Dynamic Hilbert Maps: Real-Time Occupancy Predictions in Changing Environments

Vitor Guizilini\textsuperscript{1,2}, Ransalu Senanayake\textsuperscript{3}, and Fabio Ramos\textsuperscript{1,3}

Abstract—This paper proposes a technique for predicting future occupancy levels. Due to the complexity of most real-world environments, such as urban streets or crowded areas, the efficient and robust incorporation of temporal dependencies into otherwise static occupancy models remains a challenge. We propose a method to capture the spatial uncertainty of moving objects and incorporate this information into a continuous occupancy map represented in a rich high-dimensional feature space. Experiments performed using LiDAR data verified the real-time performance of the algorithm.

I. INTRODUCTION

Occupancy maps which discern free areas of the environment (safe for traversal) from occupied areas (would result in a collision) are commonly used in autonomous vehicles. Straightforward approaches to static occupancy mapping rely on a grid-based non-overlapping discretization of the environment \cite{1}. Because grid cells are updated individually without considering the relationship among cells, this discretization process completely discards spatiotemporal dependencies. Furthermore, this representation quickly becomes infeasible for larger datasets, especially when dealing with volumetric data. The Hilbert Mapping (HM) framework \cite{2}, \cite{3} is an alternative to grid maps and can produce a continuous representation of occupancy states in a much lower computational cost.

Occupancy mapping in dynamic environments can be categorized into three classes: 1) building static occupancy maps in the presence of dynamic objects by considering moving objects as spurious data \cite{4}, \cite{5}, \cite{2} mapping the long-term dynamics of the environment \cite{6}, \cite{7}, and 3) mapping the short-term dynamics of the environment. This paper focuses on the third category. Short-term dynamics are important not only for understanding instantaneous changes in the environment, but also using this information to make predictions into the future.

Considering the limitations of previous attempts — dynamic Gaussian processes (DGP) \cite{8} and spatiotemporal Hilbert maps (STHMs) \cite{9} — to predict future occupancy, we propose a novel methodology for spatiotemporal modeling. As illustrated in Fig. 1, the area of future uncertainty around the moving vehicle is much larger due to the inherent unpredictability of future states.

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Fig. 1: (a) Data-frame captured by a LiDAR (blue: laser beams and red: laser hit points). The vehicle inside the rectangle moves from left to right (b) The current and future (8 seconds) occupancy maps produced by the Dynamic Hilbert maps (DHM) algorithm. Indicating the uncertainty of future predictions, the occupancy probability (red indicates highly probable) of the position of the vehicle and its surrounding is relatively low. The future prediction is represented as a spatial distribution peaked at one point which drops down radially, making such a map ideal for safer path planning.

II. METHOD

Following \cite{10}, we define a collection of hinged locations $\mathcal{X}$ that act as centers for anchoring kernels. With analogous to a multivariate Gaussian shape, these hinged locations have a center $\mu \in \mathbb{R}^3$ alongside another matrix $\Sigma \in \mathbb{R}^{3 \times 3}$ to denote how far the measurements affect in each direction. With the $M$ hinged locations $\mathcal{X} = \{\tilde{x}_m\}_{m=1}^M = \{\{\mu_m, \Sigma_m\}\}_{m=1}$, the occupancy probability of any point in the environment $x_* \in \mathbb{R}^3$ can be computed using a logistic model,

$$p(y_* = 1 | x_*, w, \mathcal{X}) = \left(1 + \exp\left(-w^T \Phi(x_*)\right)\right)^{-1}, \quad \text{(1)}$$

with a feature vector defined as:

$$\Phi(x_*, \mathcal{X}) = [k(x_*, \tilde{x}_1), k(x_*, \tilde{x}_2), \ldots, k(x_*, \tilde{x}_M)], \quad \text{(2)}$$

$$k(x_*, \tilde{x}_m) = \exp\left(-\frac{1}{2}(x_* - \mu_m)^\top \Sigma_m^{-1}(x_* - \mu_m)\right). \quad \text{(3)}$$

Refer \url{https://github.com/RansML/Bayesian_Hilbert_Maps/blob/master/BHM_tutorial.ipynb} for an intuitive explanation. The parameters $w$ in \cite{11} are learned by maximizing the regularized log-likelihood using stochastic gradient descent (SGD) with hit-free points $x$ collected from a LiDAR.

Our objective is to build short-term occupancy maps and make short-term predictions into the future. To accomplish this, three different Hilbert maps are maintained: $\mathcal{H}_p$, representing the previous timestep; $\mathcal{H}_c$, representing the current timestep; and $\mathcal{H}_a$, representing the accumulated model that is iteratively constructed as more data is collected. With this, we take the following four steps for each new LiDAR scan.

1. **Object segmentation:** In order to maintain memory and speed efficiency, we firstly cluster the pointcloud using the Quick-Means algorithm and discard the pointcloud. We obtain $P$ objects $O_i = \{O_i^p\}_{p=1}^P$. 

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We conducted experiments with toy datasets and the KITTI Vision Benchmark Suite. As shown in Table I and Fig. 4, DHM not only outperforms other methods, but also capable of making future predictions in 3D.

### III. EXPERIMENTS

<table>
<thead>
<tr>
<th>Time step</th>
<th>Dataset 1 (2D)</th>
<th>Dataset 2 (3D)</th>
</tr>
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<tr>
<td>$t_0$</td>
<td>HM DGP STHM DHM</td>
<td>HM DHM</td>
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<td></td>
<td>0.824 0.788 0.839 0.844</td>
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<td>$t_4$</td>
<td>0.139 0.419 0.524 0.663</td>
<td>0.189 0.625</td>
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</table>

### REFERENCES


