Safe Sequential Path Planning of Multi-Vehicle Systems Under Disturbances and Imperfect Information

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Abstract— **Multi-UAV systems are safety-critical, and guarantees must be made to ensure no undesirable configurations such as collisions occur. Hamilton-Jacobi (HJ) reachability is ideal for analyzing such safety-critical systems because it provides safety guarantees and is flexible in terms of system dynamics; however, its direct application is limited to small-scale systems typically of no more than two vehicles because of the exponentially-scaling computation complexity. Previously, the sequential path planning (SPP) method, which assigns strict priorities to vehicles, was proposed; SPP allows multi-vehicle path planning to be done with a linearly-scaling computation complexity. However, the previous SPP formulation assumed that there are no disturbances in the vehicle dynamics, and that every vehicle has perfect knowledge of the position of higher-priority vehicles. In this paper, we make SPP more practical by providing three different methods to account for disturbances in dynamics and imperfect knowledge of higher-priority vehicles' states. Each method has different assumptions about information sharing. We demonstrate our proposed methods in simulations.**

I. Introduction

Recently, there has been an immense surge of interest in using unmanned aerial systems (UASs) for civil purposes. The applications of UASs extend well beyond package delivery, and include aerial surveillance, disaster response, and other important tasks [1]–[5]. Many of these applications will involve unmanned aerial vehicles (UAVs) flying in urban environments, potentially in close proximity of humans. As a result, government agencies such as the Federal Aviation Administration (FAA) and National Aeronautics and Space Administration (NASA) of the United States are urgently trying to develop new scalable ways to organize an air space in which potentially thousands of UAVs can fly together [6]–[8].

One essential problem that needs to be addressed is how a group of vehicles in the same vicinity can reach their destinations while avoiding collision with each other. In some previous studies that address this problem, specific control strategies for the vehicles are assumed, and approaches such as induced velocity obstacles have been used [9]–[11]. Other researchers have used ideas involving virtual potential fields to maintain collision avoidance while maintaining a specific formation [12], [13]. Although interesting results emerge from these studies, simultaneous trajectory planning and collision avoidance were not considered.

Trajectory planning and collision avoidance problems in safety-critical systems have been studied using reachability analysis, which provides guarantees on the success and safety of optimal system trajectories [14]–[19]. In this context, one computes the reachable set, defined as the set of states from which the system can be driven to a target set. Reachability analysis has been successfully used in applications involving systems with no more than two vehicles, such as pairwise collision avoidance [15], automated in-flight refueling [20], and many others [21], [22]. Despite the advantages of reachability analysis, it cannot be directly applied to complex high dimensional systems involving multiple vehicles. Reachable set computations involve solving a Hamilton-Jacobi (HJ) partial differential equation (PDE) on a grid representing a discretization of the state space, causing computation complexity to scale exponentially with system dimension.

In [23], the authors presented sequential path planning (SPP), in which vehicles are assigned a strict priority ordering. Higher-priority vehicles ignore the lower-priority vehicles, which must take into account the presence of higher-priority vehicles by treating them as induced time-varying obstacles. Under this structure, computation complexity scales just *linearly* with the number of vehicles. In addition, a structure like this has the potential to flexibly divide up the airspace for the use of many UAVs; this is an important task in NASA's concept of operations for UAS traffic management [8].

The formulation in [23], however, ignores disturbances and assumes perfect information about other vehicles' trajectories. In presence of disturbances, a vehicle's state trajectory evolution cannot be precisely known *a priori*; thus, it is impossible to commit to exact trajectories as required in [23]. In such a scenario, a lower-priority vehicle needs to account for all possible states that the higher-priority vehicles could be in. To do this, the lower-priority vehicle needs to have some knowledge about the control policy used by each higher-priority vehicle. Unfortunately, perfect information about other vehicles' control strategies cannot always be realistically assumed. The main contribution of this paper is to take advantage of the computation benefits of the SPP scheme while resolving some of its practical challenges. In particular, we achieve the following:

- incorporate disturbances into the vehicle models,
- analyze three different assumptions on the control strategy information to which lower priority vehicles may have access to,

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- for each assumed information pattern, we propose a reachability-based method to compute the induced obstacles and the reachable sets that guarantee collision avoidance as well as successful transit to the destination.

II. Problem Formulation

Consider N vehicles, denoted $Q_i, i = 1, \dots, n$, whose dynamics are described by the ordinary differential equation

$$\begin{aligned} &\dot{x}_i = f_i(t, x_i, u_i, d_i), \quad t \le t_i^{\text{STA}} \\ &u_i \in \mathcal{U}_i, d_i \in \mathcal{D}_i, \quad i = 1, \dots, N \end{aligned} \tag{1}$$

where $x_i \in \mathbb{R}^{n_i}$, u_i denote the state and control of ith vehicle Q_i respectively, and d_i denotes the disturbance experienced by Q_i. In general, the physical meaning of x_i and the dynamics f_i depend on the specific dynamic model of Q_i, and need not be the same across the different vehicles. t_i^{STA} in (1) denotes the scheduled time of arrival of Q_i.

We assume that the control functions $u_i(\cdot), d_i(\cdot)$ are drawn from the set of measurable functions[1]. In addition, we assume that the disturbances $d_i(\cdot)$ are drawn from Γ, the set of non-anticipative strategies [15], defined as follows:

$$\begin{aligned} &\Gamma := \{\mathcal{N} : \mathbb{U}_i \to \mathbb{D}_i \mid u_i(r) = \hat{u}_i(r) \text{ a. e. } r \in [t, s] \\ &\Rightarrow \mathcal{N}[u_i](r) = \mathcal{N}[\hat{u}_i](r) \text{ a. e. } r \in [t, s]\} \end{aligned} \tag{2}$$

For convenience, we will use the sets $\mathbb{U}_i, \mathbb{D}_i$ to denote the set of functions from which the control and disturbance functions $u_i(\cdot), d_i(\cdot)$ can be drawn. We assume that $f_i(t, x_i, u_i, d_i)$ is bounded, Lipschitz continuous in x_i for any fixed t, u_i, d_i, and measurable in t, u_i, d_i for each x_i. Thus, given any initial state x_i^0 and any control function $u_i(\cdot)$, there exists a unique continuous trajectory $x_i(\cdot)$ solving (1) [24].

Let $p_i \in \mathbb{R}^p$ denote the position of Q_i; note that p_i in most practical cases would be a subset of the state x_i. Denote the rest of the states h_i, so that $x_i = (p_i, h_i)$. Prior to its departure, each vehicle Q_i is assumed to be at the state x_{i0}. Under the worst case disturbance, each vehicle aims to get to some set of target states, denoted $\mathcal{T}_i \subset \mathbb{R}^{n_i}$, by some scheduled time of arrival t_i^{STA}. On its way to $\mathcal{T}_i$, each vehicle must avoid the danger zones $\mathcal{A}_{ij}(t)$ of all other vehicles $j \neq i$ for all time. In general, the danger zone can be defined to capture any undesirable configurations between Q_i and Q_j. In this paper, we define $\mathcal{A}_{ij}(t)$ as

$$\mathcal{A}_{ij}(t) = \{x_i \in \mathbb{R}^{n_i} : \|p_i - p_j(t)\|_2 \le R_c\} \tag{3}$$

the interpretation of which is that a vehicle is in another vehicle's danger zone if the two vehicles are within a Euclidean distance of R_c apart. The joint path planning problem is depicted in Fig. 1.

The problem of driving each of the vehicles in (1) into their respective target sets $\mathcal{T}_i$ would be in general a differential game of dimension $\sum_i n_i$. However, due to the exponential scaling of the complexity with the problem dimension, an optimal solution is computationally intractable even for $N > 2$, with n_i as small as 3.

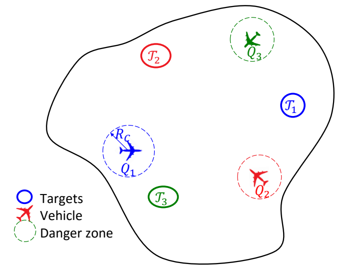

Fig. 1: Problem setup.

In this paper, we assume that vehicles have assigned priorities as in the SPP method [23]. While traveling to its target set, a vehicle may ignore the presence of lower-priority vehicles, but must take full responsibility for avoiding higher-priority vehicles. Since the analysis in [23] did not take into account the presence of disturbances d_i and limited information available to each vehicle, we extend the work in [23] to consider these practically important aspects of the problem. In particular, we answer the following inter-dependent questions that were not previously addressed:

1) How can each vehicle guarantee that it will reach its target set without getting into any danger zones, despite the disturbances it experiences?
2) How can each vehicle take into account the disturbances that other vehicles experience?
3) How should each vehicle robustly handle situations with limited information about the state, control policy, and intention of other vehicles?

Throughout the paper, we will assume that the priority ordering is given, and derive safe optimal trajectories based on the given priority ordering. The way to assign priorities is not the focus of this paper, but this important problem will be considered as a part of future work.

III. Background

This section provides a brief summary of [23], in which the SPP scheme is proposed under perfect information and absence of disturbances. Here, the dynamics of Q_i becomes

$$\begin{aligned} &\dot{x}_i = f_i(t, x_i, u_i), \quad t \le t_i^{\text{STA}} \\ &u_i \in \mathcal{U}_i, \quad i = 1, \dots, N \end{aligned} \tag{4}$$

where the difference compared to (1) is that the disturbance d_i is no longer a part of the dynamics.

In order to make the N-vehicle path planning problem safe and tractable, a reasonable structure is imposed to the problem: the vehicles are assigned a strict priority ordering. When planning its trajectory to its target, a higher-priority vehicle can disregard the presence of a lower-priority vehicle. In contrast, a lower-priority vehicle must take into account the presence of all higher-priority vehicles, and plan its trajectory in a way that avoids the higher-priority vehicles' danger zones. For convenience and without lost of generality, let Q_i be the vehicle with the ith highest priority.

[1] A function $f : X \to Y$ between two measurable spaces (X, Σ_X) and (Y, Σ_Y) is said to be measurable if the preimage of a measurable set in Y is a measurable set in X, that is: $\forall V \in \Sigma_Y, f^{-1}(V) \in \Sigma_X$, with Σ_X, Σ_Y σ-algebras on X,Y.

Under the above convention, each vehicle Q_i must take into account time-varying obstacles induced by vehicles $Q_j, j < i$, denoted $\mathcal{O}_i^j(t)$, and represent the set of states that could possibly be in the danger zone of Q_j. Optimal safe path planning of each lower-priority vehicle Q_i then consists of determining the optimal path that allows Q_i to reach its target $\mathcal{T}_i$ while avoiding the time-varying obstacles $\mathcal{G}_i(t)$, defined by

$$\mathcal{G}_i(t) = \bigcup_{j=1}^{i-1} \mathcal{O}_i^j(t) \tag{5}$$

Such an optimal path planning problem can be solved by computing a backward reachable set (BRS) $\mathcal{V}_i(t)$ from a target set $\mathcal{T}_i$ using formulations of HJ variational inequalities (VI) such as [14], [16], [17], [19]. For example, to compute BRSs under the presence of time-varying obstacles, the authors in [17] augment system with the time variable, and then applied reachability theory for time-invariant systems. To avoid increasing the problem dimension and save computation time, for the simulations of this paper we utilize the formulation in [19], which does not require augmentation of the state space with the time variable.

Starting from the highest-priority vehicle Q_1, one computes the BRS $\mathcal{V}_1(t)$, from which the optimal control and optimal trajectory $x_1(\cdot)$ to the target $\mathcal{T}_1$ can be obtained. Under the absence of disturbances and perfect information, the obstacles induced by a higher-priority vehicle Q_j, starting with $j = 1$, for a lower-priority vehicle Q_i is simply the danger zone centered around the position $p_j(\cdot)$ of each point on the trajectory:

$$\mathcal{O}_i^j(t) = \{x_i : \|p_i - p_j(t)\| \leq R_c\} \tag{6}$$

Given $\mathcal{O}_i^j(t), j < i$, and continuing with $i = 2$, the optimal safe trajectories for each vehicle Q_i can be computed. All of the trajectories are optimal in the sense that given the requirement that Q_i must arrive at $\mathcal{T}_i$ by time t_i^{STA}, the latest departure time t_i^{LDT} and the optimal control $u_i^*(\cdot)$ that guarantees arrival by t_i^{STA} can be obtained.

To compute $\mathcal{V}_i(t)$ using the method in [19], we solve the following HJ VI:

$$\begin{aligned} \max\Big\{ &\min\left\{D_t V_i(t,x_i) + H_i\left(t,x_i,D_{x_i}V_i\right),\right. \\ &\left. l_i(x_i) - V_i(t,x_i)\right\}, -g_i(t,x_i) - V_i(t,x_i)\Big\} = 0 \\ &t \leq t_i^{\text{STA}} \\ &V_i(t_i^{\text{STA}}, x_i) = \max\left\{l_i(x_i), -g_i(0,x_i)\right\} \end{aligned} \tag{7}$$

$$H_i\left(t,x_i,\lambda\right) = \min_{u_i \in \mathcal{U}_i} \lambda \cdot f_i(t,x_i,u_i) \tag{8}$$

where λ is the gradient of the value function, $D_{x_i}V_i$, and $l_i(x_i), g_i(t,x_i), V_i(t,x_i)$ are implicit surface functions representing the target $\mathcal{T}_i$, the time-varying obstacles $\mathcal{G}_i(t)$, and the backward reachable set $\mathcal{V}_i(t)$, respectively:

$$\begin{aligned} x_i \in \mathcal{T}_i &\Leftrightarrow l_i(x_i) \leq 0 \\ x_i(t) \in \mathcal{G}_i(t) &\Leftrightarrow g_i(t,x_i) \leq 0 \\ x_i(t) \in \mathcal{V}_i(t) &\Leftrightarrow V_i(t,x_i) \leq 0 \end{aligned} \tag{9}$$

The optimal control is given by

$$u_i^*\left(t,x_i\right) = \arg\min_{u_i \in \mathcal{U}_i} \lambda \cdot f_i(t,x_i,u_i) \tag{10}$$

IV. Disturbances and Incomplete Information

Disturbances and incomplete information significantly complicate the SPP scheme. The main difference is that the vehicle dynamics satisfy (1) as opposed to (4). Committing to exact trajectories is therefore no longer possible, since the disturbance $d_i(\cdot)$ is *a priori* unknown. Thus, the induced obstacles $\mathcal{O}_i^j(t)$ are no longer just the danger zones centered around positions. We present three methods to address the above issues. The methods differ in terms of control policy information that is known to a lower-priority vehicle, and have their relative advantages and disadvantages depending on the situation. The three methods are as follows:

- **Centralized control**: A specific control strategy is enforced upon a vehicle; this can be achieved, for example, by some central agent such as an air traffic controller.
- **Least restrictive control**: A vehicle is required to arrive at its targets on time, but has no other restrictions on its control policy. When the control policy of a vehicle is unknown, but its timely arrive at its target can be assumed, the least restrictive control can be safely assumed by lower-priority vehicles.
- **Robust trajectory tracking**: A vehicle declares a nominal trajectory which can be robustly tracked under disturbances.

In general, the above methods can be used in combination in a single path planning problem, with each vehicle independently having different control policies. Lower-priority vehicles would then plan their paths while taking into account the control policy information known for each higher-priority vehicle. For clarity, we will present each method as if all vehicles are using the same method of path planning.

In addition, for simplicity of explanation, we will assume that no static obstacles exist. In the situations where static obstacles do exist, the time-varying obstacles $\mathcal{G}_i(t)$ simply become the union of the induced obstacles $\mathcal{O}_i^j(t)$ in (5) and the static obstacles.

A. Method 1: Centralized Control

The highest-priority vehicle Q_1 first plans its path by computing the BRS (with $i = 1$)

$$\begin{aligned} \mathcal{V}_i(t) = \{x_i : &\exists u_i(\cdot) \in \mathbb{U}_i, \forall d_i(\cdot) \in \mathbb{D}_i, x_i(\cdot) \text{ satisfies (1)}, \\ &\forall s \in [t, t_i^{\text{STA}}], x_i(s) \notin \mathcal{G}_i(s), \\ &\exists s \in [t, t_i^{\text{STA}}], x_i(s) \in \mathcal{T}_i\} \end{aligned} \tag{11}$$

Since we have assumed no static obstacles exist, we have that for $Q_1, \mathcal{G}_1(s) = \emptyset \ \forall s \leq t_i^{\text{STA}}$, and thus the above BRS is well-defined. This BRS can be computed by solving the HJ VI (7) with the following Hamiltonian:

$$H_i\left(t,x_i,\lambda\right) = \min_{u_i \in \mathcal{U}_i} \max_{d_i \in \mathcal{D}_i} \lambda \cdot f_i(t,x_i,u_i,d_i) \tag{12}$$

where $l_i(x_i), g_i(t,x_i), V_i(t,x_i)$ are implicit surface functions representing the target $\mathcal{T}_i, \mathcal{G}_i(t), \mathcal{V}_i(t)$, respectively. From the BRS, we can obtain the optimal control

$$u_i^*(t,x_i) = \arg\min_{u_i\in\mathcal{U}_i}\max_{d_i\in\mathcal{D}_i} \lambda \cdot f_i(t,x_i,u_i,d_i) \tag{13}$$

Here, as well as in the other two methods, the latest departure time t_i^{LDT} is then given by $\arg\sup_t x_{i0} \in \mathcal{V}_i(t)$.

If there is a centralized controller directly controlling each of the N vehicles, then the control law of each vehicle can be enforced. In this case, lower-priority vehicles can safely assume that higher-priority vehicles are applying the enforced control law. In particular, the optimal controller for getting to the target, $u_i^*(t,x_i)$ can be enforced. In this case, the dynamics of each vehicle becomes

$$\begin{aligned}&\dot{x}_i = f_i^*(t,x_i,d_i) = f_i(t,x_i,u_i^*(t,x_i),d_i)\\ &d_i\in\mathcal{D}_i, \quad i=1,\dots,N, \quad t\in[t_i^{\text{LDT}}, t_i^{\text{STA}}]\end{aligned} \tag{14}$$

where u_i no longer appears explicitly in the dynamics.

From the perspective of a lower-priority vehicle Q_i, a higher-priority vehicle $Q_j, j<i$ induces a time-varying obstacle that represents the positions that could possibly be within the capture radius R_c of Q_j under the dynamics $f_j^*(t,x_j,d_j)$. Determining this obstacle involves computing a forward reachable set (FRS) of Q_j starting from $x_j(t_j^{\text{LDT}}) = x_{j0}$. The FRS $\mathcal{W}_j(t)$ is defined as follows:

$$\begin{aligned}&\mathcal{W}_j(t) = \{y\in\mathbb{R}^{n_j} : \exists d_j(\cdot)\in\mathbb{D}_j,\\ &x_j(\cdot) \text{ satisfies } (14), x_j(t_j^{\text{LDT}}) = x_{j0}, x_j(t)=y\}\end{aligned} \tag{15}$$

Conveniently, the FRS can be computed using the following HJ VI:

$$\begin{aligned}&D_t W_j(t,x_j) + H_j\left(t,x_j,D_{x_j}W_j\right) = 0, t\in[t_j^{\text{LDT}}, t_j^{\text{STA}}]\\ &W_j(t_j^{\text{LDT}},x_j) = \bar{l}_j(x_j)\end{aligned} \tag{16}$$

with the following Hamiltonian

$$H_j\left(t,x_j,\lambda\right) = \max_{d_j\in\mathcal{D}_j} \lambda\cdot f_j^*(t,x_j,d_j) \tag{17}$$

where $\bar{l}$ is chosen to be[2] such that $\bar{l}(y)=0 \Leftrightarrow y = x_j(t_j^{\text{LDT}})$.

The FRS $\mathcal{W}_j(t)$ represents the set of possible states at time t of a higher-priority vehicle Q_j given all possible disturbances $d_j(\cdot)$ and given that Q_j uses the feedback controller $u_j^*(t,x_j)$. In order for a lower-priority vehicle Q_i to guarantee that it does not go within a distance of R_c to Q_j, Q_i must stay a distance of at least R_c away from the set $\mathcal{W}_j(t)$ for all possible values of the non-position states h_j. This gives the obstacle induced by a higher-priority vehicle Q_j for a lower-priority vehicle Q_i as follows:

$$\mathcal{O}_i^j(t) = \{x_i : \text{dist}(p_i, \mathcal{P}_j(t)) \leq R_c\} \tag{18}$$

where the dist$(\cdot,\cdot)$ function represents the minimum distance from a point to a set, and the set $\mathcal{P}_j(t)$ is the set of states in the FRS $\mathcal{W}_j(t)$ projected onto the states representing position p_j, and disregarding the non-position dimensions h_j:

$$\mathcal{P}_j(t) = \{p_j : \exists h_j, (p_j,h_j)\in\mathcal{W}_j(t)\}. \tag{19}$$

Finally, taking the union of the induced obstacles $\mathcal{O}_i^j(t)$ as in (5) gives us the time-varying obstacles $\mathcal{G}_i(t)$ needed to define and determine the BRS $\mathcal{V}_i(t)$ in (11). Repeating this process, all vehicles will be able to plan paths that guarantee the vehicles' timely and safe arrival.

[2]In practice, we define the target set to be a small region around the vehicle's initial state for computational reasons.

B. Method 2: Least Restrictive Control

Here, we again begin with the highest-priority vehicle Q_1 planning its path by computing the BRS $\mathcal{V}_i(t)$ in (11). However, if there is no centralized controller to enforce the control policy for higher-priority vehicles, weaker assumptions must be made by the lower-priority vehicles to ensure collision avoidance. One reasonable assumption that a lower-priority vehicle can make is that all higher-priority vehicles follow the least restrictive control that would take them to their targets. This control would be given by

$$u_j(t,x_j) \in \begin{cases}\{u_j^*(t,x_j) \text{ given by (13)}\} \text{ if } x_j(t)\in\partial\mathcal{V}_j(t),\\ \mathcal{U}_j \text{ otherwise}\end{cases} \tag{20}$$

Such a controller allows each higher priority vehicle to use any controller it desires, except when it is on the boundary of the BRS, $\partial\mathcal{V}_j(t)$, in which case the optimal control $u_j^*(t,x_j)$ given by (13) must be used to get to the target safely and on time. This assumption is the weakest assumption that could be made by lower-priority vehicles given that the higher-priority vehicles will get to their targets on time.

Suppose a lower-priority vehicle Q_i assumes that higher-priority vehicles $Q_j, j<i$ use the least restrictive control strategy in (20). From the perspective of the lower-priority vehicle Q_i, a higher-priority vehicle Q_j could be in any state that is reachable from Q_j's initial state $x_j(t_j^{\text{LDT}}) = x_{j0}$ and from which the target $\mathcal{T}_j$ can be reached. Mathematically, this is defined by the intersection of a FRS from the initial state $x_j(t^{\text{LDT}}) = x_{j0}$ and the BRS defined in (11) from the target set $\mathcal{T}_j$, $\mathcal{V}_j(t)\cap\mathcal{W}_j(t)$. In this situation, since Q_j cannot be assumed to be using any particular feedback control, $\mathcal{W}_j(t)$ is defined as

$$\begin{aligned}&\mathcal{W}_j(t) = \{y\in\mathbb{R}^{n_j} : \exists u_j(\cdot)\in\mathbb{U}_j, \exists d_j(\cdot)\in\mathbb{D}_j,\\ &x_j(\cdot) \text{ satisfies } (1), x_j(t_j^{\text{LDT}}) = x_{j0}, x_j(t)=y\}\end{aligned} \tag{21}$$

This FRS can be computed by solving (16) without obstacles, and with

$$H_j\left(t,x_j,\lambda\right) = \max_{u_j\in\mathcal{U}_j}\max_{d_j\in\mathcal{D}_j} \lambda\cdot f_j(t,x_j,u_j,d_j) \tag{22}$$

In turn, the obstacle induced by a higher-priority Q_j for a lower-priority vehicle Q_i is as follows:

$$\begin{aligned}&\mathcal{O}_i^j(t) = \{x_i : \text{dist}(p_i,\mathcal{P}_j(t))\leq R_c\}, \text{ with}\\ &\mathcal{P}_j(t) = \{p_j : \exists h_j, (p_j,h_j)\in\mathcal{V}_j(t)\cap\mathcal{W}_j(t)\}\end{aligned} \tag{23}$$

Note that the centralized control method described in the previous section can be thought of as the "most restrictive control" method, in which all vehicles must use the optimal controller at all times, while the least restrictive control method allows vehicles to use any suboptimal controller that allows them to arrive at the target on time. These two methods can be considered two extremes of a spectrum in which varying degrees of optimality is assumed for higher-priority vehicles. Vehicles can also choose a control strategy in the middle of the two extremes, and for example use a control within some range around the optimal control, or use the optimal control unless some condition is met.

The induced obstacles and the BRS can then be similarly computed using the corresponding control strategy.

C. Method 3: Robust Trajectory Tracking

Even though it is impossible to commit to and track an exact trajectory in presence of disturbances, it may still be possible to instead *robustly* track a feasible *nominal* trajectory with a bounded error at all times. If this can be done, then the tracking error bound can be used to determine the induced obstacles. Here, computation is done in two phases: the planning phase and the disturbance rejection phase. In the planning phase, we compute a nominal trajectory $x_{r,j}(\cdot)$ that is feasible in the absence of disturbances. In the disturbance rejection phase, we compute a bound on the tracking error.

It is important to note that the planning phase does not make full use of a vehicle's control authority, as some margin is needed to reject unexpected disturbances while tracking the nominal trajectory. Therefore, in this method, planning is done for a reduced control set $\mathcal{U}^p \subset \mathcal{U}$. The resulting trajectory reference will not utilize the vehicle's full maneuverability; replicating the nominal control is therefore always possible, with additional maneuverability available at execution time to counteract external disturbances.

In the disturbance rejection phase, we determine the error bound independently of the nominal trajectory. To compute this error bound, we find a robust controlled-invariant set in the joint state space of the vehicle and a tracking reference that may "maneuver" arbitrarily in the presence of an unknown bounded disturbance. Taking a worst-case approach, the tracking reference can be viewed as a virtual evader vehicle that is optimally avoiding the actual vehicle to enlarge the tracking error. We therefore can model trajectory tracking as a pursuit-evasion game in which the actual vehicle is playing against the coordinated worst-case action of the virtual vehicle and the disturbance.

Let x_j and x_r denote the state of the actual vehicle Q_j and the virtual evader, respectively, and define the tracking error $e_j = x_j - x_r$. When the error dynamics are independent of the absolute state as in (24) (and also (7) in [15]), we can obtain error dynamics of the form

$$\begin{aligned} \dot{e_j} &= f_{e_j}(t, e_j, u_j, u_r, d_j), \\ u_j &\in \mathcal{U}_j, u_r \in \mathcal{U}_j^p, d_j \in \mathcal{D}_j, \quad t \in [0, T] \end{aligned} \tag{24}$$

To obtain bounds on the tracking error, we first conservatively estimate the error bound around any reference state $x_{r,j}$, denoted $\mathcal{E}_j(x_{r,j})$, and solve a reachability problem with its complement $\mathcal{E}_j^c$ as the target in the space of the error dynamics; $\mathcal{E}_j^c$ is the set of tracking errors violating the error bound. From $\mathcal{E}_j^c$, we compute the BRS using (7) without obstacles, and with the Hamiltonian

$$H_j\left(t, e_j, \lambda\right) = \max_{u_j \in \mathcal{U}_j} \min_{u_r \in \mathcal{U}_j^p, d_j \in \mathcal{D}_j} \lambda \cdot f_{e_j}(t, e_j, u_j, u_r, d_j) \tag{25}$$

Letting the time horizon tend to infinity, we obtain the infinite-horizon controlled-invariant set, denoted by Ω_j. If Ω_j is nonempty, then the tracking error e_j at flight time is guaranteed to remain within $\mathcal{E}_j$ provided that the vehicle starts inside Ω_j and subsequently applies the feedback control law

$$\kappa_j(e_j) = \arg\max_{u_j \in \mathcal{U}_j} \min_{u_r \in \mathcal{U}_j^p, d_j \in \mathcal{D}_j} \lambda \cdot f_{e_j}(t, e_j, u_j, u_r, d_j). \tag{26}$$

Given $\mathcal{E}_j$, we can guarantee that Q_j will reach its target $\mathcal{T}_j$ if $\mathcal{E}_j \subseteq \mathcal{T}_j$; thus, in the path planning phase, we modify $\mathcal{T}_j$ to be $\{x_j : \mathcal{E}_j(x_j) \subseteq \mathcal{T}_j\}$, and compute a BRS, with the control authority $\mathcal{U}_j^p$, that contains the initial state of the vehicle. From the resulting nominal trajectory $x_{r,j}(\cdot)$, the overall control policy to reach $\mathcal{T}_j$ can be obtained via (26).

Finally, since each vehicle Q_j can only be guaranteed to stay within $\mathcal{E}_j(x_{r,j})$, we must make sure at any given time, the error bounds of Q_i and Q_j, $\mathcal{E}_i(x_{r,i})$ and $\mathcal{E}_j(x_{r,j})$, do not intersect. This can be done by choosing the induced obstacle to be the Minkowski sum[3] of the error bounds. Thus,

$$\begin{aligned} \mathcal{O}_i^j(t) &= \{x_i : \text{dist}(p_i, \mathcal{P}_j(t)) \le R_c\} \\ \mathcal{P}_j(t) &= \{p_j : \exists h_j, (p_j, h_j) \in \mathcal{E}_i(0) + \mathcal{E}_j(x_{r,j}(t))\} \end{aligned} \tag{27}$$

where 0 denotes the origin.

V. Numerical Simulations

We demonstrate our proposed methods using a four-vehicle example. Each vehicle has the following simple kinematics model:

$$\begin{aligned} \dot{p}_{x,i} &= v_i \cos\theta_i + d_{x,i} \\ \dot{p}_{y,i} &= v_i \sin\theta_i + d_{y,i} \\ \dot{\theta}_i &= \omega_i + d_{\theta,i}, \\ \underline{v} &\le v_i \le \bar{v}, |\omega_i| \le \bar{\omega}, \\ \|(d_{x,i}, d_{y,i})\|_2 &\le d_r, |d_{\theta,i}| \le \bar{d}_\theta \end{aligned} \tag{28}$$

where $p_i = (p_{x,i}, p_{y,i}), \theta_i, d = (d_{x,i}, d_{y,i}, d_{\theta,i})$ respectively represent Q_i's position, heading, and disturbances in the three states. The control of Q_i is $u_i = (v_i, \omega_i)$, where v_i is the speed of Q_i and ω_i is the turn rate; both controls have a lower and upper bound. For illustration purposes, we choose $\underline{v} = 0.5, \bar{v} = 1, \bar{\omega} = 1$; however, our method can easily handle the case in which these inputs differ across vehicles and cases in which each vehicle has a different dynamic model. The disturbance bounds are chosen as $d_r = 0.1, \bar{d}_\theta = 0.2$, which correspond to a 10% uncertainty in the dynamics.

The initial states of the vehicles are given as follows:

$$\begin{aligned} x_1^0 &= (-0.5, 0, 0), & x_2^0 &= (0.5, 0, \pi), \\ x_3^0 &= (-0.6, 0.6, 7\pi/4), & x_4^0 &= (0.6, 0.6, 5\pi/4). \end{aligned} \tag{29}$$

Each of the vehicles has a target set $\mathcal{T}_i$ that is circular in their position p_i centered at $c_i = (c_{x,i}, c_{y,i})$ with radius r:

$$\mathcal{T}_i = \{x_i \in \mathbb{R}^3 : \|p_i - c_i\| \le r\} \tag{30}$$

For the example shown, we chose $c_1 = (0.7, 0.2), c_2 = (-0.7, 0.2), c_3 = (0.7, -0.7), c_4 = (-0.7, -0.7)$ and $r = 0.1$. The setup of the example is shown in Fig. 2.

Since the joint state space of this system is intractable for a direct application of HJ reachability theory, we repeatedly solve (7) to compute BRSs from the targets $\mathcal{T}_i, i = 1, 2, 3, 4,$

[3]The Minkowski sum of sets A and B is the set of all points that are the sum of any point in A and B.

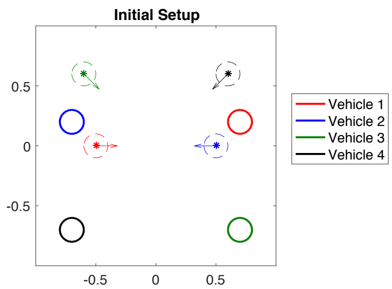

Fig. 2: Initial configuration of the four-vehicle example.

in that order, with moving obstacles induced by vehicles $j = 1, \dots, i-1$. We also obtain $t_i^{\text{LDT}}, i = 1, 2, 3, 4$ assuming $t_i^{\text{STA}} = 0$ without loss of generality. Note that even though t_i^{STA} is assumed to be same for all vehicles in this example for simplicity, our method can easily handle the case in which t_i^{STA} is different for each vehicle.

For each proposed method of computing induced obstacles, we show the vehicles' entire trajectories (colored dotted lines), and overlay their positions (colored asterisks) and headings (arrows) at a point in time in which they are in relatively dense configuration. In all cases, the vehicles are able to avoid each other's danger zones (colored dashed circles) while getting to their target sets in minimum time. In addition, we show the evolution of the BRS over time for Q_3 (green boundaries) as well as the obstacles induced by the higher-priority vehicles (black boundaries).

A. Centralized Control

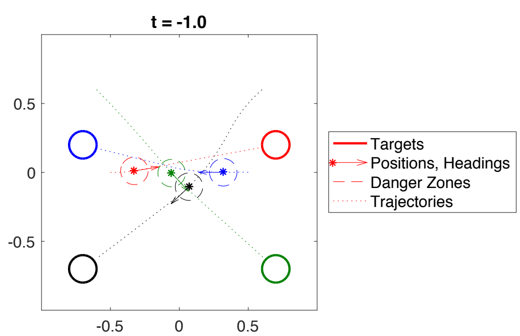

Fig. 3: Simulated trajectories in the centralized control method. Since the higher priority vehicles induce relatively small obstacles in this case, vehicles do not deviate much from a straight line trajectory towards their respective targets.

Fig. 3 shows the simulated trajectories in the situation where a centralized controller enforces each vehicle to use the optimal controller $u_i^*(t, x_i)$ according to (13), as described in Section IV-A. In this case, vehicles appear to deviate slightly from a straight line trajectory towards their respective targets, just enough to avoid higher-priority vehicles. The deviation is small since the centralized controller is quite restrictive, making the possible positions of higher priority vehicles cover a small area. In the dense configuration at $t = -1.0$, the vehicles are close to each other but still outside each other's danger zones.

Fig. 4 shows the evolution of the BRS for Q_3 (green boundary), as well as the obstacles (black boundary) induced by the higher-priority vehicles Q_1 (red) and Q_2 (blue). The locations of the induced obstacles at different time points include the actual positions of Q_1 and Q_2 at those times, and the size of the obstacles remains relatively small. t_i^{LDT} numbers for the four vehicles (in order) in this case are $-1.35, -1.37, -1.94$ and -2.04. Numbers are relatively close for vehicles Q_1, Q_2 and Q_3, Q_4, because the obstacles generated by higher-priority vehicles are small and hence do not affect t^{LDT} of the lower-priority vehicles significantly.

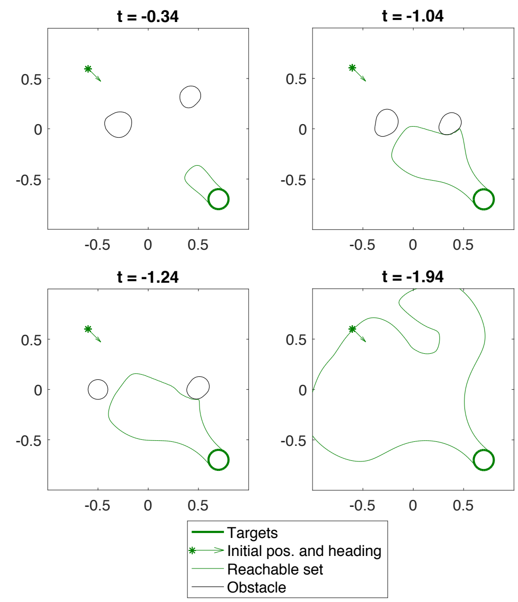

Fig. 4: Evolution of the BRS and the obstacles induced by Q_1 and Q_2 for Q_3 in the centralized control method. Since every vehicle is applying the optimal control at all times, the obstacle sizes are relatively small.

B. Least Restrictive Control

Fig. 5 shows the simulated trajectories in the situation where each vehicle assumes that higher-priority vehicles use the least restrictive control to reach their targets, as described in IV-B. Fig. 6 shows the BRS and induced obstacles for Q_3.

Q_1 (red) takes a relatively straight path to reach its target. From the perspective of all other vehicles, large obstacles are induced by Q_1, since lower-priority vehicles make the weak assumption that higher-priority vehicles are using the least restrictive control. Because the obstacles induced by higher-priority vehicles are so large, it is faster for lower-priority vehicles to wait until higher-priority vehicles pass by than to move around the higher-priority vehicles. As a result, the vehicles never form a dense configuration, and their trajectories are all relatively straight, indicating that they end up taking a short path to the target after higher-priority vehicles pass by. This is also indicated by low t_i^{LDT} values for the four vehicles, which are $-1.35, -1.97, -2.66$ and -3.39, respectively. Compared to the centralized control method, t_i^{LDT}'s decrease significantly for all vehicles, except Q_1, the highest-priority vehicle, since it need not account for any moving obstacles.

From Q_3's (green) perspective, the large obstacles induced by Q_1 and Q_2 are shown in Fig. 6 as the black boundary. As the BRS (green boundary) evolves over time, its growth gets inhibited by the large obstacles for a long time, from $t = -0.89$ to $t = -1.39$. Eventually, the boundary of the BRS reaches the initial state of Q_3 at $t = t_3^{\mathrm{LDT}} = -2.66$.

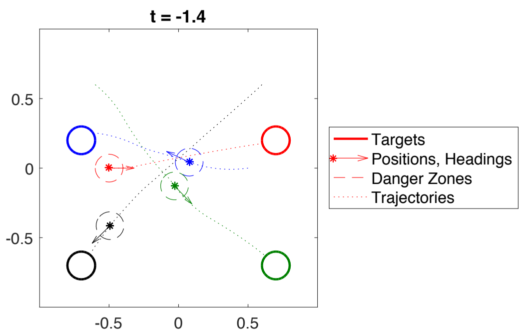

Fig. 5: Simulated trajectories in the least restrictive control method. All vehicles start moving before Q_1 starts, because the large obstacles make it optimal to wait until higher priority vehicles pass by, leading to a smaller t^{LDT}.

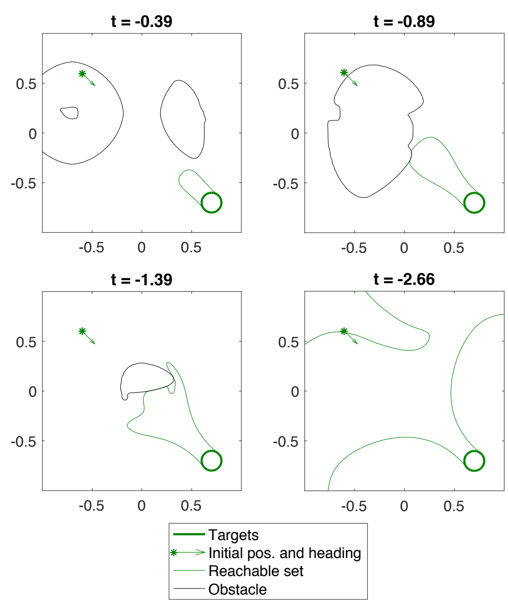

Fig. 6: Evolution of the BRS for Q_3 in the least restrictive control method. t_3^{LDT} is significantly lower than that in the centralized control method (-1.94 vs. -2.66), reflecting the impact of larger induced obstacles.

C. Robust Trajectory Tracking

In the planning phase, we reduced the maximum turn rate of the vehicles from 1 to 0.6, and the speed range from $[0.5, 1]$ to exactly 0.75 (constant speed). With these reduced control authorities, we determined from the disturbance rejection phase that a nominal trajectory from the planning phase can be robustly tracked within a distance of 0.075.

Fig. 7 shows the vehicle trajectories in the situation where each vehicle robustly tracks a pre-specified trajectory and is guaranteed to stay inside a "bubble" around the trajectory. Fig. 8 shows the evolution of BRS and induced obstacles for vehicle Q_3. The obstacles induced by other vehicles inhibit the evolution of the BRS, carving out thin channels, which can be seen at $t = -2.59$, that separate the BRS into different islands.

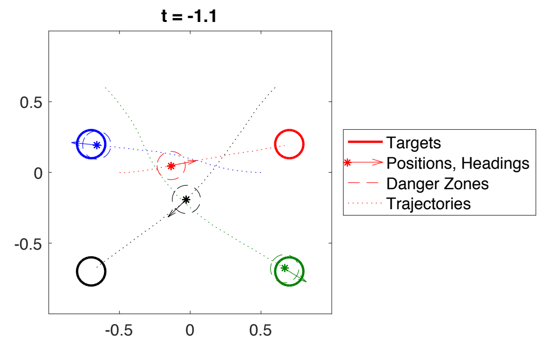

Fig. 7: Simulated trajectories for the robust trajectory tracking method.

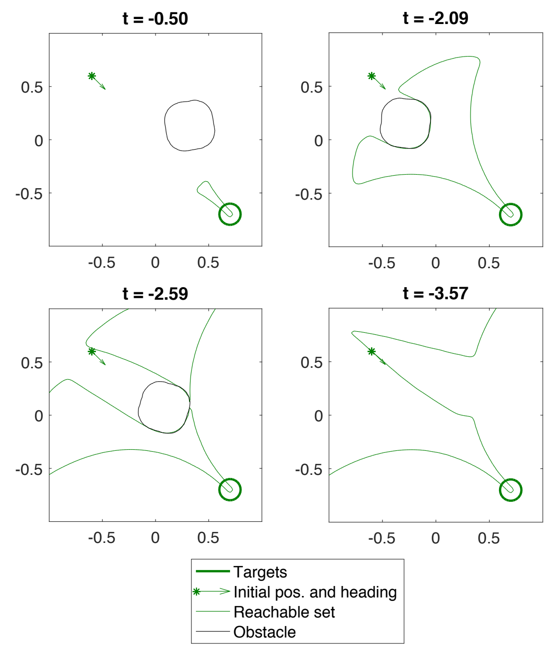

Fig. 8: Evolution of the BRS for Q_3 in the robust trajectory tracking method. As the BRS grows in time, the induced obstacles carve out a channel. Note that a smaller target set is used to compute the BRS to ensure that the vehicle reaches the target set by $t = 0$ for any allowed tracking error.

In this case, the t_i^{LDT} values for the four vehicles are $-1.61, -3.16, -3.57$ and -2.47 respectively. In this method, vehicles use reduced control authority for path planning towards a reduced-size effective target set. As a result, higher-priority vehicles tend to have lower t^{LDT} compared to the other two methods, as evident from t_1^{LDT}. Because of this "sacrifice" made by the higher-priority vehicles during the path planning phase, the t^{LDT}'s of lower-priority vehicles may increase compared to those in the other methods, as evident from t_4^{LDT}. Overall, it is unclear how t_i^{LDT} will change for a vehicle compared to the other methods, as the conservative path planning increases t_i^{LDT} for higher-priority vehicles and decreases t_i^{LDT} for lower-priority vehicles.

VI. Comparison of Proposed Methods

This section briefly compares the advantages and limitations of the proposed methods. Each method makes a trade-off between optimality (in terms of t_i^{LDT}) and flexibility in control and disturbance rejection.

A. Centralized Control

In this method, given a particular priority ordering, the vehicles have a relatively high t_i^{LDT} since a higher-priority vehicle maximizes its t_i^{LDT} as much as possible, while at the same time inducing a relatively small obstacle so as to minimize its impedance towards the lower-priority vehicles. A limitation of this method is that a centralized controller is likely required to ensure that a particular control strategy such as the optimal control is being applied by the vehicles at all times.

B. Least Restrictive Control

This method gives more control flexibility to the higher-priority vehicles, as long as the control does not push the vehicle out of its BRS. This flexibility, however, comes at the price of having a larger induced obstacle, lowering t_i^{LDT} for the lower-priority vehicles.

C. Robust Trajectory Tracking

Since the obstacle size is constant over time, this method is easier to implement from a practical standpoint. This method also aims at striking a balance between t_i^{LDT} across vehicles. In particular, the t^{LDT} of a higher-priority vehicle can be lower compared to the centralized control method, so that a lower-priority vehicle can achieve a higher t^{LDT}, making this method particularly suitable for the scenarios where there is no strong sense of priority among vehicles. This method, however, is computationally tractable only when the tracking error dynamics are independent of the absolute states, as it otherwise requires doing computation in the joint state space of system dynamics and virtual vehicle dynamics.

VII. Conclusions and Future Work

We have proposed three different methods to account for disturbances and imperfect control policy information in sequential path planning; these three methods can be used independently across the different vehicles in the path planning problem. In each method, different assumptions about the control strategy of higher-priority vehicles are made. In all of the methods, all vehicles are guaranteed to successfully reach their respective destinations without entering each other's danger zones despite the worst-case disturbance the vehicles could experience. Compared to the work in [23], our proposed methods result in lower vehicle densities so that the vehicles have enough leeway to guarantee safety in the presence of disturbances and limited information. Future work includes exploring methods for fast re-planning, and making the multi-vehicle system robust to unforeseen circumstances such as the presence of intruders.

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