Journal of Unmanned Vehicle Systems

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Journal:	<i>Journal of Unmanned Vehicle Systems</i>
Manuscript ID	juvs-2017-0004.R3
Manuscript Type:	Article
Date Submitted by the Author:	26-Apr-2019
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Keyword:	Real-Time, Path Planning, UAV, Flyability, Embedded
Is the invited manuscript for consideration in a Special Issue? :	Not applicable (regular submission)

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Recent Advances in Unmanned Aerial Vehicles Real-time Trajectory Planning

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Abstract: The growing interest in Unmanned Aerial Vehicles (UAV) can be attributed to many factors, particularly the potential for them to operate beyond visual line of sight and at increasingly higher level of autonomy. Trajectory planning defines the extent to which a vehicle is 'autonomous'. Therefore, to operate at high levels of autonomy, UAV will require real-time embedded trajectory planning that respects a minimum of flyability. This paper presents a review of recent advances in UAV trajectory planning and seeks to clarify the flyability, the real-time and the embedded aspects, which are not adequately considered by previous survey papers. This work, which specifically focuses on Class II (≥ 150 kg and ≤ 600 kg) and Class III (> 600 kg) fixed wing UAV, analyses 60 papers from this last decade that mention some real-time achievement with respect to UAV trajectory planning. From this analysis, we highlight some challenges and some suggested orientations for future works.

L'accroissement de l'intérêt pour les drones peut-être attribué à plusieurs facteurs; entre autre à celui de pouvoir voler au-delà du champ visuel avec une autonomie de plus en plus accrue. La planification de trajectoire constitue un élément définissant le niveau d'autonomie du véhicule. Ainsi,

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pour opérer à un haut niveau d'autonomie, les drones devront avoir à bord un planificateur de trajectoire en temps réel qui respecte une certaine volabilité. Cette publication passe en revue les avancements récents de la planification de trajectoire de drone et essaie de clarifier les aspects de la volabilité, du temps-réel et des besoins embarqués, qui sont trois perspectives qui n'ont pas été adéquatement considérées dans les études extensives précédentes. Ce travail, qui se concentre particulièrement sur les drones à voile fixe de Classe II (≥ 150 kg et ≤ 600 kg) et de Classe III (> 600 kg), analyse 60 publications de cette dernière décennie qui mentionnent avoir atteint certaines performances en temps-réel avec leur planificateur de trajectoire de drones. Cette analyse souligne les défis qui restent à surmonter et offre certaines suggestions pour de futurs travaux dans le domaine.

Key words: Real-Time, Path Planning, UAV, Flyability, Embedded

Section 1. Introduction

Real-time Unmanned Aerial Vehicle (UAV) trajectory planning has been the center of interest of multiple publications in this last decade. Many books and survey papers have synthesized some aspects of the work completed within that field. Three aspects have been addressed with less rigour: the flyability, the real-time and the embedded aspects. As many nations are trying to set regulations to allow Class II (≥ 150 kg and ≤ 600 kg) and Class III (> 600 kg) UAV to operate beyond line of sight and conduct autonomous operations, real-time UAV trajectory planning, which can be embedded on board the UAV while keeping the proper level of flyability, will play an important contribution to that effort.

This paper acts as a reference for UAV trajectory planner designers with a focus on Class II and Class III fixed wing UAV autonomous operations. It

presents a critical analysis of 60 recent publications that claim real-time achievements in UAV trajectory planning. The objectives of our analysis are to:

- 1) give an overview of the surveyed publications characteristics;
- 2) analyze the flyability used for the UAV trajectory planning;
- 3) highlight the different real-time criteria aimed at; and
- 4) evaluate the considerations given to UAV embedded constraints.

In Section 1.1 we address the importance of real-time UAV trajectory planning within the context of UAV autonomy. We then clarify in Section 1.2 the distinction between path and trajectory planning and in section 1.3 explain the circumstances where UAV trajectory re-planning is required. In Section 1.4 we define the flyability, real-time and embedded aspects of UAV trajectory re-planning, and in Section 1.5, Sections 1.6 and 1.7 we detail some elements of the flyability, real-time and embedded aspects of UAV trajectory re-planning.

The rest of this paper is organized as follows: Section 2 reviews previous survey papers to distinguish the scope of this paper from other works. Section 3 presents characteristics of the surveyed publications. Section 4 provides an overview of the UAV trajectory planning process to set the foundation of our analysis. In Section 5 we analyze the flyability aspect, in Section 6 the real-time aspect, and in Section 7 the embedded aspect of the UAV trajectory planners of the surveyed papers. In Section 8 we summarize our observations and recommendations and present our conclusions.

1.1 UAV Autonomy

As per the Autonomy Level for Unmanned System (ALFUS) Working Group, autonomy refers to the UAV's own ability of "operating (independently from human involvements)" to achieve its goals as assigned by its human operator(s) (Huang 2008). The UAV autonomy levels presented by (Kendoul 2012) (as summarized in Table 1), based on the National Institute of Standards

and Technology ALFUS frame work (Huang et al. 2005), show that real-time trajectory planning is one of the basic abilities required for achieving autonomy level 4.

1.2 Path Planning or Trajectory Planning

Although the difference is not often made in the literature, it is useful to distinguish between path and trajectory planning. Trajectory planning is planning the vehicle motion from point A to point B while avoiding collision over time. This can be computed in both discrete and continuous methods. Trajectory Planning is sometimes referred to as Motion Planning and erroneously as Path Planning. Trajectory planning is distinct from path planning in that it is parameterized by time. Essentially trajectory planning encompasses path planning in addition to planning how to move based on velocity, time, and kinematics.

1.3 Requirement for UAV Trajectory Re-Planning

Commercial aircrafts operate in dedicated flight corridors (as shown in Figure 1), which are somewhat similar to the roads for our cars. Hence, airline flights have their trajectory planned once before departure and the trajectory is usually flown as planned during the whole flight.

However, as analysed in (Dadkhah and Mettler 2012), unforeseen events in UAV flights may occur; for example: weather changes, unforeseen obstacles detected and, for dangerous tasks, presence of unforeseen threats. To react to unforeseen events, a UAV operating autonomously needs to quickly react to the event and to re-plan its trajectory based on the new flight conditions. Hence, for a UAV to be capable of autonomous operation, it is necessary to have a trajectory planner module within its architecture.

1.4 Flyability, Real-time and Embedded Criteria Definition

UAV trajectory planning needs to meet a minimum set of flyability, real-time and embedded criteria.

The minimum **flyability** criterion that a UAV trajectory planner shall meet is the assurance that it never generates a “false positive solution” (i.e. the planner shall never propose to the UAV an unfeasible trajectory that the planner assessed as feasible). This requires the planner to evaluate the UAV’s dynamics within its 3D environments.

The minimum **real-time** criterion that a UAV trajectory planner shall meet is for the situation to be analysed and the answer (i.e. the task to be executed) to be provided within a given timeframe that equates as close as possible to real-time (Chatterjee and Campbell 1998). This means that the worst-case execution time of a task has to be within its respective deadline (i.e. its real-time condition) (Altendbernd and Hansson 1998): Section 1.6 details the real-time condition related to UAV trajectory planning.

In addition to its flyability and real-time requirements, an on-board UAV trajectory planner presents challenges related to its **embedded** aspect. The UAV needs to have the computing power to support the complexity of an embedded planner while minimizing the power size and weight of the computing device in order to maximize the endurance of the UAV (Jung et al. 2009).

1.5 Flyability Aspect of UAV Trajectory Re-Planning

(Gardi et al. 2013) highlighted the fact that UAV embedded real-time trajectory planners, as part of Next Generation of Flight Management System (NG-FMS), require flyability as they will be responsible for sending globally optimal trajectories to the Four Dimensional Trajectory (4DT) Planning, Negotiation and Validation (4-PNV) system. 4-PNV will soon be a corner stone

of the next generation Communications, Navigation and Surveillance/Air Traffic Management (CNS/ATM) in Europe. Therefore, a UAV trajectory planner solution will have to be flyable so CNS/ATM can rely on its input. Figure 2 gives a simplified overview of the expected handshake that an UAV will have to do with the 4-PNV of next generation CNS/ATM.

1.6 Real-Time Aspect of UAV Trajectory Re-Planning

(Canny 1988) demonstrated that the complexity of UAV trajectory planning with flyability is a Non-Polynomial-Hard problem, which means that it is likely to be too computationally demanding for finding the optimal trajectory for non-trivial scenarios (Altendbernd and Hansson 1998) within the required deadline. That deadline can be either a hard real-time condition or a soft real-time condition. By definition, if the computing time of a task cannot meet its hard real-time condition, a catastrophic result will affect the system; while if it doesn't meet a soft real-time condition, only degradation in the quality of the service occurs (Shi et al. 2005).

A generic definition of the hard real-time condition of an UAV trajectory planner could be the requirement to generate the trajectory solution before getting into an unavoidable collision or inextricable situation. Re-computing locally the trajectory in the region where the unforeseen event occurs may be an approach to speed-up the generation of a new solution; however, this approach could lead the UAV to be trapped in a confined location from which its current fuel and/or power will not allow it to escape. The hard real-time condition should therefore apply to the global UAV trajectory re-computation time.

A generic real-time deadline, which is technology and scenario independent, should encompass the UAVs operational regulations. The Federal Aviation Administration (FAA) held a workshop to provide guidance for future policies and rules with respect to the Sense and Avoid capability of UAVs (FAA

Sponsored "Sense and Avoid" Workshop 2009). Within their final report, they present four different regions around the UAV: the Air Traffic Controller (ATC) Separation Services, the Self Separation Threshold, the Collision Avoidance Threshold, and the Collision Volume (see Figure 3).

Of the four regions identified, only the Collision Volume is properly defined in regulations for all flying scenarios. The Collision Volume refers to the Near Mid Air Collision (Federal Aviation Administration 2012), which was defined as when an aircraft passes within 150 m (500 feet) horizontally, or within 30 m (100 feet) vertically of another aircraft. This rule has been simplified in 2014 (Federal Aviation Administration 2014), by requiring that no aircraft comes within a 150 m (500 feet) radius from an UAV. From this 150 m (500 feet) rule and from the maximum speed of an UAV, an operational real-time deadline can be fixed. For example, the Heron (Israel Aerospace Industries MALAT Division 2014) – a Class II UAV – would only have 2.4 s to re-compute its trajectory.

In addition to the real-time deadline identification, two more aspects need to be addressed to clarify the real-time performance of a UAV trajectory planner. Since the easiest approach to reduce UAV trajectory planning computing time is to reduce the size of the search space of the environment representation, it is essential that at least the following two elements be clearly identified to be able to define the level of reality that the trajectory planner takes into consideration:

- 1) Size and resolution of the flying environment area; and
- 2) Time to perform the environment modeling (if any).

The size and the resolution of the representation of the flying environment are closely interrelated; when separated from each other, they are meaningless. For example, if a trajectory planner is designed to consider a 16 m UAV as a dot on a map, and is required to plan a trajectory in a 65 536 m² flying area: strictly looking at the size, Map A from Figure 4 seems to be an adequate environment representation, while strictly looking at the resolution of the map, Map B of

Figure 4 seems to be adequate; however Map A doesn't respect the resolution requirement and Map B doesn't respect the size requirement. It is therefore required to provide both the size (longitude, latitude and maximum height) and the resolution information of the UAV trajectory planner map to allow meaningful discussion of real-time computation.

As it is presented in Section 4, the search space of the raw Map Data can be reduced by many environment modeling techniques. Because of the dynamic nature of the UAV environment, it is essential to include the environment modeling computing time into the trajectory planning computing time to be able to talk about real-time UAV trajectory planning.

1.7 Embedded Aspect of UAV Trajectory Re-Planning

As mentioned in Section 1.4, an embedded UAV trajectory planner presents its own challenges. The airborne environment limitations vary between the types of UAV, because of their different characteristics (see Table 2).

From the endurance information in Table 2, we note that no matter the size of the UAV, UAV are limited in terms of power available onboard. Additionally, in terms of weight, even within the Class III UAV classification, a bigger UAV could potentially have about 5 times more avionics/computing power than a smaller Class III UAV. Despite these differences, all UAV platforms gain in endurance by using a lighter and lower power computing device.

Section 2. Analysis of Previous Surveys

Many researchers have worked in trajectory planning and more recently in UAV trajectory planning, which resulted in over one thousands papers and many books written in the field; for instance, (Gill et al. 1981), (Dennis Jr. and Schnabel 1983), (Schwartz and Yap 1987), (Canny 1988), (Latombe 1991), (Fujimura and

Tunii 1992), (Choset et al. 2005), (LaValle 2006), (Valavanis 2007), (Fletcher 2013), and (Carbone and Gomez-Bravo 2015) are some reference books concerned with motion planning. Among this vast literature many survey papers analyzed different aspects of the trajectory planning problem:

- 1) (Hwang and Ahuja 1992), (Betts 1998), (Ferguson et al. 2005), (Masehian and Sedighizadeh 2007), (Marzouqui and Jarvis 2011), (Conway 2012), (Souissi et al. 2013) and (Pol and Murugan 2015) are survey papers related to trajectory planning in general;
- 2) (Judd 2001), (Goerzen et al. 2010), (Hongguo et al. 2011), (Kendoul 2012), (Huang et al. 2012), (Dadkhah and Mettler 2012), and (Cheng et al. 2014) are survey papers specific to UAV trajectory planning; and
- 3) (Ollero and Merino 2004), (Chen et al. 2009), and (Chao et al. 2010) are survey papers that look at UAV controllers, which are ultimately the users of the UAV trajectory planner outputs.

Here are the limits of these previous surveys:

- 1) (Masehian and Sedighizadeh 2007) provided an analysis through an extensive amount of publications, which highlighted a trend in the researches of using more heuristic based trajectory planning than deterministic ones; however this survey paper only analyzed the deterministic and the non-deterministic aspect of the surveyed papers.
- 2) Both (Judd 2001) and (Ferguson et al. 2005) provided a formal comparison of trajectory planners; however their testing scenarios were only in 2D, which isn't sufficient for the 3D environment of UAV trajectory planning.
- 3) (Hwang and Ahuja 1992) and (Goerzen et al. 2010) evaluated the computing speed and the completeness of the motion planning solutions; however neither covered the analysis of the embedded aspect linked to real world implementations.

- 4) (Kendoul 2012) and (Souissi et al. 2013) provided an interesting real-time discussion among different trajectory planning techniques, however neither analyzed the flyability required to respect the UAV's aerodynamics, nor the embedded aspect of the trajectory planner.
- 5) (Betts 1998), (Marzouqui and Jarvis 2011), (Huang et al. 2012), (Conway 2012), (Hongguo et al. 2011) and (Cheng et al. 2014) made theoretical comparisons among different trajectory planning techniques; their analysis stayed at the theoretical level without looking into the implementation aspects.
- 6) (Dadkhah and Mettler 2012) and (Pol and Murugan 2015) offered a dynamic environment discussion among different trajectory planning techniques, however neither analyzed the flyability, the real-time nor the embedded aspect of these techniques.

Here are some common observations from these surveys:

- 1) UAV trajectory planning requires considering both a dynamic 3D environment and the UAV aerodynamics to achieve a decent level of flyability;
- 2) Real-time and embedded aspects of real implementations of UAV trajectory planners should be further studied;
- 3) Benchmarking for UAV trajectory planning is still required; and
- 4) Combination of trajectory planning techniques are promising avenues; some suggesting that Evolutionary Algorithms be used for global planning, while using refined techniques for local planning.

Section 3. Characteristics of Surveyed Publications

In our survey, we found 67 publications that explicitly claimed real-time achievements in UAV trajectory planning: (Allaire et al. 2009), (Babaei and Mortazavi 2010), (Çekmez et al. 2014), (Çekmez et al. 2014), (Chen and Zhang

2013), (Chen et al. 2016), (Chen et al. 2012), (Chen et al. 2011), (Cocaud 2006), (Dong et al. 2011), (Ducard et al. 2007), (Gardi et al. 2015), (Ghosh et al. 2011), (Guanglei et al. 2014), (Guo et al. 2009), (Holub et al. 2012), (Hossain et al. 2014), (Hota and Ghose 2014), (Jung and Tsiotras 2008), (Jung et al. 2009), (Kim et al. 2008), (Kok et al. 2010), (Kok et al. 2013), (Kothari and Postlethwaite 2013), (Kuwata and How 2004), (Lim et al. 2010), (Lin and Saripalli 2014), (Ling and Hao 2015), (Liu et al. 2013), (Newaz et al. 2013), (Omar and Gu 2009), (Ozalp and Sahingoz 2013), (Palossi et al. 2016), (Ramana et al. 2016), (Redding et al. 2007), (Ren and Huo 2010), (Roberge et al. 2013), (Roberge et al. 2014), (Ronfle-Nadaud 2009), (Sanci and Isler 2011), (Swartzentruber et al. 2010), (Ten Harmsel et al. 2016), (Turnbull et al. 2016), (Wan et al. 2011), (Wang et al. 2014), (Wang et al. 2014), (Weib et al. 2006), (Wen et al. 2015), (Wzorek and Doherty 2006), (Xiaowei and Xiaoguang 2014), (Yan et al. 2012), (Yang and Sukkariéh 2008), (Yang et al. 2010), (Yang et al. 2014), (Yao et al. 2015), (Yu et al. 2009), (Zejun et al. 2015), (Zhan et al. 2014), (Zheng et al. 2003), (Zhuoning et al. 2010), (Barkaoui et al. 2014), (Beard et al. 2002), (Yongbo et al. 2016), (He and Dai 2013), (Hu et al. 2011), (Kothari et al. 2009), (Sun et al. 2015).

As depicted by Figure 5, 10% of these papers covered multiple-UAVs real-time trajectory planning ((Barkaoui et al. 2014), (Beard et al. 2002), (Yongbo et al. 2016), (He and Dai 2013), (Hu et al. 2011), (Kothari et al. 2009), (Sun et al. 2015)). As multi-UAVs trajectory planners have different focus than single UAV ones, we did not include those publications in our analysis. Figure 6 shows that the remaining 60 papers were in majority published within the past 10 years.

Here is an overview on how these 60 papers addressed the three stages of UAV trajectory planning. As for the world representation, Figure 7 shows that, being geared towards dynamic environments, a majority of the real-time UAV trajectory planners worked directly with the raw data avoiding the computing time of environment modeling.

For the path and trajectory generation phases, Figure 8 gives an interesting picture of the different techniques used by the surveyed papers. Instead of going through the analysis of the individual technique, we will analyze their common characteristics.

For the path planning, we observe from Figure 9 that both deterministic and the non-deterministic approaches were actively studied.

As can be seen in Figure 10, the majority of the papers performed some form of smoothing of their planned UAV path, while a quarter of the papers dispensed with that phase in order to achieve their real-time objectives. This brings the question: “How much flyability do recent researches keep while aiming for real-time UAV trajectory planning?” Before analyzing the answer to that question, we note that although we are focusing on fixed-wing UAV trajectory planning, a small portion of the surveyed papers (Figure 11) dealt with rotary-wing UAVs. We kept them in our analysis as they aimed to satisfy the same evaluation criteria that we detail in Section 5.

Section 4. UAV Trajectory Planning Process

(Hwang and Ahuja 1992) defined the Motion Planning problem for robotic motion in general, including robot arm manipulators. (Goerzen et al. 2010) further specified the motion planning problem definition for UAV. Both problem definitions were presented with the theoretical approach required for their algorithm analysis. Moreover, (Betts 1998) defined clearly the trajectory optimization problem with a numerical method perspective, which is based on the kinematic model of the UAV. Our work doesn't intent to repeat these definitions. Instead, it will simply provide the contextual information related to UAV trajectory planning to allow the reader to understand the discussion done over the surveyed publications.

4.1 Trajectory Planning Within the UAV

From the UAV general architecture presented by (Chen et al. 2009) and simplified in Figure 12, we can see that an UAV trajectory planner usually receives its directives from a higher control layer, which is usually hosted on a control station; while the coordination and the execution levels are typically hosted onboard the UAV. In addition, one should note that the trajectory planner gives its trajectory to an integrated control module.

A trajectory planner could provide a path, and let the Integrated Controller (or autopilot) of an UAV compensate at the discontinuous-velocity points at the intersections of the line segments. However, as shown in Figure 13, the autopilot, likely based on second order control loops (Kendoul 2012) (Chao et al. 2010), will make the UAV overshoot from the desired path if it has been tuned to follow it tightly. Hence the final step of trajectory planning is the generation of a desired trajectory (Goerzen et al. 2010) that avoids this feature.

A standard trajectory planning approach (as described in (Goerzen et al. 2010)) could be resumed in the following steps:

- 1) Define the world representation or environment modeling;
- 2) Generate a path; and then
- 3) Generate a trajectory from the path.

This three-step approach is applicable to most trajectory planners, except in the case of the numerical method, where the last two steps are combined into one step – as the trajectory is directly computed from the kinematic model of the UAV. This approach is called trajectory optimization.

4.2 World Representation

The flying environment information may be captured within a world representation architected into different layers (Nelson 1995). The main layer is the Map Data layer to which the spatial information of all other data (such as obstacles, danger zones, restricted zones, etc.) is linked.

The raw map data, available from satellite images, can be found under the Digital Elevation Model (DEM) (U.S. Geological Survey 1998) format; which consists of a conventional Cartesian grid, where each cell contains the elevation value of the terrain as illustrated in Figure 14.

Many techniques are used to reduce the search space of the fixed grid representation. (Goerzen et al. 2010) presented a lengthy list of such, with their theoretical characteristics. (Souissi et al. 2013) did a comprehensive review of some of these techniques, referred to as Environment Modeling. With no intent to repeat both (Goerzen et al. 2010) and (Souissi et al. 2013) works, but rather to complement them, we present in Table 3 a list of commonly used techniques with some implementation related comments.

4.3 Path Generation

There is a great variety of path generation techniques which have been presented in many publications (Hwang and Ahuja 1992), (Betts 1998), (Ferguson et al. 2005), (Masehian and Sedighizadeh 2007), (Conway 2012), (Souissi et al. 2013), (Judd 2001), (Goerzen et al. 2010), (Huang et al. 2012), (Dadkhah and Mettler 2012). Instead of repeating the presentation of these well documented techniques, we simply present three levels of classifications, based on Souissi (Souissi et al. 2013), to guide our analysis on flyability, on the real-time and embedded aspects of UAV trajectory planning (see Figure 22).

The first classification refers to the Environment Modeling. In static scenarios, the “Environment Modeling” would be done before the mission begins, leaving a simple and quick “Search for Optimal Path” to be done in real-time onboard of the UAV. However, when the dynamic nature of the UAV environment is considered (Dadkhah and Mettler 2012), both the modeling and the search need to be computed in real-time. Hence, some path planners use Environment Modeling and some don’t.

The second classification refers to the deterministic concept. A deterministic algorithm will always find the same solution for the same initial conditions. Deterministic algorithms are typically computationally demanding (e.g.: Dijkstra’s algorithm (Ferguson et al. 2005), A* algorithm (Ferguson et al. 2005), Numerical Methods (Betts 1998)...). A non-deterministic algorithm could use probabilistic approaches, some randomness and/or some heuristics to generate a solution; its solution is not necessarily the optimal solution, and sometimes iterative processes can be used to improve the solution and achieve near-optimality (e.g.: Genetic Algorithm (GA) (Goldberg 1989), Differential Evolution Algorithms (DEA) (Storn and Price 1997), Simulated Annealing (SA) (Kirkpatrick et al. 1983), Particle Swarm Optimization (PSO) (Kennedy et al. 2001), Ant Colony Optimization (ACO) (Dorigo et al. 1996), ...). Non-deterministic algorithms are typically less computationally demanding than deterministic ones.

The third classification distinguishes the global path planners from the local ones. The global path planner looks at all the environment at once, while the local path planners look iteratively through the local environment as the UAV progresses towards its goal. Global path planners are naturally slower than the local path planners because of the larger search space that they use. However, local path planners cannot ensure the same level of optimality as the global path planner would, and cannot guarantee the achievement of a feasible trajectory.

4.4 Trajectory Generation

The third stage of UAV trajectory planning is the generation of the trajectory from the planned path to ensure that the aerodynamic constraints of the UAV are respected in its 3D environment providing the required flyability for the 4-PNV of next generation CNS/ATM. Rotor UAVs (helicopter, quadcopter...) don't share the same aerodynamic constraints as the fixed-wing UAVs. Since (Kendoul 2012) has already done a thorough survey on rotor UAVs, our analysis will focus on the fixed-wing UAV.

The aerodynamic constraints for fixed-wing aircraft are complex. To the author's knowledge, no UAV trajectory planner has yet taken realistically into account the dynamics of airplanes. A reason for this situation is that the solutions to their equation of motion, even for elementary flight segments, had not been obtained until very recently by (Labonté 2012), (Labonté 2015), (Labonté 2015), (Labonté 2016) and (Labonté 2016) for straight, circular and helical segments of trajectories (see Figure 23). From now on, it is then possible to use these motion primitives to construct more complex trajectories. We shall hereafter classify the trajectory planners according to which of the dynamical requirements they incorporate.

Most UAV trajectory planner studies use smoothing techniques that consider too simplistically the airplane dynamical constraints to be realistic. Table 4 gives a list of most common smoothing techniques.

We now survey briefly the constraints that fixed-wing aircraft must satisfy; the feasibility of each segment of the trajectory is affected by the following fixed-wing aircraft parameters:

- 1) Speed;
- 2) Lift;
- 3) Load factor;

- 4) Power; and
- 5) Fuel.

Existing studies incorporate, at best, oversimplified constraints on the speed, on the angle of climb and on the turning radius of the airplane. In reality, however, all these parameters depend very strongly on the altitude and on the inclination of the trajectory. For example, when a Heron Class III UAV flies, at sea level, on a circular trajectory, inclined at 5° with the horizon at the speed of 40 m/s, the minimum turning radius is 86 m, while, if its speed is 60 m/s, it is 1200 m. When it flies on a horizontal circular trajectory at a speed of 35 m/s, its minimum turning radius at sea level is 91 m, while at an altitude of 3000 m, it is 123 m. Furthermore, the possible speeds at which an airplane can fly also depend on the altitude and the inclination of the trajectory.

The complexity of the dynamical constraints, for airplane motion, is such that most algorithms, which can deal successfully with other vehicle routing problems, cannot realistically be extended to airplane trajectory planning.

4.5 Trajectory Flyability Evaluation

For automatic trajectory construction, it is necessary to define a cost function C that will give a value to each trajectory T so that the algorithm knows how to compare trajectories. That is: it can determine objectively that one trajectory is feasible or not, and if it is "better" than another one.

The cost function is usually defined as a sum of terms, each corresponding to a physical attribute of the trajectory, and each given more or less importance by adjusting a weigh coefficient " w ". Clearly, the notion of "best" trajectory depends on the mission at hand. In one mission, flying very fast will be preferred over saving fuel, if a danger zone has to be evaded. In another mission, saving fuel may be preferred etc. An example of cost function is (Roberge 2011):

$$C(T) = w_1 C_{\text{length}} + w_2 C_{\text{altitude}} + w_3 C_{\text{no-fly zones}} + w_4 C_{\text{collision}} + w_5 C_{\text{power}} + w_6 C_{\text{fuel}} + w_7 C_{\text{smoothing}}$$

- with C_{length} : an increasing function of the total trajectory length;
 C_{altitude} : an increasing function of the average trajectory altitude;
 $C_{\text{no-fly zones}}$: an increasing function of the time spent in no-fly zones;
 $C_{\text{collision}}$: high cost increasing with the distance the trajectory is under the ground;
 C_{power} : high cost increasing with the distance through which the UAV does not have enough power;
 C_{fuel} : high cost increasing with the distance without fuel;
 $C_{\text{smoothing}}$: high cost increasing with the number of corners of the straight line path that cannot be connected with a smooth curve.

Some of these criteria ($C_{\text{collision}}$, C_{power} , C_{fuel} and $C_{\text{smoothing}}$), the feasibility criteria (Roberge 2011), affect the technical airworthiness of the drone (how safe to fly without neither human nor material damages) – and the other ones (C_{length} , C_{altitude} and $C_{\text{no-fly zones}}$), the optimization criteria (Roberge 2011), affect its operational airworthiness (how efficiently the operational goals are achieved). The cost of violating each one of the feasibility criteria must be larger than the largest cost of any feasible trajectory.

In order to provide the flyability required by the 4-PNV of next generation CNS/ATM, an UAV trajectory planner shall ensure that its solutions always meet the four feasibility criteria in a 3D environment that are detailed in Section 5.

Section 5. Flyability Criteria

UAV trajectory planners should consider at least the following four feasible criteria in its 3D environment to ensure the generation of a safe trajectory:

- 1) No collision of the trajectory with the terrain;
- 2) Sufficient power available to travel the trajectory;
- 3) Fuel consumption on the trajectory doesn't exceed the fuel available;
and
- 4) Smoothing of the path allows the trajectory to be dynamically flown.

Typically UAV trajectory planners would also consider the following optimization criteria to ensure an efficient trajectory: Length of the trajectory to be minimized; altitude of the trajectory to be optimized; and no-fly zone/ obstacle to be avoided.

Our flyability analysis will be based on the above evaluation criteria, which will be discussed in the following order:

- 1) Length and altitude criteria;
- 2) No collision and no-fly zones in 3D environment;
- 3) Power and Fuel criteria; and
- 4) Smoothing criterion.

We present in Table 5 a quick assessment of what criteria each paper has considered for its UAV trajectory planner.

5.1 Length and Altitude Criteria

The first observation in light of Table 5 is that all surveyed papers aimed at minimizing the length of the trajectory, which is expected as this is part of the intrinsic definition of trajectory planning. We can also notice that only 15% of the

surveyed papers considered minimizing the altitude. This can be explained by the fact that the vertical distance is partially optimized when minimizing the overall distance of the trajectory. However, over a long distance the vertical distance become negligible compared to the horizontal distance – hence adding the altitude criterion in the trajectory evaluation cost function will re-enforce the requirement for a low-level flight when needed ((Cocaud 2006), (Roberge et al. 2013), (Wang et al. 2014) and (Yao et al. 2015)).

5.2 3D Terrain Collision and No-fly Zone Criteria

As per Table 5, the second most considered evaluation criterion is the no-fly zone/obstacle avoidance. Because of the UAV requirement for an obstacle sense and avoid capability in order to fly in segregated airspace, obstacle avoidance became a focal point of interest in many UAV trajectory planning researches to such a point that actually 45% of the surveyed researches focused only on the obstacle avoidance, while 33% of which used a UAV environment simplified to a 2D representation (Figure 28). Only 28% of the surveyed papers ((Allaire et al. 2009), (Chen et al. 2011), (Cocaud 2006), (Gardi et al. 2015), (Guo et al. 2009), (Holub et al. 2012), (Ling and Hao 2015), (Ozalp and Sahingoz 2013), (Roberge et al. 2013), (Roberge et al. 2014), (Swartzentruber et al. 2010), (Wan et al. 2011), (Wang et al. 2014), (Wen et al. 2015), (Yan et al. 2012), (Zhan et al. 2014), (Zheng et al. 2003)) considered both 3D terrain and obstacle avoidance; these are the ones of which we will further analyze the flyability.

5.3 Power and Fuel Criteria

The Power requirement of UAV trajectory is dependent on the density of the air in which the UAV is flying. As for the Fuel requirement, the length optimization of the UAV trajectory is not providing an exact evaluation of the UAV fuel consumption because it does not take into account the fact that on an

ascending trajectory more fuel is burned than on a level flight trajectory of a same length. Both the power and the fuel criteria are important factors of the UAV trajectory planner flyability. As per Table 5, only three groups of researchers from the surveyed papers took the time to compute the power and/or the fuel requirements of the UAV trajectory.

- 1) In 2013 (Roberge et al. 2013), – and then in 2014 (Roberge et al. 2014) – presented an UAV trajectory optimization method that used a cost function, which employed the 3D arcs of circles and helical curves trajectory smoothing technique for which (Labonté 2012), (Labonté 2015), (Labonté 2015), (Labonté 2016) and (Labonté 2016) have provided the equations for computing both the power and the fuel requirements of the UAV trajectory. These works will be taken as a reference point for the rest of our analysis.
- 2) In 2015, (Gardi et al. 2015) explained the 4DT optimization algorithm that uses the Matlab GPOPS for Multiple-Phase Optimal Control Problem (Rao and Benson 2010) and a smoothing algorithm (Gardi et al. 2015) similar to the 3D Dubin curves. Above the feasible criteria, their approach proposed to optimize the UAV trajectory with respect to the weather conditions, the required time of arrival, the required initial and final trajectory headings. The only feasible criterion not taken into consideration by (Gardi et al. 2015) was the power requirement over the trajectory.
- 3) In 2016, (Ten Harmsel et al. 2016) developed a trajectory planner able to react to emergency landing requirements close to an urban environment. They used a relatively small search area in which the A* algorithm searched, based on a power model, an energy model, the trajectory length, a 3D obstacle avoidance and the people density information that was provided to the UAV. Their trajectory planner didn't consider the aerodynamic constraints of the UAV as it was

assumed to be covered by another subsystem, allowing them to focus solely on finding a safe location to land. They also omitted the evaluation of the 3D terrain avoidance.

5.4 Smoothing Criterion

Out of the 17 papers that gave a consideration for both 3D terrain and obstacle avoidance, (Ozalp and Sahingoz 2013) and (Zheng et al. 2003) didn't make use of any smoothing techniques, while the 15 others did. Three of these 15 were discussed in Section 5.3 and the reminding 12 will be analyzed with respect to:

- 1) Deterministic and non-deterministic approach;
- 2) Local/Global approach; and
- 3) Environment modeling approach.

Looking globally at the raw data (no-modeling) of the terrain yields the largest search space that a UAV trajectory planner can be faced with. This explains that some papers used non-deterministic optimization methods to strive for real-time computing. Both (Ozalp and Sahingoz 2013) and (Zheng et al. 2003) UAV trajectory planners were based on GA. (Swartzentruber et al. 2010) uses PSO as a path planner and the B-Spline curves to generate the trajectory. (Holub et al. 2012) built over (Swartzentruber et al. 2010) worked and modified the PSO algorithm for improving its computing time. (Roberge et al. 2013) implemented both a GA and a PSO and demonstrated that its GA implementation provides better trajectories than the PSO implementation. (Roberge et al. 2014) combined a GA with a PSO to improve the quality of the generated trajectory. Other than (Roberge et al. 2013) and (Roberge et al. 2014), no one used a cost function that incorporates both the power and the fuel criteria.

To reduce the global search space, environment modeling has also been used by non-deterministic UAV trajectory planners. (Cocaud 2006) and (Allaire

2007) used a 3D quad-tree for modeling the UAV environment to speed up the computing time of their GA and used 3D arcs of circles for smoothing. (Guo et al. 2009) proposed to first compute a potential field through which a 3D PSO path planner performed the search/optimization; the path smoothing was thus integrated within the path planning stage. (Ling and Hao 2015) used a similar approach but used a 3D ACO path planner to search through a potential field. The 3D arcs of circles technique didn't consider the load factor; and the potential field approach didn't consider the air density varying with altitude, both of which impact the lift of the UAV, hence its power and its fuel requirement.

The papers that have used deterministic algorithms either combined them with some environment modeling or reduced the search space to a local area. (Wen et al. 2015) developed an improved RRT, then used A* to generate the shortest path and finally generated the trajectory with 3D Dubin curves. (Yan et al. 2012) improved PRM by combining it with a 3D quad-tree, the resolution of which was large enough to respect at all times the minimum turning radius of the UAV. A* was then used to find the shortest path. (Zhan et al. 2014) designed a "2.5D grid" that significantly reduced the 3D search space, by modeling a DEM map into a routing network allowing computing time to mathematically manipulate the shortest path from their A* algorithm and to respect the minimum turning radius of the UAV. However, these papers did not consider that the minimum turning radius varies with the UAV altitude and the trajectory inclination.

One of the local planning strategies is the Receding Horizon (RH), according to which the search space of the planner is limited to a specific distance away from the UAV, while being re-computed as the UAV progresses on its trajectory. Among the surveyed papers who took this approach ((Chen et al. 2012), (Kothari and Postlethwaite 2013), (Kuwata and How 2004), (Turnbull et al. 2016), (Wan et al. 2011), (Wang et al. 2014), (Xiaowei and Xiaoguang 2014),

(Yao et al. 2015), (Yu et al. 2009), and (Zejun et al. 2015)), only (Wan et al. 2011) and (Wang et al. 2014) did consider both 3D terrain and obstacle avoidance:

- 1) (Wan et al. 2011) developed a local path planner (with no global planning) that generated a path towards the goal by using the visibility graph principle; the path was then smoothed with an Euler spiral, which ensures both continuity of the speed and of the acceleration of the UAV; and
- 2) (Wang et al. 2014) presented a trajectory planner that was based on 3D Model Predictive Control (which has a RH nature) and an improved DEA to optimize the trajectory – their approach respected the minimum turning radius, the maximum climbing and descent angle of the UAV.

None of these two approaches calculated the required power or fuel. Moreover, as for any local path planner, their overall trajectory optimization cannot be guaranteed, as it was highlighted by (Chen et al. 2012), who compared their RH method with two optimization methods (GA and ACO) and demonstrated that their RH approach were quicker in finding a feasible solution but that the optimization methods could find better optimal solutions after some iterations – (Zhan et al. 2014) came to a similar conclusion two years later.

In summary, the observations that can be drawn from our flyability analysis are:

- 1) The majority of the surveyed papers (72% as per Figure 28) over simplified their search environments in order to achieve real-time computation – further researches should always consider at least 3D terrain and obstacle avoidance for UAV trajectory planning.
- 2) Most of the studies incorporated, at best, oversimplified constraints on the speed, on the angle of climb and on the turning radius of the

airplane. Only four of the surveyed papers looked at the satisfaction of the fuel and power requirements. As these two feasibility criteria are important factor of the UAV trajectory flyability, further studies should find efficient ways of integrating these two criteria into UAV trajectory planning.

- 3) Among the surveyed papers, only non-deterministic optimization methods provided a global optimization without requiring environment modeling; deterministic approaches required environment modeling to provide global optimization – further studies should focus on ways to improve the computation time of global UAV trajectory planning.

Section 6. Real-Time Criterion

As the main subject of this survey is the real-time aspect of the published UAV trajectory planners, we now analyze the following three real-time aspects: the real-time objective/deadline, the map size and resolution, and the world representation.

6.1 Real-Time Objective/Deadline

Figure 29 shows the seven ways which the real-time achievements of the UAV trajectory planners have been expressed.

Most works (about 42%) aimed at achieving the quickest possible computing time, which provided little information with respect to the real-time condition/deadline considered. The second most popular approach (33%) was to compare the computing time with the computing time requirement of another trajectory planner – the lack of a benchmark testing environment makes it hard to compare results between these papers.

Less than a third of the researches defined some precise real-time condition. These real-time conditions can be categorized as follow:

- 1) Quick enough to support simulation;
- 2) As fast as the UAV operator reaction time;
- 3) Autopilot update frequency;
- 4) Distance based UAV reaction time; and
- 5) Life experimentation.

Computing time supporting simulation requirements. This real-time condition is about ensuring that the UAV trajectory is computed in a timely manner that will allow the simulated UAV to react to unforeseen events. One can easily manipulate the speed of the simulation (its sampling frequency) to give time to the UAV trajectory planner computing device to complete its task before the simulated UAV has to react. It is therefore essential to have the simulation frequency provided to enable any future comparison. Among the surveyed papers; only (Jung et al. 2009) and (Yao et al. 2015) have provided their simulation sampling frequency. The drawback of this real-time condition is the fact that it is too technology specific for using it as a reference benchmark; e.g. (Jung et al. 2009) had a 20 Hz sampling frequency and (Yao et al. 2015) had a 1 Hz sampling frequency, while nothing guarantees that real UAVs are designed to operate at either of these frequencies.

UAV operator reaction time. (Swartzentruber et al. 2010) provided multiple trajectories (with deferent optimization criteria) to support UAV operators in re-tasking UAV trajectory. As per their work, UAV operators have 30 s for re-tasking a UAV on a new trajectory; therefore they claimed real-time compliance with their average computing time of 3.1 s and their max computing time of 8 s. The UAV operator's reaction time can be an appropriate generic operational real-time deadline for non-autonomous UAV. However (Swartzentruber et al. 2010) should have presented a human factor analysis that

sets the deadline to 30 s, so that one can understand if the proposed deadline is scenario dependent, if it is specific to a technology or if it is generic to common UAV operations.

Autopilot update frequency. (Kok et al. 2013) mentioned that a typical autopilot system has an update frequency of 10 Hz, based on the work of (Kang and Hedrick 2009), which made use of a Piccolo Autopilot. While this real-time condition is more appropriate for autonomous UAVs than the operator reaction time, it presents the same issue as the simulation time, which is being technology specific (not all autopilots operate at that frequency).

Distance based UAV reaction time. A more generic approach to set the real-time deadline is to make it based on the reaction time expected from the UAV faced with unforeseen events, which can be translated into the maximum distance a UAV can safely travel before knowing its new trajectory (Weib et al. 2006). (Kim et al. 2008) suggested that unforeseen obstacles are always detectable 6 km in advance, without explaining how that distance was set. This constraint seems arbitrary, when presented without explanations to justify its logic, thus it cannot easily be reused or scaled to any operational applications. (Roberge et al. 2013) set the deadline at 10 s, explaining that trajectory generated in their testing scenarios had a length between 5 and 60 km, and that within 10 s the fastest UAV (within their comparison set) was traveling 1.7 km; which was deemed acceptable. (Roberge et al. 2014) reduced the deadline to 5 s for a distance of 882 m. In (Liu et al. 2013) the minimum flight time for a trajectory segment was 5 s. In their simulation the UAV was flying at 50 m/s therefore their shortest trajectory segment was 250 m long. (Ronfle-Nadaud 2009), set her deadline to ensure giving 150 m to two UAV facing each other to change their respective heading; this being the same distance as in the Near-Mid-Air collision regulation (Federal Aviation Administration 2014).

Life Experimentation. (Lin and Saripalli 2014) had tested their trajectory planner in life experimentation and demonstrated that their small quadrotor UAV (flying at 0.5 and 1.0 m/s) was able to avoid (19 times out of 20), with a 1.5 m safety distance a moving obstacle (running at 0.5 m/s).

Among these different approaches in defining real-time achievement, the most generic ones are those considering that the real-time condition should allow to avoid collisions by respecting a safety margin distance. Again for outdoor UAVs, typical national rules impose a 150 m safety radius. Therefore future work could consider expressing their real-time achievement with respect to that distance (e.g. “the proposed work meets the 150 m real-time requirement for UAVs flying with max speed of x m/s”).

6.2 Real-Time Map Size and Resolution

Despite their real-time orientation, a third of the surveyed papers didn't provide the information required for knowing the size of their search space (see Figure 30). Another third took the approach of considering a small search space (smaller or equal to 400 x 400 cells). There are still 29% that used a significant search space (between 500x500 and 5000x5000 cells). Three papers distinguish themselves with regard to the size of their search space. (Babaei and Mortazavi 2010) presented results on a map of 1500 x 10,000 cells (with a resolution of 1m x 1m), while addressing only the trajectory generation part of the three stages UAV trajectory planning task. (Guanglei et al. 2014) ran their simulation in a 20,000 x 20,000 cell map (with a resolution of 1m x 1m), while simplifying their search space to a 2D representation, with no terrain information other than the presence of a number of obstacles. (Zhan et al. 2014) tested their approach with a map of 52,700 x 52,700 cells (with a resolution of 30m x 30m), while focusing on local optimization with no global optimization.

When considering the 150 m safety radius regulation (Federal Aviation Administration 2014) as real-time condition for the UAV trajectory planner, we should set some boundaries with respect to the map resolution, which should never be coarser than 150 m x 150 m, in order to allow the capability of identifying near mid-air collisions without negative positive-detections. Based on this boundary, Figure 31 shows that the majority of those who provided their resolution information respected this limit. It is also notable that 43% of the surveyed papers didn't provide their resolution information, reducing significantly the possibilities for robustly comparing further works to their results.

Another observation, which can be made on the size of the search space used for achieving real-time UAV trajectory planning, is that more than a third of the surveyed papers simplified the problem to a 2 D map (see Figure 32). Among the papers that have used a 3D representation, more than a third did not provide the maximum height boundary of their search space. For further comparison it is essential to provide the full information with respect to the map size and the resolution of the search space to enable real-time achievement discussion. Moreover, the third dimension is required for the flyability of a UAV trajectory planner; hence the upper and lower bounds of the height need to be provided for a full characterization of the search space.

6.3 Real-Time World Representation

We have seen that the world representation defines the details taken into consideration by the UAV trajectory planner. To provide a firm comparison reference, in addition to the real-time deadline met by the UAV trajectory planner, it is essential to mention the environment modeling and its related computing time – when the environment modeling is used with the proposed UAV trajectory planner.

Figure 33 depicts the world representation that the surveyed papers selected. The first observation that can be drawn from this figure is the fact that, being geared towards dynamic environment, the majority (about 47%) of the real-time UAV trajectory planners worked directly with the raw data (2D and 3D grid map) avoiding the computing time required for environment modeling. The second point of interest is that RRT is the principal environment modeling that has been used. Initially, RRT was analyzed in comparison with other world representation (Wzorek and Doherty 2006) or in combination with other world representation (Redding et al. 2007). Then different smoothing techniques were tested with RRT (Kothari and Postlethwaite 2013), (Ramana et al. 2016), (Yang and Sukkarieh 2008), (Yang et al. 2010). Recently (Yang et al. 2014) worked at improving the RRT speed of convergence. (Lin and Saripalli 2014) and (Wen et al. 2015) have worked towards an iterative expansion of the RRT to support both local trajectory reactive planning and global trajectory planning. All these RRT researches integrated the environment modeling computing time within the trajectory planner computing time. Among the 13 other works that used environment modeling only (Jung et al. 2009), (Ghosh et al. 2011), (Omar and Gu 2009), (Ren and Huo 2010), (Yan et al. 2012) provided information about the environment modeling computing time: (Jung et al. 2009) and (Ghosh et al. 2011) provided an integrated computing time, while (Omar and Gu 2009), (Ren and Huo 2010), (Yan et al. 2012) provided the environment modeling computing time separately from the trajectory planner.

In summary here are the observations drawn from our real-time analysis:

- 1) While no common real-time condition has been aimed at by the surveyed papers, one could consider the 150 m safety radius (Federal Aviation Administration 2014) as the reference real-time condition to be met.

- 2) For further comparisons, it is essential to provide the full information about the map size and the resolution of the search space in order to be able to discuss real-time achievement.
- 3) The three dimensions are essential for a UAV trajectory planner to respect the UAV flyability and therefore the lower and upper boundaries of the height should also be provided.
- 4) While environment modeling can reduce the search space, its computing time needs to be presented with the results of the trajectory planner as UAV environment dynamically changes, requiring environment re-modeling.

Section 7. Embedded Criterion

We've seen that the challenge with embedded UAV trajectory planner is to have a large computing power within a small computing device that is energy wise. Figure 34 shows that 85% of the surveyed papers have simply used a PC without any consideration to the power consumption, nor to the size of the computing device.

Those who gave less considerations to the embedded criterion are the ones that even omitted to mention the computing device used, for which we can simply assume that they used PCs. Figure 35 demonstrates that Graphics Processing Unit (GPU) and Field Programmable Gate Array (FPGA) were the main substitutes to PCs as the principal computing device. (Palossi et al. 2016) demonstrated that their parallel implementation on a GPU saved between 95 to 98% in energy compared to their sequential one on the CPU of a PC. The energy saving is attributed to the reduced execution time of the parallel implementation. (Mueller et al. 2009) discussed how the lower clock frequency of the FPGA will necessarily use less power than a high clock frequency CPU. The same observation can be applied to Micro-controllers.

We now analyze the flyability of the surveyed researches that have considered these alternate computing devices to the CPU of a PC. The following papers did a GPU implementation of a UAV trajectory planner.

- 1) (Sanci and Isler 2011), (Çekmez et al. 2014), and (Hossain et al. 2014) simplified the UAV trajectory planning problem into a 2D Traveling Salesman Problem (TSP), where only the trajectory length was optimized through a GA implemented on a GPU.
- 2) (Çekmez et al. 2014) suggested an ACO on GPU to solve the 2D TSP.
- 3) (Palossi et al. 2016) designed a parallel implementation of the Dijkstra algorithm to allow real-time re-computing a 2D UAV trajectory in an unknown environment as the UAV explores the area, while avoiding discovered obstacles.

The main observation about these GPU implementations is that all of them simplified the search space into 2D representations and none of their trajectory planners took into consideration the aerodynamic constraints of the UAV.

Among the surveyed papers three did a FPGA implementation of their trajectory planner. (Allaire et al. 2009) did a partial implementation of a GA based 3D path planner on a FPGA. Their cost function, which evaluated the UAV turning radius, 3D terrain avoidance, obstacle avoidance and the maximum flyable altitude (Cocaud 2006), was running on a PC. (Kok et al. 2010) and (Kok et al. 2013) completed a full implementation of GA based 3D UAV trajectory planner on an FPGA. Their cost function considered the 3D terrain avoidance and the optimization of the trajectory length, without incorporating aerodynamic constraints.

(Jung et al. 2009) designed an UAV trajectory planner that used the wavelet multi-resolution environment modeling, the A* algorithm to generate a path and the B-Spline to smooth the path. Their approach used the iterative RH local planning method with no global planning. Their UAV trajectory planner was

embedded on-board an autopilot, which is based on the Rabbit RCM-3400 micro-controller (30 MHz with 512 KB RAM). This computing device limited their trajectory planner to a 2D representation.

In summary, here are the observations that can be drawn from our embedded consideration analysis.

- 1) From the surveyed papers, all those that implemented the full UAV trajectory planner on GPU, on FPGA or on micro-controller have not considered the full UAV aerodynamic constraints, nor the fuel and the power requirements.
- 2) Among the fully embedded trajectory planners, only two papers considered 3D terrain avoidance (instead of a 2D representation), while considering the trajectory length optimization as the only other criterion to be evaluated.
- 3) 27% of the surveyed papers didn't specify the hardware used for their implementation.
- 4) In addition to these hardware considerations, we noted that 47% of the surveyed papers have not specified the software used, which is also important information to be presented to enable future timing performance comparisons.

Section 8. Conclusion

In this paper, we surveyed 60 publications that mentioned some real-time computing achievement for UAV trajectory planners. With a review of the three stages of UAV trajectory planning (world representation – path generation – trajectory generation/ trajectory evaluation), we introduced the flyability, the real-time condition and the embedded aspect related to UAV trajectory planning. This provided the foundation for our analysis.

From our analysis with respect to flyability, real-time and the embedded aspect of UAV trajectory planning, we arrived at the conclusion that there are too many details omitted when UAS trajectory planner researches are presented in publications to allow for the possibility of giving strong comparison. To enable further improvements in UAV trajectory planning, an enabler for Class II and Class III UAV autonomous operations, we recommend the followings:

- 1) Further researches should always consider at least 3D terrain and obstacle avoidance.
- 2) Further works should focus on ways to improve the computation time of global trajectory planners.
- 3) A common real-time condition that could be considered for a future reference point is the 150 m safety radius (Federal Aviation Administration 2014), which is technology independent.
- 4) Full information of the implementation environment shall be provided to enable further comparison of real-time achievement; this should include at the minimum the answers to the following questions:
 - a. Is environment modeling used? If yes, what is its computing time?
 - b. What is the map size considered - in number of cells ($X \times Y$)?
 - c. What is the map resolution considered ($x \text{ m} \times y \text{ m}$)?
 - d. What is the height resolution considered (min & max height, or number of cells)?
 - e. What are the details of the HW used (PC, FPGA, GPU..., clock speed, memory available and operating system)?
 - f. What are the details of the SW used (programming language)?
- 5) Further researches should try to implement on embedded platforms UAV trajectory planner that consider the full UAV aerodynamic constraints, the fuel and the power requirements – all this within a 3D environment with obstacles to be avoided.

- 6) A benchmark testing environment should be developed for allowing comparison of UAV trajectory planning algorithms.

Acknowledgments. This work was founded in parts by the Directorate of Technical Airworthiness and Engineering Support 6 from the National Defence of Canada.

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Tables

Table 1. Autonomy Level Scale

Level	Level Descriptor
10	Fully Autonomous
9	Swarm Cognizance and Group Decision Making
8	Situational Awareness and Cognizance
7	Real-Time Collaborative Mission Planning
6	Dynamic Mission Planning
5	Real-Time Cooperative Navigation & Path Planning
4	Real-Time Obstacle/Event Detection & Path Planning
3	Fault/Event Adaptive Unmanned Air Vehicle
2	External System Independence Navigation (<i>e.g. Non-GPS</i>)
1	Automatic Flight Control
0	Remote Control

Table 2. Typical Characteristics of UAV

Heron (Israel Aerospace Industries MALAT Division 2014) (smaller Class III UAV)		Global Hawk (Northrop Grumman 2016) (bigger Class III UAV)

Wingspan:	16.6 m	Wingspan:	39.9 m
Max. Take-off Weight:	1200 kg	Max. Take-off Weight:	11,612 kg
Max. Payload Weight:	250 kg	Max. Payload Weight:	1,360 kg
Endurance:	20 to 45 hrs	Endurance:	32 hrs
Cruise Speed:	30 to 41 m/s	Cruise Speed:	159.5 m/s

Table 3: Environment Modeling Techniques

Technique	Description	Advantage/ Disadvantage	Figure
<i>Visibility graph</i> (summarized in (Souissi et al. 2013))	Similar to Navigation Mesh, consists in inflating the obstacle by a security distance of at least the size of the UAV. Corners of the inflated obstacles are then interconnected by straight lines so that the UAV, considered as a moving dot, can travel from one corner to another.	Forces the UAV to travel as close as possible to obstacles, which may not be the desired behavior in all scenarios	Figure 15
<i>Voronoi diagram</i> (summarized in (Souissi et al. 2013))	Consists of finding lines that are equidistant to all surrounding obstacles. The intersections of these lines are the points through which the UAV can travel.	Forces the UAV to travel as far as possible to obstacles, which may not be the desired behavior in all scenarios	Figure 16
<i>Quad-tree cell-decomposition</i> (summarized in (Souissi et al. 2013))	Consists of developing a reference tree; where if a specific node contains an obstacle then that node/leaf is split into four smaller nodes. The cells/nodes keep on being divided into smaller cells until the smallest cell-resolution available is reached. The octo-tree (described in (Cocaud 2006)) is a 3D version of the quad-tree concept.	The processing requirement for such reference trees becomes more intensive for a clustered 3D area and for high resolution maps.	Figure 17
<i>Wavelet Transform</i> (explained in (Jung and Tsiotras 2008))	Consists of using a high resolution global map with a fast mathematical transform operation to provide the high resolution around the UAV and a lower resolution further from the UAV. This transformation is continuously calculated as the UAV is progressing on its trajectory.	This cell decomposition allows more precise calculations near the UAV and a coarser/quicker evaluation further from the UAV.	Figure 18
<i>Probabilistic Road Map (PRM)</i> (explained in (Kavraki et al. 1996))	Consists of generating a fixed number of random points, which could be called milestones in the search space. Millstones within an obstacle are discarded. All remaining milestones are sequentially interconnected by straight lines, starting from the robot starting point. Straight line segments within obstacles are discarded. The remaining line segments become the edges through which the robot can travel collision free.	Probabilistic Roadmap doesn't guarantee the optimality of the solution.	Figure 19

Technique	Description	Advantage/ Disadvantage	Figure
<i>Rapidly-exploring Random Tree (RRT)</i> (introduced in (La Valle 1998))	Consists of generating iteratively new random vertexes of a path, starting at an initial position until the goal position is reached. New vertexes are generated in the obstacle-free space	RRT is a generic method that can be adapted in multiple ways to address the specifics of the problem (e.g.: integration of the UAV kinematic constraints; use of heuristics to guide the search towards the goal...)	Figure 20
<i>Pre-set of Waypoints</i>	Consists of simplifying the search space to a pre-set of waypoints that need to be visited by the UAV (e.g. in the case of a surveillance mission). The trajectory planning problem becomes an optimization problem to find the optimal sequence that will minimize the cost of traveling through these waypoints - this is a Traveling Salesman Problem (TSP) as explained in (Dantzig et al. 1954).	This approach requires either a prior knowledge of the desired waypoints and/or the use of a random waypoint generator.	Figure 21

Table 4. Simplistic Smoothing Techniques

Technique	Description	Advantage/ Disadvantage	Figure
<i>Dubins' Arc of Circle</i> (presented in (Dubins 1957))	It is proven that the shortest trajectory between two points (considering UAV position, heading and minimum turning radius) is composed of a straight line and arcs of circles (Dubins 1957).	The shortfall of that smoothing technique is that for small angle intersections there could be a significant long distance between the waypoint i and the smoothed waypoint P , which could lead to undesirable behavior like flying into no-fly zones or, even worse, into obstacles.	Figure 24
<i>Three Arcs of Circle</i> (presented in (Anderson et al. 2005))	It is proven (Anderson et al. 2005) that the shortest trajectory to go from the waypoint $i-1$ to waypoint $i+1$, by passing through the smoothed waypoint P , is gotten by the three arcs of circle smoothing technique.	The distance shortfall, of smoothing with a single arc of circle, is overcome by using three arcs of circle (Anderson et al. 2005), this allows to adjust precisely the distance between the waypoint i and the smoothed waypoint P .	Figure 25
<i>Spline</i> (explained in (Eslam Pour 2009))	This is a curve with a polynomial form that requires less parameter to compute than multiple arcs of circles.	Spline trajectories are necessarily longer than trajectories composed of lines and arcs of circles. Moreover, to the best of our knowledge, no effective aerodynamic constraint analysis of these curves has yet been developed. Numerical analysis methods would require complex computations on-board of the UAV, as every spline has its specific aerodynamic characteristics.	Figure 26
<i>3D Euler Spiral</i> (explained in (Harary and Tal 2010))	This curve ensures continuity at the acceleration level; however, only continuity at the velocity level is necessary to ensure the dynamic feasibility of a UAV trajectory.	The equation of a 3D Euler Spiral includes integral operators, which are even more computationally demanding than (Labonté 2009) equations.	Figure 27

Table 5. Flyability Evaluation Criteria

Publication	3D Representation	Collision	Power	Fuel	Smoothing	Length	Altitude	No-fly Zones
1 - Allaire (2009)	X	X			X	X	X	X
2 - Babei (2010)	X				X	X		
3 - Cekmez (2014)						X		
4 - Cekmez2 (2014)						X		
5 - ChenX (2013)	X	X			X	X		
6 - ChenX (2016)					X	X		X
7 - Chen Yang (2012)	X				X	X		X
8 - Chen Yingchun (2011)	X	X			X	X		X
9 - Cocaud (2006)	X	X			X	X	X	X
10 - Dong (2011)					X	X		X
11 - Ducard (2007)					X	X		X
12 - Gardi (2015)	X	X		X	X	X		X
13 - Ghosh (2011)					X	X		X
14 - Guanglei (2014)					X	X		X
15 - Guo (2012)	X	X			X	X		X
16 - Holub (2012)	X	X				X		X
17 - Hossain (2014)						X		
18 - Hota (2014)	X				X	X		
19 - Jung (2008)		X			X	X		
20 - Jung (2009)		X			X	X		X
21 - Kim (2008)						X		X
22 - Kok (2010)	X	X				X		
23 - Kok3 (2013)	X	X				X		
24 - Kothari (2013)						X		X
25 - Kuwata (2004)	X				X	X		X
26 - Lim (2010)					X	X		X
27 - Lin (2014)	X				X	X		X
28 - Ling (2015)	X	X			X	X		X
29 - Liu (2013)					X	X		X
30 - Newaz (2013)	X					X		X
31 - Omar (2009)						X		X
32 - Ozalp (2013)	X	X				X		X
33 - Palossi (2016)						X		X
34 - Ramana (2016)	X				X	X		X
35 - Redding (2007)						X		X
36 - Ren (2010)	X	X			X	X	X	
37 - Roberge (2013)	X	X	X	X	X	X	X	X
38 - Roberge2 (2014)	X	X	X	X	X	X	X	X
39 - Ronfle-Nadeau (2009)					X			X
40 - Sanci (2011)						X		
41 - Swartzentruber (2010)	X	X			X	X		X
42 - Ten Harmsel (2016)	X	X	X	X		X		
43 - Turnbull (2015)					X	X		X
44 - Wan (2011)	X	X			X	X		X
45 - WangQ (2014)	X	X			X	X	X	X
46 - WangZ (2014)					X	X		X
47 - Weiß (2006)	X	X			X	X		
48 - Wen (2015)	X	X			X	X		X
49 - Wzorek (2006)					X	X		X
50 - Xiaowei (2014)					X	X		X
51 - Yan (2012)	X	X			X	X		X
52 - YangK (2008)		X			X	X		
53 - YangK (2010)		X			X	X		
54 - YangL (2014)	X				X	X		X
55 - Yao (2015)	X				X	X	X	X
56 - Yu (2009)					X	X		X
57 - Zejun (2015)	X	X			X	X		
58 - Zhan (2014)	X	X			X	X	X	X
59 - Zheng (2003)	X	X				X	X	X
60 - Zhuoning (2010)		X				X		X

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