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Cooperative Sensing and Path Planning in a Multi-vehicle Environment ⋆

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Abstract: We study the cooperation of an unmanned ground vehicle (UGV) and micro air vehicle (MAV) in a path planning task. The UGV requests the MAV to execute observation missions which provide stereo image data on areas that the UGVs sensors cannot observe. The problem is formulated as a partially observable decision making problem. The solution is a decision policy that determines conditional on current information whether the UGV should move along a certain route or request an observation mission. A case example for a real-world demonstration of the cooperative path planning task is described. We discuss the features of single-vehicle control systems and propose a multi-vehicle communication framework that is tolerant against communication breaks.

Keywords: Autonomous mobile robots, Path planning, Dynamic programming, Markov decision processes, Stereo vision

1. INTRODUCTION

Cooperation between humans and robots or among several unmanned vehicles has been recognized as a technology that has the potential to enhance the capabilities of all participants of the cooperative action. Ideally, the result is a situation where the whole is greater than the sum of its parts: the support provided by other vehicles will allow each individual vehicle to complete their tasks in a safer and more efficient manner.

Micro aerial vehicles (MAVs) have recently received a great amount of attention in research literature. MAVs have many abilities that are complementary to those of unmanned ground vehicles (UGVs) that make them a suitable candidate for effectively supporting UGV missions ranging from path planning to exploration and manipulation tasks. In particular, the constraints for motion and sensing are different for the two vehicle types. MAVs are unaffected by any obstacles on the ground that prevent an UGV from moving or sensing beyond them. The ability of MAVs to sense the environment from a higher vantage point enables them to provide observation data that is not available to UGVs. The high velocities that MAVs are capable of further increase the area that can be sensed.

However, MAVs are subject to constraints such as limited battery power and uncertain localization that limit their applicability. Thus, it is necessary to plan the use of MAV resources in supporting the completion of the UGVs task. In this paper, we consider the problem of a MAV supporting path planning of a UGV in a partially observable environment. The MAV acts as an additional observation resource that is commanded by the UGV. The planning problem consists of jointly finding the optimal UGV and MAV action to perform, conditional on 1) the current information on the environment state and 2) expected future data obtained by each sensing action of the MAV. We formulate the problem as a general partially observable Markov decision process (POMDP) (Kaelbling et al., 1998) that is solved applying algorithms suitable to the specific type of environment and vehicle models applied in each case. Along with the formulation of the problem, we present a concrete case example and analyze the implied requirements on the system structure, for instance from the point of view of multi-vehicle communication. Relevant system components are identified and described, providing a basis for an eventual real-world demonstration of the proposed system.

The remainder of the paper is organized as follows. We briefly describe the basic problem of cooperative path planning in Section 2. A case example of the problem is described in Section 3. In Section 4, we review the overall architecture for facilitation of cooperation between a MAV and an UGV, including single-vehicle operation and multi-vehicle operation with communication. Section 5 introduces the hardware for a potential use case. Relevant aspects of their measurement and control with respect to supporting the path planning task are discussed in Section 6. Finally, Section 7 concludes the paper.

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2. COOPERATIVE PATH PLANNING

Consider an UGV navigating in a partially observable environment, supported by a MAV that can provide data to assist in choosing paths that have a low cost, e.g. they are not blocked by obstacles, or are easy to traverse considering the capabilities of the UGV. We assume that the MAV is commanded by the UGV, allowing treatment as a single-agent decision-making problem. Let s_t denote the state of the system at time t, including both the states of the UGV and MAV, and the state of the environment being navigated. Since the environment and possibly the states of the vehicles are partially observable, to describe current information, a probability density function (pdf) $p(s_t) \equiv b_t$ over the state, called the belief state, is maintained to model the current information.

At time t, the UGV must make a decision $a_t \in A_m \cup A_s$ that is either in the space of movement actions A_m carried out by the UGV or sensing actions A_s carried out by the MAV. The action effects are described by a stochastic transition function $p(s_{t+1} \mid s_t, a_t)$. If a sensing action is selected, an observation $z_{t+1} \in Z$ is provided as feedback according to a probabilistic observation model $p(z_{t+1} \mid s_{t+1}, a_t)$. Let $b_{t+1} \equiv \tau(b_t, a_t, z_{t+1})$ denote the Bayesian filtering operation that recursively estimates the new belief state given the current belief, action and observation.

Assuming the objective of the UGV is to reach the goal while minimizing the prior expectation of the cumulative sum of costs $C(s_t, a_t)$ accrued along the way, the problem can be formally stated as a recursive dynamic programming problem (omitting the time indices of the variables above)

$$\begin{aligned} Q_{t+1}(b,a) &= \mathbb{E}\Big[C(s,a) \\ &\quad + \gamma \sum_{z \in Z} p(z \mid b,a) J_t(\tau(b,a,z)) \Big| b\Big] \\ J_t(b) &= \min_{a \in A_m \cup A_s} Q_t(b,a), \end{aligned} \tag{1}$$

starting from $Q_1(b,a) = \mathbb{E}\left[C(s,a) \mid b\right]$,where $\gamma \in [0,1)$ is a discount factor determining the relative importance of immediate and future costs and $p(z \mid b,a)$ is the prior probability of observing z. The cost functional J_t determines the expected minimum cost reachable over a horizon of t decisions, and the desired solution is an optimal policy $\pi^* = [\pi_1^*, \ldots, \pi_T^*]^\top$ for some desired horizon T – possibly infinite – where $\pi_t^* = \operatorname{argmin}_a Q_t(b,a)$ determines the optimal action to execute when t decisions remain. This problem is an instance of a partially observable Markov decision process (POMDP) (Kaelbling et al., 1998).

Depending on the specifics of how the environment is modeled and how the cost function $C(s_t, a_t)$ is defined, there are various practical ways to solve the problem. In particular, we are considering to model the environment as a directed acyclic graph (DAG). The case where sensing actions do not have any cost and the objective is to minimize the expected value of the sum of costs has been studied earlier e.g. in Fu (2001); Gao and Huang (2012). Currently, we have examined cases with a nonzero cost for sensing and various observation modalities for the MAV, defining the cost function such that the objective is either to maximize the probability of reaching the goal with a cost under some critical cost (Lauri et al., 2015), or to minimize the expected cost of reaching the goal plus a term penalizing for taking actions that have a high risk, i.e. uncertainty about the resulting cost (Ropponen et al., 2015).

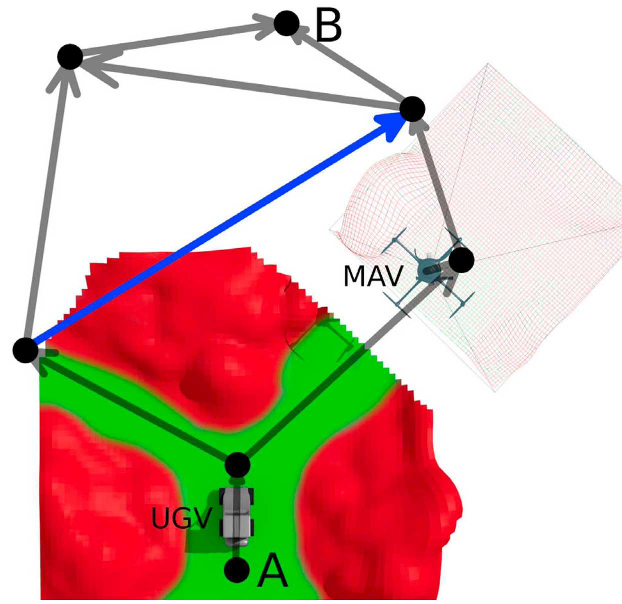

Fig. 1. The case where the UGV is traveling from node A to node B. The red color represents obstacles and the green color marks the areas where the UGV can travel. The underlying directed acyclic graph is depicted by the dot markers as nodes and arrows as edges. The blue arrow represents decision to be done after the initial planning step.

3. CASE EXAMPLE

In this section, we present a concrete case example of the co-operation framework for the UGV and MAV presented above. This case is the basis for a real-world demonstration of the system planned and currently being implemented.

Consider an UGV traveling from node A to node B, as shown in Figure 1. The UGV must reach point B while traversing along a given roadmap, presented as a DAG. The traversal costs of the graph edges are however unknown. The UGV operates autonomously with only the goal node B as an input. The UGV must plan both its traversal actions on the graph and possible execution of observation missions by the MAV, which will result in an observation of the traversal cost, taking into account the new information that it will receive. This uncertain information on edge traversal costs models the case where the potential paths to the target node B are known (graph topology), but their relative attractiveness in the cumulative cost sense is not certain.

Once a measurement mission is initiated, the MAV provides the UGV with additional information about the environment. The MAV will be operating autonomously while its in the air, receiving only a mission in the form of an edge to be observed from the UGV. MAV will keep transmitting its location and other status data back to the UGV during the mission. Terrain elevation is measured by