature review shows that it is common to only use a few objectives, this should be less challenging than in situations with a large number of objectives. Another potential disadvantages with a posteriori approaches is that they in general are more computational expensive, since a number of optimization problems need to be solved. Recently, there has been an increased use of population-based methods for solving multi-objective optimization problems, such as evolutionary algorithms, particle swarm optimization and ant colony optimization [4]. It is therefore plausible that these methods will be used more in the future.

5 Conclusions and Suggestions for Future Work

Route planning for air missions within hostile environments can be regarded as multi-objective optimization problems, where the aircraft should be able to accomplish the mission tasks without being exposed to unnecessary risks. This work has reviewed the different approaches for multi-objective route planning found in the literature with respect to the formulations of objectives and constraints as well as the methods to handle the decision maker's preferences. It is concluded that most of the route planners only optimize two or three objectives, which typically include threat exposure and route length. These objectives are sometimes complemented with constraints in order to ensure that the routes are feasible with respect to fuel consumption, altitude limitations and flight dynamics.

The most common approach to handle the decision maker's preferences is to aggregate all objectives into cost function, for instance with a weighted sum of the objective costs. It is then straightforward to apply single-objective optimization algorithms in order to find the solution. The main disadvantage is that it can be difficult for the decision maker to comprehend the weights and give them suitable values. An alternative approach is to use a posteriori methods that generates a set routes and thereafter let the decision maker select the best alternative. The main disadvantage with this approach is that it is typically more computational expensive and that the set of solutions need to be presented in a understandable way.

This work has performed a literature review in order to identify which objectives to include in a route planner and which methods for handling preferences that have previously been used. In order to validate the findings, it would be suitable to perform an study with the potential users of a route planning system, i.e., pilots and UAV operators. Such as study should aim at finding their options regarding how the cost functions should be modeled as well as how their preferences regarding the objectives should be captures. Furthermore, when designing a route planner, it is important to select an optimization algorithm that generates suitable routes in a feasible amount of time. In future work, it is therefore interesting to analyze also these aspects of multi-objective route planning.

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