Learning Enabled Fast Planning and Control in Dynamic Environments with Intermittent Information

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Abstract—This paper addresses a safe planning and control problem for mobile robots operating in communication- and sensor-limited dynamic environments. In this case the robots cannot sense the objects around them and must instead rely on intermittent, external information about the environment, as e.g., in underwater applications. The challenge in this case is that the robots must plan using only this stale data, while accounting for any noise in the data or uncertainty in the environment. To address this challenge we propose a compositional technique which leverages neural networks to quickly plan and control a robot through crowded and dynamic environments using only intermittent information. Specifically, our tool uses reachability analysis and potential fields to train a neural network that is capable of generating safe control actions. We demonstrate our technique both in simulation with an underwater vehicle crossing a crowded shipping channel and with real experiments with ground vehicles in communication- and sensor-limited environments.

I. INTRODUCTION

Safe motion and task planning for multi-robot systems in known and static environments has been studied extensively under the assumption that all robots are connected and synchronously exchanging information about their local states and actions [1]. However, when robots are deployed in communication- and sensor-limited dynamic environments, data about the current state of the environment may not always be available. For example, consider unmanned underwater vehicles (UUVs), which have been growing in popularity in recent years [2]. UUVs must deal with vessels that typically are not aware of their presence in the water. In fact, UUVs obtain information about the states of the other vessels only when they surface; see, e.g., Fig. 1. Hence, when they are underwater they can only rely on old, deprecated data to plan their motion to avoid colliding with these vessels. This sensory limitation may threaten the safety of such systems. For example, on February 8, 2021, a Japanese submarine collided with a commercial ship off the country’s Pacific coast. The submarine surfaced right under the Japanese submarine. This sensory limitation may threaten the safety of such systems. For example, on February 8, 2021, a Japanese submarine collided with a commercial ship off the country’s Pacific coast. The submarine surfaced right under the Japanese submarine. This sensory limitation may threaten the safety of such systems. For example, on February 8, 2021, a Japanese submarine collided with a commercial ship off the country’s Pacific coast. The submarine surfaced right under the

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To address this challenge, we design a novel reachability-based potential field method to avoid collisions with future obstacle configurations. Specifically, reachability analysis is employed to compute the future states of obstacles based on the most recent information the robot received while potential fields are used to avoid these reachable sets. Since reachability analysis is too computationally expensive to perform at runtime, we use this reachability-based potential field method to train a neural network (NN) control framework at design time. At runtime, given intermittent information, this NN component generates control actions to safely navigate the dynamic environment.

Fig. 1. Pictorial representation of a UUV tasked to navigate through a shipping channel under intermittent communication.
tonian optimization for motion planning [3], [4], [5], real-time adaptive motion planning [6], [7], [8], [9], [10] and reinforcement learning [11]. However, these methods require real-time sensor information about the dynamic obstacles. Dimension reduction methods have also been proposed [12], but they do not handle noise in the obstacle dynamics.

Relevant approaches on motion planning under intermittent information have been proposed recently. For instance, [13], [14], [15] propose distributed intermittent connectivity controllers for multi-robot systems that are tasked with navigation and estimation tasks in communication-denied environments. Conditions on the time interval between intermittent communication events to ensure stability and consensus in multi-agent systems are also provided in [16]. Similar to this work, mission planning problems under uncontrolled intermittent communication have recently been proposed as well in which localization [17], [18], [19] and object tracking [20] rely on intermittent information. The above works consider cooperative multi-agent systems whereas our work considers robots navigating in environments occupied with uncertain, dynamic, and uncooperative obstacles. Additionally, reachability analysis has been employed for control design [21], [22], [23], [24], [25], [26], [27], monitoring [19], [28], and providing run-time safety guarantees [29], [30]. The most relevant works to ours are: [23], where reachability analysis and potential fields are mixed for planning, and [27], which combines stochastic reachability analysis and RRT for path planning. Differently from our work, [23] assumes periodic observations which does not address intermittent information challenges and [27] does not account for the computational complexity of stochastic reachability analysis.

**Contribution:** The contribution of this paper is four-fold: 1) we present a novel algorithm that combines reachability analysis (RA) with potential fields for safe navigation in uncertain and dynamic environments in the presence of intermittent information; 2) we propose an NN-based compositional method that leverages the time elapsed since the last intermittent data to perform fast planning bypassing the use of expensive RA at runtime; 3) we implement and validate our approach with realistic simulations and experiments on UUVs and ground vehicles in cluttered dynamic environments; 4) we use comparative experiments against planning methods in dynamic environments that ignore motion uncertainties to demonstrate the safety-related benefits of our approach.

### II. Problem Description

Consider a robot governed by the following dynamics:

\[
\dot{x} = f(x(t), u(t)), \tag{1}
\]

where \(x(t)\) and \(u(t)\) denote the state (e.g., position and heading) of the robot and the control input at time \(t\), respectively. The robot is assumed to operate in an environment with an a priori unknown number \(n \geq 0, n \in \mathbb{N}\) of dynamic, non-cooperative obstacles governed by the following dynamics:

\[
\dot{o}_i = g(o_i(t), d_i(t), w_i(t)), \quad i = 1, \ldots, n \tag{2}
\]

where \(o_i(t) \in O\), \(d_i(t) \in D\) and \(w_i(t) \in W\) denote the state, control input and process noise of obstacle \(i\) at time \(t\), respectively. Hereafter, we assume that all obstacles follow the same control policy, which is known to the robot. In addition, the system noise is considered unknown but bounded by an a priori known bound \(\|w_i(t)\| \leq \delta_w\).

The key assumption of this work is that the robot gets intermittent information about the obstacle state \(o_i(t_s)\), which could be planned (e.g., when the UUV surfaces) or at unknown time instants \(t_s\) (e.g., a UGV entering a communication denied environment).

The problem we address in this paper is as follows:

**Problem 1 (Safe Planning with Intermittent Information):**

Given a robot with dynamics in (1), design a planner to guide it to a goal region \(x_g\) while always avoiding dynamic vehicles modeled as in (2). This is specified in the following safety condition:

\[
\|x(t) - o_i(t)\| \geq \delta, \quad \forall t \geq 0, \quad \forall i \in \{1, \ldots, n\} \tag{3}
\]

with safety threshold \(\delta\) under intermittent obstacle-related information \(I(t_s)\) provided at unknown time instants \(t_s\).

### III. Planning Framework

To solve Problem 1, we propose to leverage (i) reachability analysis, which allows us to predict future states of the obstacles in the presence of uncertainty during the periods between intermittent information and (ii) potential fields to navigate the robot in the environment while avoiding the reachable sets associated with the obstacles. Nevertheless, a key challenge in employing reachability analysis (RA) is that it is computationally expensive, resulting in limited applicability in online operations. To mitigate this challenge, we consider a learning-based approach leaving RA offline and enabling fast online planning and control. The proposed learning-based framework is summarized in Fig. 2 and consists of 1) an offline phase where a neural network (NN) controller is trained under RA and potential fields and 2) an online phase in which the NN controller, given the most recently received data, generates safe control actions to quickly navigate the dynamic environment. In what follows, we describe in detail the components of the proposed method depicted in Fig. 2.
A. Reachability Analysis for Dynamic Obstacles

In this section, we discuss how reachability analysis methods can be used to predict future states of the dynamic obstacles. In particular, given a dynamic obstacle \( i \), as defined in (2), along with a set of initial conditions \( O_{t_0}^i \) at time \( t_0 \), our goal is to compute the set of possible states that obstacle \( i \) can be in from a time instant \( t_1 \geq t_0 \) until a time instant \( t_2 \geq t_1 \). Hereafter, we call such sets reachable sets, denote them by \( O_{[t_0,t_1,t_2]}^i \), and define them as follows:

\[
O_{[t_0,t_1,t_2]}^i = \{ o \in O \mid \exists o_0 \in O_{t_0}^i, t' \in [t_1,t_2], d_{[t_0,t_1]} \in D, \text{ and } w_{[t_0,t_1]} \in W, \ o = G_{t_0,t_1}(o_0,d_{[t_0,t_1]},w_{[t_0,t_1]}) \},
\]

where \( G_{t_0,t_1}(O,D,W) \) is the system’s transition function (i.e., the state the system will be in at time \( t' \) when it is in state \( o_0 \) at time \( t_0 \) and is applied input signal \( d_{[t_0,t_1]} \) and process noise signal \( w_{[t_0,t_1]} \)). There exist various methods to compute the reachable set (4), such as Taylor models [31], Hamilton-Jacobi theory [32], \( \delta \)-reachability [33], and ellipsoids [34]. Our framework is agnostic to the method used, provided that we can extract the reachable sets over time.

B. Potential Fields for Navigating Dynamic Environments

In what follows, we design potential field controllers to navigate the robot through dynamic environments. The key idea is to design a controller capable of avoiding all reachable obstacle states from current time \( t \) until the next batch of information arrives, denoted as \( O_{[t,t,t+1]} \), and therefore, the dynamic obstacles within the time interval \([t, t+1]\); recall that \( t \) and \( t+1 \) stand for consecutive time instants where the robot receives information about the obstacles.

To design a potential field controller for dynamic environments, we first define the following potential field:

\[
U(x_p) = U_{\text{att}}(x_p) + \sum_{i=1}^{n} U_{i,\text{rep}}(x_p),
\]

where \( U_{\text{att}}(x_p) \) denotes an attractive field driving the robot towards the goal location \( x_p \) and \( U_{i,\text{rep}}(x_p) \) is a repulsive field pushing the robot away from dynamic obstacle \( i \). The attractive field is designed to take small values near the robot’s goal and large values far from the goal while the repulsive field is constructed to take large values near the obstacles and small values far from them. The control policy is to simply perform gradient descent down this field until the goal is reached.

Letting \( x_p \) denote the current robot position, the attractive field is defined as:

\[
U_{\text{att}}(x_p) = \frac{1}{2} K_p \left( ||x_p - x_g||^2 \right).
\]

Since the control action is to follow the negative gradient of the composed field, potential field controllers can make the system get stuck in dynamic minima. These occur when a dynamic obstacle repels the robot in the same direction that the obstacle is moving; see, e.g. Fig. 3. To minimize the effects of dynamic minima, we leverage the temporal properties of reachability analysis. Every time obstacle information is provided to the robot, we construct the obstacles’ forward reachable set defined in (4). Exploiting the conic structure of the reachable sets, we design repulsive potential fields that tend to push the robot behind the obstacle, thus mitigating the dynamic minima behavior seen in Fig. 3. For instance, Fig. 4 shows an example of the repulsive forces from the reachable set of an obstacle starting at position \([0,0]\) and moving in the positive \( x \) direction.

We formally describe this process for obstacle \( o_i \) as follows: Let \( t \) be the current global time, \( x_p \) be the location of the robot at the current time, \( t_0 \leq t \) be the time of the most recently received obstacle state, denoted \( o_i^{t_0} \). Also, let \( O_{[t_0,t_0+T]} \) be the set of reachable states of \( o_i \) from time \( t \) to \( t_0 + T \) (see (4)), given that \( o_i \) was at state \( o_i^{t_0} \) at time \( t_0 \).

Finally, define \( o_i^t(x_p) \) to be the closest point in \( O_{[t_0,t_0+T]} \) to the robot’s position \( x_p \):

\[
o_i^t(x_p) := \arg \min_{o \in O_{[t_0,t_0+T]}} ||x_p - o||.
\]

The repulsive field that we use to compute the avoidance command for obstacle \( o_i \) at robot location \( x_p \) and time \( t \) is:

\[
U_{i,\text{rep}}(x_p) = \frac{1}{2} K_r \left( \frac{1}{||x_p - o_i^t(x_p)|| - \delta} \right)^2,
\]

where \( \delta \) is given from (3).

C. Compositional Controller

The final step for our control scheme is composing the attractive and repulsive fields. By combining the attractive (6) and repulsive (8) field equations, based on the composition defined in (5), the composed field becomes:

\[
U(x_p) = \left( \frac{1}{2} K_p \left( ||x_p - x_g||^2 \right) \right) + \sum_{i=1}^{n} \frac{1}{2} K_r \left( \frac{1}{||x_p - o_i^t(x_p)|| - \delta} \right)^2.
\]
Our controller uses the same principle of following the negative gradient down the composed potential field as the standard potential field setup. Using the linearity of the gradient, the control output becomes:

\[ u = -\nabla \left( \frac{1}{2} K_p \left( ||x_p - x_g||^2 \right) \right) - \sum_{i=1}^{n} \frac{1}{2} K_r \left( \frac{1}{||x_p - O_i(x_p)|| - \delta} \right)^2 \,. \tag{10} \]

Next, we discuss intuitively under what conditions the controller in (10) satisfies the safety constraint (3).

**Safety Discussion:** First, note that if the reachable set of obstacle \( i \) from times \( t \) to \( t_0 + T \), \( O_i^i_{[t_0,t_0 + T]} \), is convex, the repulsive field vector produced by that obstacle, \( \nabla \frac{1}{2} K_r \left( \frac{1}{||x_p - O_i(x_p)|| - \delta} \right) \), points away from every point of the obstacle’s forward reachable set.

For a collision to occur, the repulsive field \( U_t(x_p) \) must take an infinite value, since the distance from the robot to the obstacle appears in the denominator of each obstacle’s repulsive field. So to prove safety it is sufficient to show that \( U_t(x_p) \) is always upper bounded.

At time \( t \), as the robot approaches the reachable set of obstacle \( i \), denoted by \( O_i^i_{[t_0,t_0 + T]} \), the repulsive force generated by the reachable set will become so large as to render the forces from every other obstacle reachable set (assuming the distance between the reachable sets is large enough) and the goal negligible. Thus, as the robot approaches the reachable set of obstacle \( i \), it holds that:

\[ U_t(x_p) \approx \frac{1}{2} K_r \left( \frac{1}{||x_p - O_i(x_p)|| - \delta} \right)^2 \tag{11} \]

\[ u \approx \nabla \frac{1}{2} K_r \left( \frac{1}{||x_p - O_i(x_p)|| - \delta} \right)^2 \tag{12} \]

Assuming simple robot dynamics of the form \( \dot{x}(t) = u \), as e.g. in [35], this control command pushes the robot farther away from every point of \( O_i^i_{[t_0,t_0 + T]} \). In addition the reachable sets of the obstacles do not grow, since \( O_i^i_{[t_0,t_0 + T]} \supseteq O_i^i_{[t_0,t_0 + T]} \), \( \forall t' \geq t \). Thus \( U_t(x_p) \) is decreasing and is hence upper bounded.

By construction of the reachable sets, the above argument assures safety up to a time threshold \( T \), which depends on how far the forward reachable sets get extended. If \( T = \infty \) then the safety guarantee holds for all time and as \( T \) decreases safety gets sacrificed, but the controller produces less conservative paths. In practice, this threshold should be picked to ensure safety until the next batch of intermittent information arrives. This threshold also gives a way to balance having conservative or aggressive paths.

**D. Compositional Neural Network Controller**

The attractive gradient in (10) is computed using standard gradient techniques. However, each of the \( n \) repulsive field gradients requires running reachability analysis, which is generally not computationally feasible at runtime. To get around this issue, we train a neural network to compute the repulsive field gradient of each obstacle.

The NN computes the repulsive field gradient of each obstacle separately. This is due to the compositionality inherent in the linearity of the gradient operator, as shown in (10) and the fact that all obstacles share the same control policy by assumption. The compositionality is a key aspect of our approach, since it means we do not need to know the number of obstacles at training time and the NN based planner can generalize to arbitrary numbers of obstacles.

For each obstacle, the NN takes as input the obstacle information and the time since that information was received and outputs the gradient of the repulsive field given in (8). Thus, the reachability analysis is baked into the weights of the NN during training, along with the repulsive field calculations. This ensures that our planning framework incorporates the uncertainties from the reachability analysis while running in crowded environments in real time.

We generate the neural network training data by fixing the robot position at \( x_p \) and iterating over a grid of obstacle states \( \alpha \), robot headings \( x_h \), and times \( t \). For each tuple of these values, we compute the gradient of the repulsive field from (8) for robot location \( x_p \) assuming obstacle information \( \alpha \) was received \( t \) seconds prior:

\[ \nabla \left( \frac{1}{2} K_r \left( \frac{1}{||x_p - O_i(x_p)|| - \delta} \right)^2 \right) \tag{13} \]

So the control output at time \( t + t_0 \) is:

\[ u = \nabla \left( \frac{1}{2} K_p(||x_p - x_g||^2) + \sum_{i=1}^{n} \text{NN}(x_p, x_h, \alpha_i, t) \right) \tag{14} \]

where \( \text{NN}(x_p, x_h, \alpha_i, t) \) is the neural network’s output when run from robot location \( x_p \) and heading \( x_h \) on obstacle information \( \alpha_i \) from time \( t_0 \) at the current time \( t + t_0 \).

**IV. EXPERIMENTAL ANALYSIS**

To evaluate our planning framework, we ran our approach on a case study of a UUV crossing a crowded shipping
channel in a simulation environment and on unmanned ground vehicles (UGV) in a lab environment. Videos of the experiments can be found in the supplemental material.

A. UUV Case Study

For our UUV case study, the scenario we considered is as follows: a UUV needs to cross a shipping channel, in which ships are traveling at a constant 5 m/s with noise bounded by 0.05 m/s, each going opposite directions, similar to how cars would travel on a two-lane road. In addition, all ships have a 0.01 radian noise bound on their headings. Each ship is 75 m long and 25 m wide and there is a 375 m gap in between each successive ship. The total width of the channel is 230 m. The UUV surfaces around 500 m before the channel to receive the location, heading, and speed of each of the ships. The UUV then dives down to a depth of 45 m and travels to a predefined waypoint directly across the channel. The UUV used for the simulation is 2 m long, 15 cm in radius, and travels at a maximum speed of 2.5 m/s. To ensure that there is always at least a 2 UUV lengths distance to the ships, the safety threshold is set to \( \delta = 5 \) m. The simulations were run on a real-time, physics-based ROS Gazebo UUV simulator [36].

The obstacle forward reachable sets were extended out by \( T = 600 \) seconds using Flow* [31]. We found that this was enough to prevent most collisions while still allowing the UUV to quickly cross the channel. The potential field constants were \( K_p = 5 \) and \( K_r = 15000 \). The NN architecture consisted of 15 fully-connected ReLU layers, each with 16 neurons, along with linear layers on the input and output, and was trained using around 8 million data points. We trained the NN using the Keras library.

We ran 20 trials of the UUV crossing the shipping channel, varying the initial positions of the ships traveling in each direction. Our planning framework safely guided the UUV through the channel while avoiding the ship reachable sets (and hence the ships themselves). The closest the UUV came to any ship across all trials was 7.5 m. One example path can be seen in blue in Fig. 5. We also plotted the minimum distance to the ship reachable sets for each of the 20 trials in Fig. 6. Each scenario took around 12 minutes and the UUV got the ship information 190 seconds into the scenario. So the UUV had to plan using information which was up to 9 minutes old to complete the scenarios. Finally, the average runtime of each control iteration was 27 ms and the largest runtime was 81 ms, whereas computing the reachable set of each ship 600 seconds into the future took Flow* an average of 67 seconds. In fact, this large runtime prohibits the direct application of reachability tools for online safety analysis in dynamic environments.

We also ran the same 20 trials using the controller from (10) with precomputed reachable sets for each ship, which we refer to as the reach set PF planner. The closest the UUV came to any ship reachable sets was 18.8 m. One example path can be seen in orange in Fig. 5. The minimum distance to the ship reachable sets for each of the 20 trials can be seen in Fig. 6. This demonstrates both that the control technique proposed in (10) is safe and effective and that our NN reasonably approximates the repulsive field gradients of the ship reachable sets.

Finally, we ran the same 20 trials using the controller from (10) assuming no uncertainty in the ship speeds and headings. One example path can be seen in purple in Fig. 5. The minimum distance to the ship reachable sets for each of the 20 trials can be seen in Fig. 6. In 11 of the 20 trials the UUV came within the allowed \( \delta = 5 \) m of the reachable sets and in one of the trials the UUV actually collided with one of the reachable sets. This collision can be seen in Fig. 5(c).
Robots’ paths

Fig. 7. Experiment results with a ground vehicle and two dynamic obstacles moving in the opposite directions. The robot was tasked to reach its goal location at [2.5, 0]m moving with desired speed of 0.5 m/s while avoiding the other two vehicles which moved straight also with a speed of 0.5 m/s. The ground vehicle observed the position and heading of the mobile obstacles only in the beginning of the operation, then lost its connection. We also assumed here that the robot did not have any onboard sensors to detect the obstacles. A Vicon motion capture system was used to detect the state of the ground vehicle and the initial position and heading of the dynamic obstacles.

We tested our approach on two different scenarios. In the first case, the mobile obstacles were moving in opposite directions in between the robot’s start and goal locations. Fig. 7(a) demonstrates the behavior of the ground vehicle and mobile obstacles over time. Fig. 7(b) shows the actual paths of these vehicles and Fig. 9(a) shows the minimum distance between the ground vehicle and the obstacles over time. For this case study, the minimum distance from any of the obstacles was recorded as 58.26 cm which is larger than the safety threshold $\delta = 51$ cm (summation of the ground vehicle and obstacle radius), which means that the ground vehicle was able to take necessary actions to avoid both obstacles. The second scenario we tested was with two obstacles moving in the same direction as shown in Fig. 8(a). The resultant paths of the vehicles are demonstrated in Fig. 8(b) and the minimum distance to the obstacles over time is shown in Fig. 9(b). Similar to the previous case, the ground vehicle successfully avoided collision with both obstacles with the closest distance recorded as 61.60 cm.

B. UGV Experiments

To demonstrate the applicability of the approach to different types of vehicles, we conducted unmanned ground vehicle experiments. The experiments were performed on a Clearpath Jackal UGV and two TurtleBot2 UGVs were used as mobile obstacles. In the offline stage, the reachable sets of the dynamic obstacles were extended out by 8 seconds using Flow*[31] as explained in Section III-A and an NN was trained to compute the desired repulsive fields for each obstacle fast at runtime as presented in Section III-D. The NN was trained using around 3 million data points and had an architecture of 4 fully-connected ReLU layers, each with 16 neurons, along with linear layers on the input and output. The potential field constants were $K_p = 5$ and $K_r = 10$.

At runtime, the robot was tasked to reach its goal location at [2.5, 0] m with desired speed of 0.5 m/s while avoiding the other two vehicles which moved straight also with a speed of 0.5 m/s. The ground vehicle observed the position and heading of the mobile obstacles only in the beginning of the operation, then lost its connection. We also assumed here that the robot did not have any onboard sensors to detect the obstacles. A Vicon motion capture system was used to detect the state of the ground vehicle and the initial position and heading of the dynamic obstacles.

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V. Conclusion and Future Work

In this work, we have presented a fast path planning framework for operating in dynamic environments with intermittent obstacle information. We combine reachability analysis and artificial potential fields as the backbone of our planning framework and leverage neural networks to ensure our control loop runs in real time. We have applied our approach on a simulation of a UUV crossing a shipping channel and presented experiments with ground vehicles. Thanks to our technique, the robot is able to avoid both collision and getting trapped into dynamical minima.

In the future, we will consider extensions of the proposed framework to account for additional sources of uncertainty, such as localization uncertainty or model uncertainty of the ego-vehicle. We also plan to consider cases in which some vehicles are cooperative while others are not. Additionally, we will investigate the use of verification tools to provide safety guarantees for the proposed learning-based control framework. Finally, we are planning to investigate the inclusion of this control framework into a confidence monitoring framework by leveraging other sources of measurements on these robot, such as the expected measurements from range sensors during a communication denied mission in a dynamic environment.
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