Online Active Gaussian Process Motion Planning in Unknown Environments

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Abstract

In this paper, we propose an online motion planning algorithm in an unknown environment using a factor graph with active sensing. Motion planning is demanding in unknown environments where the robot doesn't have any prior knowledge of the environment, since the robot has to complete the goal task while figuring out about the environment. In our work, we aim to plan in an unknown environment, where the robot has a certain goal to reach. The planning is formulated with a factor graph and optimized via the maximum a posteriori (MAP) inference, following the idea of GPMP2 (Mukadam et al., 2018). In order to consider the information of the environment required for motion planning in unknown environments, we incorporate active sensing by adding a factor regarding information gain to the graph. Our approach is validated in simulations, in comparison to GPMP2 without any consideration of information gain.

1. Introduction

Motion planning has been an old, but challenging problem in robotics. The main challenges in motion planning are collision avoidance and reducing computation speed, which become more demanding in unknown or dynamic environments. In unknown or dynamic environments, obstacle configurations are not known, which may incur collision during the execution of the planned trajectory. Therefore, an online motion planning is usually adopted along with suitable sensors (e.g., LIDAR) to update the map and re-plan the trajectory. Reduction of computation is critical at this point, because if the online re-planning cannot be executed in a very short time, it becomes impossible to follow the re-planned trajectory.

There have been many approaches to motion planning that enable fast and safe motion planning. One of such approaches is Gaussian Process Motion Planning 2 (GPMP2) (Mukadam et al., 2018), where fast collision checking is possible using a pre-computed signed distance field. Although GPMP2 is a very efficient motion planning algorithm, it has a strong and impractical assumption that the environment is completely known a priori. Other studies that deal with online motion planning in unknown environments are also present (Bircher et al., 2016; Schmid et al., 2020; Tordesillas et al., 2019). However, most of them (Bircher et al., 2016; Schmid et al., 2020) only address a pure exploration problem rather than with certain tasks (e.g., goal reaching), and the safety is enforced only by emergency strategies(i.e., emergency stop or backup trajectories) (Tordesillas et al., 2019).

In this work, we aim to handle online motion planning with a certain task to complete, in unknown environments while the robot only has a sensor of finite range that can observe the local environment. We construct a factor graph as in GPMP2 and add an information factor in the spirit of active sensing, inspired by an intuition that exploration could be beneficial to get more sense of the environment and move safely in unknown environments. The trajectory is then optimized from a probabilistic inference from the factor graph. The information factor helps the robot to reach the goal safely, by encouraging the information gathering to completely avoid collision in partially observed settings, rather than naively moving towards the goal using local observation.

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2. Background and Related Works

2.1. Gaussian Process Motion Planning

In contrast to the other trajectory optimization algorithm using discrete-time states in practice, Gaussian process motion planning (GPMP) was introduced to represent the continuous-time trajectory as a sample from a Gaussian process provided by a linear time-varying stochastic differential equation (Mukadam et al., 2016). In this approach, the distribution of the trajectory is expressed as:

$$\boldsymbol{\theta}(t) \sim \mathcal{GP}(\boldsymbol{\mu}(t), \boldsymbol{\mathcal{K}}(t,t')) \;\; t_0 < t, t' < t_{N+1}, \quad (1)$$

where $\boldsymbol{\mu}$ is a vector-valued mean function and $\boldsymbol{\mathcal{K}}(t,t')$ is a maxtirx-valued covariance function. Based on the definition of vector-valued Gaussian Process (Alvarez et al., 2012), $\boldsymbol{\theta}$ has a joint Gaussian distribution for any collection of times $t = \{t_0, \cdots, t_N\}$:

$$\boldsymbol{\theta} = \begin{bmatrix}\boldsymbol{\theta}_0 & \cdots & \boldsymbol{\theta}_N\end{bmatrix}^T \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\mathcal{K}}) \quad (2)$$

with the mean vector $\boldsymbol{\mu}$ and covariance kernel $\boldsymbol{\mathcal{K}}$ defined as

$$\boldsymbol{\mu} = \begin{bmatrix}\boldsymbol{\mu}_0 & \cdots & \boldsymbol{\mu}_N\end{bmatrix}, \; \boldsymbol{\mathcal{K}} = [\boldsymbol{\mathcal{K}}(t_i, t_j)]|_{ij, 0\leq i,j\leq N}. \quad (3)$$

The notation of bold $\boldsymbol{\theta}$ and $\boldsymbol{\mu}$ respectively imply the matrix formed by vectors $\boldsymbol{\theta}_i$ and $\boldsymbol{\mu}_i$, which are support states to parameterize $\boldsymbol{\theta}(t)$ and $\boldsymbol{\mu}(t)$.

To formulate trajectory optimization as probabilistic inference (Dong et al., 2016), Eq. (2) is regarded as the prior trajectory with the Gaussian process prior distribution:

$$P(\boldsymbol{\theta}) \propto \exp\Big\{ -\frac{1}{2}\|\boldsymbol{\theta} - \boldsymbol{\mu}\|^2_{\boldsymbol{\mathcal{K}}}\Big\}. \quad (4)$$

With this prior distribution, the collision-free likelihood is defined as a distribution in the exponential family

$$l(\boldsymbol{\theta}; \boldsymbol{e}) = \exp\Big\{-\frac{1}{2}\|\boldsymbol{h}(\boldsymbol{\theta})\|^2_{\Sigma_{obs}} + \frac{1}{2}\|\boldsymbol{h}(\boldsymbol{X})\|^2_{\Sigma_{\text{obs}}} + \Big\}, \quad (5)$$

where $\boldsymbol{h}(\boldsymbol{\theta})$ is a vector-valued obstacle cost for the trajectory, and Σ_{obs} is a diagonal matrix and the hyperparameter of the distribution. Given a Gaussian process prior Eq. (4) and exponential family likelihood function Eq. (5), the nonlinear least square problem is derived from the MAP posterior trajectory as

$$\boldsymbol{\theta}^* = \arg\max_{\theta}\Big\{P(\boldsymbol{\theta})l(\boldsymbol{\theta}; \boldsymbol{e})\Big\} \quad (6)$$

$$= \arg\min_{\theta}\Big\{ -\log\big(P(\boldsymbol{\theta})l(\boldsymbol{\theta}; \boldsymbol{e})\big)\Big\} \quad (7)$$

$$= \arg\min_{\theta}\Big\{\frac{1}{2}\|\boldsymbol{\theta} - \boldsymbol{\mu}\|^2_{\boldsymbol{\mathcal{K}}} + \frac{1}{2}\|\boldsymbol{h}(\boldsymbol{\theta})\|^2_{\Sigma_{obs}}\Big\} \quad (8)$$

This MAP problem can be represented in a factor graph, which is analyzed well and efficiently solved in SLAM community (Dellaert et al., 2017). Also, using the factor graphs, it is implemented more easily to update trajectory incrementally to solve problems like rapid replanning.

GPMP has been improved in several ways. For example, GPMP-GRAPH was proposed considering a graph-based initialization that simultaneously explores multiple trajectories in a topological approach (Huang et al., 2017; Kolur et al., 2019), helping to contend with the local minima problem. Also, the method was developed in which motion constraints were introduced as additional factors (Mukadam et al., 2018). Further, differential Gaussian process motion planning was proposed to readily adjust the covariance parameters based on the learning algorithm (Bhardwaj et al., 2020).

2.2. Exploration Based on Map Information

The occupancy grid map is a useful model providing a simple probabilistic spatial representation of the environment. To consider the map information in optimal exploration, the entropy (*Shannon information*) of the map was introduced as a metric of the knowledge for the map acquired so far (Bourgault et al., 2002). From this entropy, the expected mutual information gain can be computed, which is exploited as the exploration term maximizing the knowledge of the environment in the objective function of the optimization.

This approach using the map information gain has been revised for the advanced exploration methods. For example, to reduce the discretization effect on grid maps, the mutual information-based exploration on continuous occupancy maps was developed (Jadidi et al., 2015). Furthermore, for the 3D environment, the volumetric map model and the responding entropy were introduced (Rocha et al., 2005). Based on this approach using the mutual information gain, the other optimal exploration method has been studied, modifying the entropy by using some quantities such as Rényi entropy (Carrillo et al., 2015) and Cauchy-Schwarz quadratic mutual information (Nelson & Michael, 2015).

3. Proposed Method

3.1. Overview, Intuition, and Comparison with SOTA

We propose a motion planning framework based on factor graphs in unknown environment. The proposed method is a modification of factor graph-based motion planning to integrate active sensing. Based on an algorithm proposed in (Mukadam et al., 2018) (GPMP2), we add a factor regarding active sensing, to encourage exploration of the robot to enlarge its knowledge of the environment. This is inspired from the intuition that encouraging exploration would help planning a successful trajectory in unknown environments,

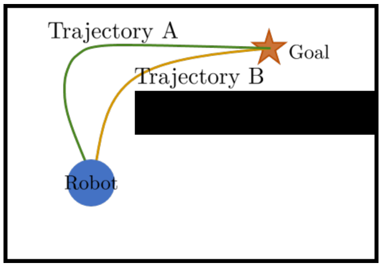


Figure 1. A mobile robot on a 2D world with a goal and an obstacle (black area). There are two candidate trajectories, A and B.

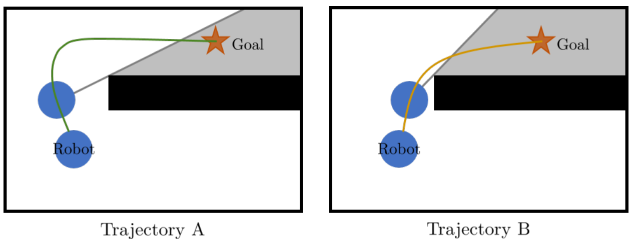


Figure 2. A comparison of observation ranges for trajectories A and B, where the grey area represent the occluded region. In the case of trajectory A, more space is observed.

rather than planning a purely goal-directed trajectory. For example, consider a situation in Figure 1. Trajectory A is certainly better than B in that it is shorter, but in case of unknown environment, trajectory A might be better. It is because trajectory B renders the environment more uncertain by restricting the range of area that can be observed as can be seen in Figure 2. Therefore, if the environment is unknown, it would be more beneficial to choose the safer trajectory A.

GPMP2 is one of the state-of-the-art algorithms of motion planning. However, it is built in the assumption that the environment is fully known and is done offline to compute a trajectory a priori. Thus it may not be successful in unknown environments. Compared to this, our method exploits a new factor to boost the information gathering to better perform in unknown environments.

3.2. Details of Formulation

3.2.1. Factor Graph Formulation

We construct a factor graph considering active sensing, as shown in Figure 3. The nodes are robot poses ($X_t \in \mathbb{R}^N$) sampled in a small time interval. A map is the knowledge about the environment accumulated over time up to the current time step. The map is not explicitly presented in the graph as nodes, but it is implicitly defined as a function of the pose. The factors accommodate the constraints and objectives of the motion planning: start/goal position constraints, trajectory smoothness, collision avoidance, and active sensing. The start/goal position constraints are realized through the factors at the initial and final nodes, and the smoothness of the trajectory is induced by the Gaussian Process (GP) prior factors between neighboring nodes. For collision avoidance and active sensing, they are achieved by the collision factor and the information factor, respectively. The collision factor is to prevent collision of the robot with obstacles, which is defined on the nodes of the graph and also on interpolated poses between the nodes. The information factor encourages active exploration of the robot to enlarge the knowledge of the environment. The collision and information factors are further detailed in the following subsections.

3.2.2. Collision Factor

The factors regarding collision avoidance (collision factors) are defined using the signed distance function (SDF) of the occupancy map as

$$\phi^{\text{collision}}(X_t) = \exp\{-\frac{1}{2}\|\mathrm{h}(\mathrm{X_t})\|^2_{\sigma_{\text{obs}}}\} \tag{9}$$

where $h(\cdot) \in \mathbb{R}^M$ is a cost function of the SDF, $\sigma_{\text{obs}} \in \mathbb{R}^{M\times M}$ is the hyperparameter to calculate the norm as $\|h\|^2_{\sigma_{\text{obs}}} = h^T \sigma_{\text{obs}}^{-1} h$ which is analogous to the expected covariance, and M is the number of primitives (e.g., spheres) constituting the robot body. h can be designed as any function that increases as the SDF value decreases, and in this work we define it as the hinge loss function of the SDF. Looking into the definition, the collision factor is related to the likelihood of collision so that the factor has a high value if it is not likely to be in collision status, and vice versa.

The collision factor of interpolated poses between neighboring nodes, $\phi^{\text{intp}}(X_t, X_{t+1})$, is defined as

$$\phi^{\text{intp}}(X_t, X_{t+1}) = \exp\{-\frac{1}{2}\|\mathrm{h}^{\text{intp}}(\mathrm{X_t}, \mathrm{X_{t+1}})\|^2_{\sigma_{\text{obs}}}\} \tag{10}$$

where $\boldsymbol{h}^{\text{intp}}(X_t, X_{t+1})$ is the vector of costs of interpolated poses defined as

$$\boldsymbol{h}^{\text{intp}}(X_t, X_{t+1}) = [h(X^1_{t,t+1}); h(X^2_{t,t+1}); ...; h(X^{n_{\text{ip}}}_{t,t+1})],$$

where $X^i_{t,t+1}$ is the i-th interpolated pose of X_t and X_{t+1}, and n_{ip} is the number of interpolation. This factor is introduced to ensure collision avoidance which may not be always guaranteed due to the discretization of continuous trajectories. Together with the collision factor defined on each node, the total collision factor of the graph as a whole can be formulated as

$$\phi^{\text{total col}}(\boldsymbol{X}) = \exp\{-\frac{1}{2}\|\mathrm{h}(\mathrm{X})\|^2_{\Sigma_{\text{obs}}}\} \tag{11}$$

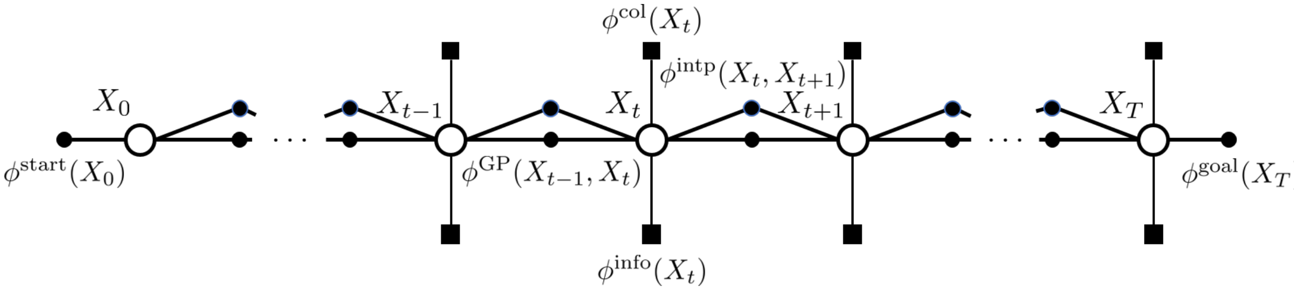


Figure 3. Graph structure of online motion planning using active sensing. The nodes are robot poses (X) where the subscript t represents the time index. The start/goal factors $\phi^{\text{start}}(X_0)$, $\phi^{\text{goal}}(X_T)$ address the start and goal position constraints. The factors between nodes are GP prior factors $\phi^{\text{GP}}(X_{\star-1}, X_\star)$ to enforce smoothness and collision factor of interpolated poses of two neighboring nodes $\phi^{\text{intp}}(X_{\star-1}, X_\star)$. The collision factor $\phi^{\text{col}}(X_\star)$ and the information factor $\phi^{\text{info}}(X_\star)$ are defined with respect to the pose and the map defined as a function of the pose.

where $\boldsymbol{X} = [X_0; X_1, ..., X_T]$, the collision cost vector

$$\begin{aligned}\boldsymbol{h}(\boldsymbol{X}) = [&h(X_0); h(X^1_{0,1}); ...; h(X^{n_{\text{ip}}}_{0,1});\\ &h(X_1); h(X^1_{1,2}; ...; h(X^{n_{\text{ip}}}_{1,2};\\ &h(X_2); h(X^1_{2,3}); ...;\\ &h(X_{T-1}); h(X^1_{T-1,T}; ...; h(X^{n_{\text{ip}}}_{T-1,T};\\ &h(X_T)],\end{aligned}$$

and the hyperparameter to compute the weighted norm is a block diagonal matrix

$$\Sigma_{\text{obs}} = \begin{bmatrix}\sigma_{\text{obs}} & & & \\ & \sigma_{\text{obs}} & & \\ & & \ddots & \\ & & & \sigma_{\text{obs}}\end{bmatrix}.$$

Although the factor requires the actual occupancy map to be computed, the groundtruth occupancy map is not known in advance since the environment is partially known. Therefore, we approximate the collision factor using the occupancy map up to the current best knowledge which is updated as the trajectory is executed. The occupancy map is initialized with all grid values of 0.5 (i.e., uncertain), and updated using new observations at each time step to either 0 for free space or 1 for occupied.

3.2.3. Information Factor

For the active sensing, the factors (information factors) that represent the knowledge (i.e., occupancy map) of the robot about the environment are defined using the information gain. The information gain is the difference of the entropies of the current and previous occupancy maps (i.e., the reduction of uncertainties). The entropy of an occupancy map is

$$H(M_t) = -\sum_i \sum_j p_{ij} \log p_{ij} \tag{12}$$

where M_t is the occupancy map at time t, $p_{ij} \in \{0, 0.5, 1\}$ is the occupancy grid value at grid (i, j), which represents the probability of being occupied. The entropy is maximized when all p_{ij}'s are 0.5 (i.e., all grids are uncertain) and minimized with a value of zero when all p_{ij}'s are 0 or 1 (i.e., all grids are observed). Then the information gain is

$$\text{IG}(M_t, M_{t-1}) = H(M_t) - H(M_{t-1}) \in \mathbb{R} \tag{13}$$

and the information factor is defined as

$$\phi^{\text{info}}(X_t) = \exp(-\frac{1}{2}\|\text{IG}(M_t, M_{t-1}) - \text{IG}^{\max}\|^2_{\sigma_{\text{info}}}) \tag{14}$$

where $\text{IG}^{\max}$ is the maximum information gain (i.e., when all grids in the sensor range are updated to either 0 or 1 from 0.5), and σ_{obs} is the hyperparameter to compute the norm. The information factor is defined in a way to increase the information gain, or to quickly reduce the map uncertainty. This can accelerate the determination of collision factors by encouraging exploration to enlarge the knowledge.

Similar to the collision factor, since the groundtruth map is unknown, we use the current map knowledge to compute the information factors. Additionally, for the efficiency of optimization, we approximate the information gains of time $\star$ with respect to the current map M_t rather than $M_{\star-1}$ as

$$\text{IG}(M_{t+1}, M_t) \approx \text{IG}(\mathbb{E}_{M_t}(M_{t+1}, X_{t+1}), M_t) \tag{15}$$

$$\text{IG}(M_{t+2}, M_{t+1}) \approx \text{IG}(\mathbb{E}_{M_t}(M_{t+2}, X_{t+2}), M_t) \tag{16}$$

where $\mathbb{E}_{M_t}(M_\star, X_\star)$ is the expected map at time $\star$ given the map M_t with the robot pose $X_\star$. The information factor can be summarized as

$$\phi^{\text{info}}(\boldsymbol{X}_{t:T}) = \exp(-\frac{1}{2}\|\hat{\mathbf{IG}}(M_t, \boldsymbol{X}_{t:T})\|^2_{\Sigma_{\text{info}}}) \tag{17}$$

where

$$
\begin{aligned}
\hat{\mathbf{IG}}(M_t, \boldsymbol{X}_{t:T}) = [&\mathrm{IG}(M_{t+1}, M_t) - \mathrm{IG}^{\max}; \\
&\mathrm{IG}(M_{t+2}, M_{t+1}) - \mathrm{IG}^{\max}; \\
&...; \\
&\mathrm{IG}(M_{T-1}, M_T) - \mathrm{IG}^{\max}].
\end{aligned}
$$

Because we only know the map M_t, the information factor would become less correct as the time step increases (i.e., farther from t). Thus, we weight the information factors with exponentially decreasing weights as

$$
\Sigma_{\text{info}}^{-1} = \begin{bmatrix} \sigma_{\text{info}}^{-1} & & & \\ & \sigma_{\text{info}}^{-1} \cdot 2^{-1} & & \\ & & \ddots & \\ & & & \sigma_{\text{info}}^{-1} \cdot 2^{-(T-t)} \end{bmatrix}. \tag{18}
$$

3.2.4. Inference

Using these factors, we perform a maximum a posteriori (MAP) inference to plan the robot motion as

$$
\begin{aligned}
\boldsymbol{X}^* &= \arg\max_{\boldsymbol{X}} p(\boldsymbol{X}|\boldsymbol{e} = \mathbf{0}) &(19)\\
&= \arg\max_{\boldsymbol{X}} p(\boldsymbol{X}) p(\boldsymbol{e} = \mathbf{0}|\boldsymbol{X}) &(20)\\
&= \arg\min_{\boldsymbol{X}} -\log p(\boldsymbol{X}) p(\boldsymbol{e} = \mathbf{0}|\boldsymbol{X}) &(21)
\end{aligned}
$$

where $\boldsymbol{e}$ is the binary events with $e_i = 0$ for no-collision and $e_i = 1$ for collision. Here, the probabilities are

$$
\begin{aligned}
p(\boldsymbol{X}) =& \phi^{\text{start}}(X_0) \cdot \phi^{\text{goal}}(X_T) \\
&\cdot \prod_{t=0}^{T-1} \phi^{\text{GP}}(X_t, X_{t+1}) \cdot \prod_{t=1}^{T} \phi^{\text{info}}(X_t) &(22)\\
=& \exp(-\frac{1}{2}\|\boldsymbol{X} - \boldsymbol{\mu}\|_{\mathcal{K}}^2 - \frac{1}{2}\|\hat{\mathbf{IG}}(M_t, \boldsymbol{X})\|_{\Sigma_{\text{info}}}^2) &(23)
\end{aligned}
$$

and

$$
\begin{aligned}
p(\boldsymbol{X}|\boldsymbol{e} = \mathbf{0}) &= \prod_{t=0}^{T} \phi^{\text{col}}(X_t) \cdot \prod_{t=0}^{T-1} \phi^{\text{intp}}(X_t, X_{t+1}) &(24)\\
&= \phi^{\text{total col}}(\boldsymbol{X}).
\end{aligned}
$$

We perform this inference online on the window of $\{X_t, X_{t+1}, ..., X_T\}$ using the current map information M_t. The online inference can be summarized into the equation

$$
\begin{aligned}
\boldsymbol{X}_{t:T}^* &= \arg\min_{\boldsymbol{X}} -\log p(\boldsymbol{X}) p(\boldsymbol{e} = \mathbf{0}|\boldsymbol{X}) &(25)\\
&= \arg\min_{\boldsymbol{X}} \Big\{ \frac{1}{2}\|\boldsymbol{X} - \boldsymbol{\mu}\|_{\mathcal{K}}^2 + \frac{1}{2}\|\hat{\mathbf{IG}}(M_t, \boldsymbol{X})\|_{\Sigma_{\text{info}}}^2 \\
&\quad + \frac{1}{2}\|\boldsymbol{h}(\boldsymbol{X})\|_{\Sigma_{\text{obs}}}^2 \Big\} &(26)
\end{aligned}
$$

Algorithm 1 Online motion planning algorithm

$t \leftarrow 0$
Initialize pose nodes $\boldsymbol{X} := \{X_t, \cdots, X_T\}$ as a line
Initialize factors $\phi_{t:T}^{\text{collision}}$ and $\phi_{t:T}^{\text{information}}$
MAP inference $\boldsymbol{X}_{t:T} = \text{argmax}_{\boldsymbol{X}} p(\boldsymbol{X}|\boldsymbol{e})$
Gaussian process interpolation to obtain $\boldsymbol{X}_{t:T}^{\text{GP}}$
while $t < T$ **do**
  Put the trajectory $\boldsymbol{X}_{t:t+\Delta t}^{\text{GP}}$ to the robot motion queue
  Reconstruct the factor graph (remove $\boldsymbol{X}_{t:t+\Delta t-1}$, set the start $X_{t+\Delta t}^{\text{GP}}$)
  Update the occupancy map M_t
  $t \leftarrow t + \Delta t$
  Update the collision factors $\phi_{t:T}^{\text{collision}}$ using M_t
  Compute the information factors $\phi_{t:T}^{\text{information}}$
  MAP inference $X_{t:T} = \text{argmax}_{\boldsymbol{X}} p(\boldsymbol{X}|\boldsymbol{e})$
  Gaussian process interpolation of the trajectory: $\boldsymbol{X}_{t:T}^{\text{GP}}$
end while

Although the graph is represented in discrete-time with sampled poses, the robot operates continuously in the real world. Thus when we apply the motion on the robot, we perform the Gaussian Process (GP) interpolation on the sampled poses to obtain a continuous-time trajectory. This method is adopted from previous works (Mukadam et al., 2018; Huang et al., 2017) where we can interpolate the trajectory in any resolution.

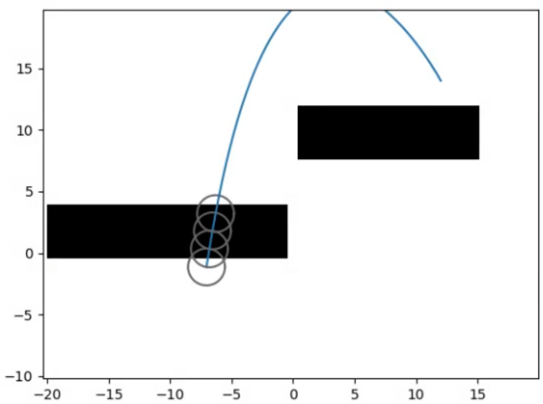
The algorithm is summarized in Algorithm 1.

4. Experiments

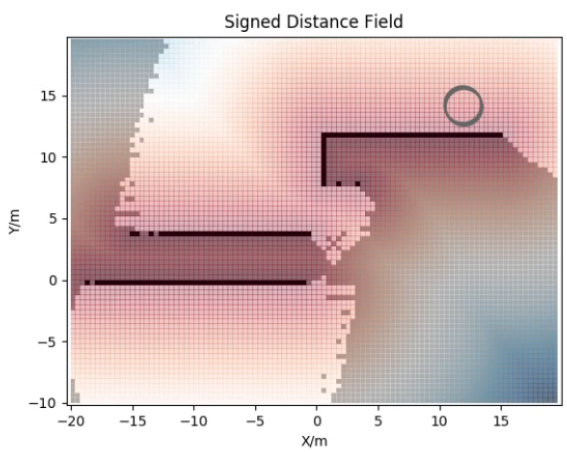
In this section, we show the experimental results on a mobile point robot on a 2D world with a LiDAR sensor in a simulation setting. The LIDAR sensor observation is assumed to be accurate, i.e., with zero uncertainty, and of a finite range.

Figure 4(a) to Figure 5(b) show the planning results of scenario 1. Figure 4(a) shows the online planned trajectory of the robot when using original GPMP2 planner. As shown in Figure 4(a), the robot fails to avoid the obstacle. In contrast, when using our modified planner, the online planned trajectory of the robot at same time step manages to avoid the obstacle, as shown in Figure 5(a). This is an effect of information factor, since it forces the robot to explore the unknown environment. In Figure 4(b) and Figure 5(b), the final observed maps are shown. Although the ratio of observed parts to unobserved parts seems to be similar, taking into account that the robot with GPMP2 planner collided with the obstacle in the middle of scenario, it is more plausible that our modified planner showed higher performance in active sensing.

Figure 6(a) to Figure 7(b) show the planning results of sce-

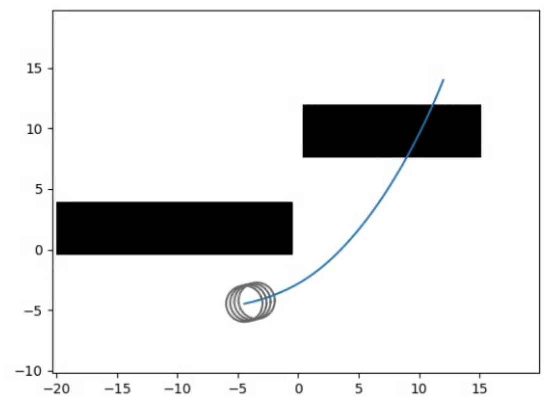


(a) A snapshot of generated trajectory

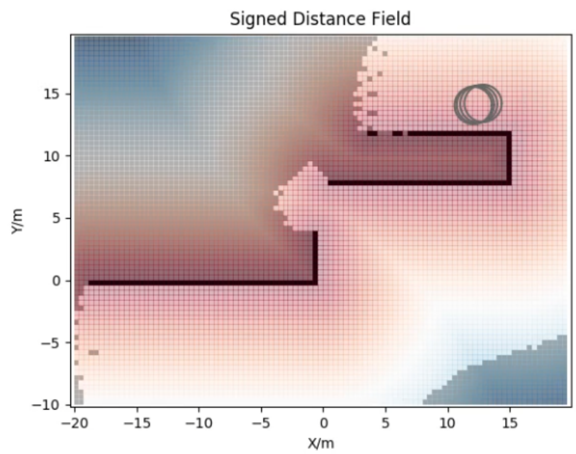


(b) Final observed map

Figure 4. Scenario 1: GPMP2



(a) A snapshot of generated trajectory



(b) Final observed map

Figure 5. Scenario 1: Proposed

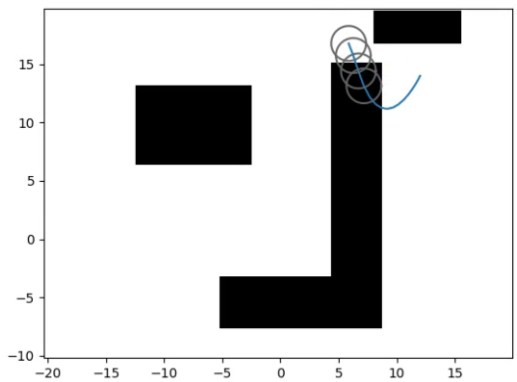
nario 2. Similar to scenario 1, Figure 6(a) shows the online planned trajectory of the robot when using original GPMP2 planner, and the robot fails to avoid the obstacle in Figure 6(a). However, when using our modified planner, the robot manages to avoid the obstacle, as shown in Figure 7(a). In Figure 6(b) and Figure 7(b), the final observed maps are shown. Similar to scenario 1, considering the fact that tor robot with GPMP2 planner collided with the obstacle in the middle of scenario, our modified planner showed higher performance in active sensing.

Further experiments and planning videos are presented in our presentation video.

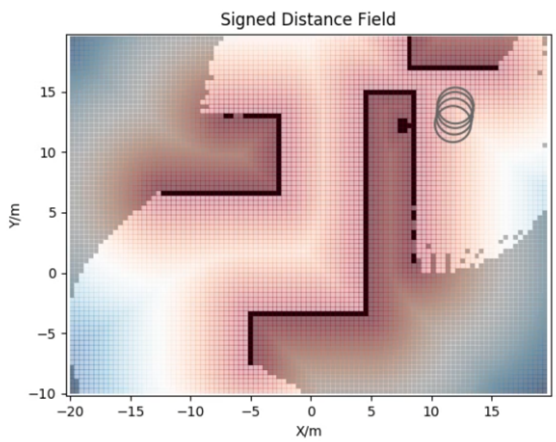
5. Conclusion

As shown from the experiment results, our proposed algorithm more stably reaches the goal while avoiding the unknown obstacles, compared to the original GPMP2 planner. This is because planning was not done every time step due to the delay of Δt. Also, during planning, the remaining time step becomes very small at the end of planning, which was also a reason of failure. The modified GPMP2 planner could avoid obstacles more stably, even in complex unknown environment, since it actively moved to gain the information of the unknown environment. In the modified algorithm, the robot tends to observe the environment as mush as it can, while also stably avoiding obstacles, which is a realization of active sensing. One drawback that has to be handled is hyperparameters. Previous GPMP2 planner was very vulnerable hyperparameters. There are several hyperparameters that we have to adjust for stable planning, such as sigma observation and epsilon in the obstacle cost function. Our modified GPMP2 was also vulnerable to such hyperparameters.

Future works will include varying the number of graph nodes rather than using a pre-determined value, which can be extended to direct time minimization in the trajectory

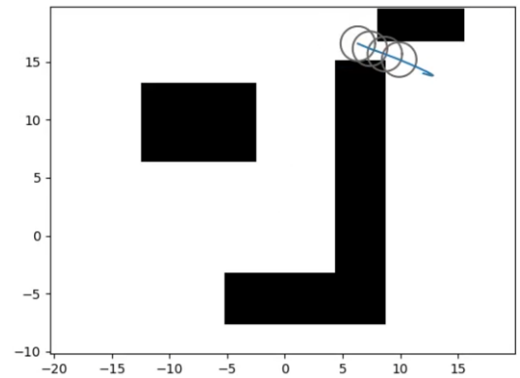


(a) A snapshot of generated trajectory

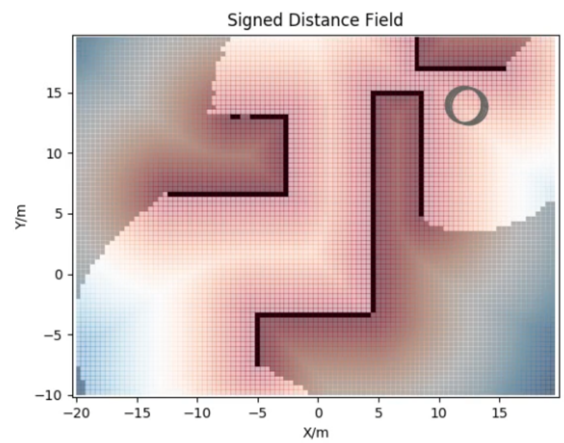


(b) Final observed map

Figure 6. Scenario 2: GPMP2



(a) A snapshot of generated trajectory



(b) Final observed map

Figure 7. Scenario 2: Proposed

optimization. Validation on nonholonomic mobile robots with a limited field of view may also a future work. Moreover, experiments under a dynamic unknown envrionment may be also used to test the performance of proposed algorithm. Lastly, since our proposed algorithm is susceptible to hyperparameters, differentiable GPMP can be used to manage hyperparameters. In differentiable GPMP, the hyperparameters are trained end-to-end from data.

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