Multi-Objective Autonomous Exploration on Real-Time Continuous Occupancy Maps

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1 Motivation, Problem Statement, Related Work

Autonomous exploration in unknown environments is a needed capability for many robotic applications. Existing exploration frameworks rely on either geometric frontiers [1–4] or information-theoretic frontiers [5–10], with which separate planners are required to plan collision-free paths towards the selected frontiers. However, just because a frontier itself is informative does not necessarily mean that the robot will be in an informative “area” after reaching that frontier. For example, in Fig. 1, exploring the green arrow pointed open areas will uncover more unknown spaces compared to visiting those indicated by blue arrows. Thus the frontiers of blue arrows will lead to “less informative” actions compared with those of the green arrows. In this work, we propose to use a multi-objective variant of Monte-Carlo tree search — ParetoMCTS — that provides a non-myopic Pareto optimal action sequence and hence leads the robot to frontiers with the greatest extent of unknown area uncovering (Fig. 2 demonstrates that our planner prefers the frontier at the bottom because it leads to a larger uncovered space). Also importantly, some “fake” frontiers (circled in orange) can present in the discrete occupancy grid map (Fig. 1) due to the underlying inappropriate assumption that grids are independent to each other. To fix such issue, we need to explicitly model the inter-dependencies among occupancy values, and hereby we adopt the Bayesian Hilbert Map (BHM) [11] for continuous occupancy mapping which, however, is computationally prohibitive for large complex problems. We propose strategies and preliminary results for addressing above issues for real-time environment exploration applications.

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2 Technical Approach

Bayesian Hilbert Map [11] is an extension of Hilbert Map [12], which represents the environment with a continuous occupancy map by using a logistic regression classifier in a Hilbert space. The probability of a query location \( x \) being occupied, i.e., \( y = 1 \), can be computed by

\[
p(y = 1|\mathbf{x}, \mathbf{w}) = \left(1 + \exp(-\mathbf{w}^T \Phi(\mathbf{x}))\right)^{-1} = \sigma(-\mathbf{w}^T \Phi(\mathbf{x})),
\]

where \( \mathbf{w} \) is the model parameters to be optimized, \( \Phi(\mathbf{x}) \) is a radial basis function (RBF) feature transformation of \( \mathbf{x} \) centered at some spatially fixed points called hinge points, and \( \sigma(\cdot) \) represents the logit function. As a Bayesian approach, BHM places a factorized Gaussian prior \( p(\mathbf{w}|\alpha) = \mathcal{N}(\mathbf{w}|0, \text{diag}(\alpha)) \) on the model parameter and infers its posterior. Analytical posterior is intractable due to the nonconjugacy between the Gaussian prior and Bernoulli likelihood. Therefore, the posterior \( p(\mathbf{w}, \alpha|\mathbf{x}, y) \) is approximated by a variational distribution \( q(\mathbf{w}, \alpha) \), and we implicitly minimize the Kullback-Leibler (KL) divergence between \( q \) and \( p \) so that the approximate distribution is close to the true posterior [11].

Monte Carlo tree search (MCTS) methods belong to best-first search algorithms which expand the most promising subtrees first. We have been developing the Pareto Monte Carlo tree search (ParetoMCTS) [13], which is a multi-objective extension of MCTS that seeks for the Pareto optimal decisions where any objective cannot be further improved without hurting (or compromising) other objectives. Starting from the root node, we select the child node according to Pareto Upper Confidence Bound (UCB) criterion at each level until an expandable node with unexpanded children is encountered. A random child node is expanded and its value is evaluated through forward simulation. We update the statistics in all the visited nodes using the estimated value to bias the searching process in the next round. Fig. 3 shows the result of a ParetoMCTS when optimizing two exploration objectives in a confined environment. ParetoMCTS grows an asymmetric tree towards the high-reward area.
and tries to optimize both objectives. The resulting tree is collision-free and satisfies robot’s motion constraints.

In this paper, the inputs of ParetoMCTS include current robot pose, a occupancy map, an entropy map and a frontier dynamics map. Given a grid $m_i$ and its occupancy probability $P_i$, the entropy is given by

$$H(m_i) = -P_i \log(P_i) - (1 - P_i) \log(1 - P_i).$$

(2)

We defined the frontier dynamics map to be the absolute difference between two consecutive occupancy maps.

ParetoMCTS outputs the most informative trajectory (red line in Fig. 3) for exploration given the current perception information. One can simply follow this trajectory and plan again when reaching the end. However, considering that the perception information is continuously updating, we only take the first action (blue line in Fig. 3) in the resulting trajectory and replan in a receding horizon manner to avoid newly encountered obstacles and keep the informative trajectory up to date.

3 Results

In this section, we demonstrate that by simultaneously considering two (potentially reward-diverging) objectives – maximization of frontier dynamics and minimization of map entropy, our system could efficiently explore unknown environments in real time even though our map is continuous. We use BHM to build the occupancy map and reward maps for ParetoMCTS, and use OctoMap [14] to build a 3D map.

![Fig. 4](Fig. 4 Exploration results in a simulated environment. (a) The simulated environment that needs to be explored. (b) The mapping results from BHM. Green, red, brown colors represent free, occupied and uncertain spaces, respectively. (c) 3D view of the mapping result.

Our experiments are conducted in a Gazebo simulator and the environment to be mapped is shown in Fig. 4(a). The occupancy and 3D mapping results after exploration are shown in Fig. 4(b) and Fig. 4(c), respectively. Fig. 5 shows the exploration process. Specifically, the frontiers are detected by subtracting two consecutive occupancy maps (the bigger the discrepancy, the larger the reward of that frontier). Then we quantify the occupancy entropy as another rewarding metric. Typically, low-entropy values appear in explored areas while high-entropy values appear in unexplored areas. Therefore, subtrees with more branches stick out of the unknown area enjoy higher entropy reward. This means that the resulting path is likely to
encourage the robot to uncover more unknown areas. This behavior is achieved in
our experiment. In Fig. 5(a), before planning, the robot could move either up (and
then left) or down since both directions have frontiers. Our system chooses the latter
direction (see Fig. 5(b)), which turns out to be a right decision. Although the up
direction has more and nearer frontiers, the unexplored areas beyond those frontiers
are smaller than that of our selected frontiers.

![Fig. 5 3D Exploration process on top of Bayesian Hilbert Map with ParetoMCTS.](image)

4 Main Experimental Insights

The quality and computation time of BHM highly rely on the choice of kernel
bandwidth and number of hinge points. To make BHM more applicable for real-time
scenarios, we propose a convex-hull-based hinge points selection strategy. At each
time step, a slightly enlarged convex hull is built based on the training points within the field of view or sensing radius. This tighter “bounding box” will enclose the most relevant hinge points. We generate a more compact feature vector using these selected hinge points and only predict the occupancy probability locally.

In the child node selection of ParetoMCTS, there is a weight parameter that balances exploitation of the recently discovered most promising child node and exploration of alternatives which may turn out to be a superior choice at later time. Normalizing the exploitation scores or multiplying the exploration weight by the maximum exploitation score makes the weight parameter insensitive to the scales of objectives. In addition, when the tree enters unknown areas, everywhere seems equally uncertain or informative, which makes the tree unable to grow asymmetrically, limiting the searching depth.
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