Navigation and guidance strategy online planning and execution for autonomous UAV

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1 Introduction

Unmanned Aerial Vehicles (UAVs) can nowadays, in certain conditions, be employed for different applications ranging from service robotics to surveillance applications in network monitoring or in search and rescue missions. For this aim, and for widening the UAV application field, it is mandatory for an UAV to have some capabilities for autonomous safe navigation in cluttered environments. This navigation capability includes environment mapping, localization and guidance functionalities relative to the environment. Especially, one can find intensive research work proposing different UAV relative localization and guidance solutions based on vision: visual odometry, visual SLAM (Simultaneous Localization and Mapping), visual servoing, etc. Such solutions can be embedded in the UAV onboard flight system as an alternative navigation function to the nominal ones (in most cases, the GPS/INS localization with the waypoint navigation).

However, the decision of switching the navigation and guidance modes among those available onboard in function of the environment has not been studied much by the scientific community. In this context, the objective of this thesis is to develop an *online planning approach to decide on the navigation and the guidance strategy, with which an UAV can fly to a goal in an efficient (minimum distance, minimum time) and safe (avoiding obstacles) way with its navigation capabilities.* The output of such a planner will define a flight path along with the navigation and guidance modes to be used on each segment of the path.

2 Scientific context and related works

As stated above, most outdoor UAVs have an automatic navigation capability based on the GPS/INS localization and waypoint navigation. However, this kind of navigation depends on the quality of the perceived GPS signal. It is known that the GPS signal can be masked or degraded due to occlusion in cluttered environments. [Kleijer et al., 2009] proposes a method to predict the availability of the GPS signal from an environment model. It is known that the INS-only navigation solution diverges very quickly due to accumulation of inertial measurement bias. Consequently, UAV will lose its automatic flight capability in the absence of GPS signal if it does not have any alternative navigation and guidance system which do not rely on GPS information. Such alternative systems based on 2D or 3D vision sensors have been studied by researches, especially for UAV indoor operation where no GPS signal is available. For example, a variety of visual odometry and SLAM techniques have been proposed to estimate UAV state by either using purely vision or by fusing vision with INS and/or other available sensors ([G. Chowdhary and Shein, 2013]−[S. Lynen and Siegwart, 2013] and many others). Landmark or map-based navigation methods have been also investigated [Karpenko et al., 2015]. Besides, visual servoing approaches can be applied to UAV guidance and control relative to its environment without using UAV absolute state. For example, UAV terrain following, corridor navigation or landing can be achieved by using optical flow information directly in flight guidance and control [B. Herisse and Russotto, 2010, S. Zingg and Siegwart, 2010].

It is important to notice that the applicability of such approaches depends on how the environment is modeled and perceived. For instance, the landmark-based localization is operational only when such a landmark is in the field of view of the UAV onboard camera, or visual SLAM and optical flow techniques require rich texture on the image.

Surprisingly, the decision on which type of navigation and guidance modes one should use during different phases of the mission in function of the surrounding environment has not been much studied by the scientific community. On this subject, we have proposed the first approach that explores the use of classical planning algorithms to obtain a flight plan (i.e., a list of waypoints) and the navigation and guidance modes associated to each path segment between two consecutive waypoints of the flight plan [Watanabe et al., 2016].

Nevertheless, this approach has some limitations. For instance, in the work of [Watanabe et al., 2016], the path execution uncertainty is propagated along the path according to a model associated with each combination of the navigation and guidance modes. Then it is used for the traversability check and the cost calculation, but not really treated as uncertainty in node transitions (i.e. UAV displacement). That is, with such path execution uncertainty, the node transition should include more than one possibilities with corresponding probabilities for an applied guidance law. Hence, the planner needs to deal with this "uncertain" node transition associated with the path execution uncertainty. Moreover, the approach proposed in [Watanabe et al., 2016] does not consider any "observation" process. During a mission execution, the UAV onboard system is capable to detect a current availability of each navigation and guidance mode (e.g. GPS signal reception, landmark detection, etc.). Therefore, this approach must adapt the model and replan a strategy online in function of this observation result.

Planning approaches that consider uncertainties have treated different problems:

scheduling waypoints under the travel execution time uncertainty [Evers et al., 2014], planning strategies to identify targets [Chanel et al., 2013], treating the uncertainty on the formal underling framework[Bertuccelli et al., 2012] or over the different possible measurements available during the path execution [Van Den Berg et al., 2011]. During the mission execution, it is necessary to evaluate (observe) the current situation regarding the mission phase, the services and resources available onboard the UAV in order to switch over (act) to a different state. However, the observation is not necessarily perfect or deterministic. For example, it is possible to obtain a map of the probabilities of the GPS availability for a given environment [Kleijer et al., 2009], but the effective availability is only known once there [Van Den Berg et al., 2011]. Another thing is that it is possible to model a state transition between two estimated execution states for each navigation and guidance modes. These estimated execution states, or belief states, are often described by a Gaussian function [Van Den Berg et al., 2011, Bai et al., 2014, Delamer et al., 2017b] with the uncertainty.

Formal models from optimal control theory can be applied to the sequential decision making problem under uncertainties. Partially Observable Markov Decision Process (POMDP) [Smallwood and Sondik, 1973, Kaelbling et al., 1998] proposes an elegant framework to handle decisional problems where the resulting state transition after a selected action is uncertain, and where the observations of discrete states are partial or imprecise. It should be noted that, in this problem of navigation and guidance strategy planning, the state estimation (localization) and path execution (guidance) results (= belief state) are defined over a continuous space. Some researchers have worked in enriching the POMDP framework to handle with continuous state space [Brooks et al., 2006], and have proposing algorithmic approaches [Brooks et al., 2006, Brechtel et al., 2013] to solve such models.

The first difficulty in applying the POMDP to continuous state space for such a navigation and guidance planning problem is the definition of the transition and observation functions over states [Delamer et al., 2017b]. In this particular problem, the transition function depends on the current belief state (not the state) as well as on a selected action, which includes the UAV displacement and the choice of its navigation and guidance modes [Delamer et al., 2017a]. No additional information concerning the system state, even an imprecise and/or partial one, is available [Delamer et al., 2019]. The only information that can be exploited to define an observation function is the one concerning the availability of each navigation and guidance mode . For example, the actual GPS signal availability at each location is not known a priori, but only a probability of such an availability can be modeled in certain conditions. In this sense, the semantics of observations in the POMDP context changes, because knowing the current availability of the navigation and guidance modes at a given instant does not give additional/directly information (correction) on the state estimation uncertainty. A current PhD candidate have proposed approaches and algorithms to solve such a problem [Delamer et al., 2018, Delamer et al., 2019], see Figure 1. His approach: (i) exploits a factorization of states variables in fully and non observable states variables while considering states transition functions that includes the path execution error generated by

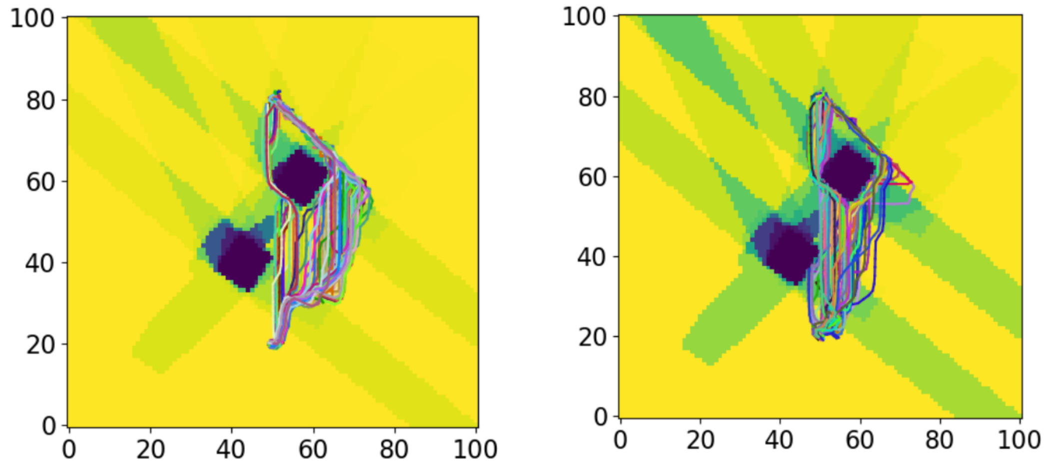

Figure 1: Example of results for a $100m \times 100m$ benchmark problem. Different paths are obtained given different GPS availabilty probability maps.

the navigation solution being uses; and (ii) it proposes a promising solving algorithm for Mixed-Observability Stochastic Shortest Path (MO-SSP) problems (POMDP goal oriented problems). But much more research is need to increase the efficience of these proposals, in particular concerning evolutions on the modelling to decrease computation time needed for planning.

The second difficulty is to make the planner run onboard in real-time to adapt the model and replan when necessary, for instance when considering a new goal state, or upon new perception of the environment, or when the UAV state estimation during its flight does not match anymore with the model. Considering only when the model and the goal do not change, and for a finite-dimension discrete state, action and observation spaces, it is possible to compute a policy for every possible reachable belief state before the mission. However, it is not so easy when having a continuous state space and a dynamic environment.

To our knowledge, there is no current approach able to solve a continuous state space POMDP online considering a new goal or new perception of the environment. This can be explained by the exponential complexity of such a model, which may be prohibitive for an embedded computation. Since some years, we have proposed AMPLE - Anytime Meta Planner, a generic framework, to solve planning problems online during the mission execution, and it has been applied to solve a discrete POMDP problems [Chanel et al., 2013, Chanel et al., 2014, Chanel et al., 2019]. However, this framework can be extended so far being able to handle with such a navigation and guidance strategy online planning and execution.

2.1 Thesis Objective

This project aims to study Mixed-Observability Stochastic Shortest Path (MO-SSP) models to address the planning problem of the navigation and the guidance strategy for an autonomous UAVs that evolve in cluttered environments. In particular to handle with the possible evolutions of the environment, including mission goals, during the execution which could engender a need of a continuous and online re-planning process.

3 Innovation

The problem treated in this project is located in the frontier at two different research areas: the automated planning domain and the GNC (guidance, navigation and control) domain. In a robotic architecture, these areas are often perceived in an hierarchical order where a mission planner sends commands to GNC components without caring how these commands will be executed. The originality of this project lies in the aspect of proposing a framework where the performances and choices of the lower-level GNC systems are taken into account in the upper-level mission planning. This project is expected to provide with methodological solutions to advance the interaction between mission planning (upper-level) and acting modules (lower-level) in an embedded deliberative architecture in order to obtain a safe mission execution policy.

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