Predictive Localization Uncertainty-aware Planning for Safe Exploration

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Abstract. This paper introduces a novel learning-based method particularly concerning the safety against localization uncertainty during exploration of unknown environments. The proposed method comprises a couple of learning networks to predict the uncertainty, followed by a planning algorithm under uncertainty: First, from the sensor measurements, features that affect localization uncertainty is extracted, and used to construct a 3D feature map. This map is then used to predict localization drift for the corresponding planning action. Based on the predicted localization drift information, we evaluate collision risks and expected information gain to plan the safe yet best exploration action. A sampling-based algorithm is employed to facilitate these evaluations to determine the safest and most efficient exploration paths. The proposed method is validated through simulations, demonstrating an enhanced collision rate and exploration rate in comparison to the existing work.

Keywords: autonomous system, uncertainty-aware planning

1 Introduction

Recent advancements in autonomous agent exploration have significantly improved their capabilities, with applications in areas such as infrastructure inspection, disaster response, and environmental monitoring.

Despite progress, safe exploration in unknown environments remains challenging due to localization uncertainty, which can lead to increased collision risks, state estimation failures, and mapping inaccuracies.

Perception-aware planning methods have tackled this by focusing on preserving measurement quality to reduce future uncertainty, such as maintaining visibility of detected features. However, these methods often neglect proper uncertainty quantification, limiting their ability to assess risks and provide safety guarantees. Additionally, they do not effectively integrate exploration objectives, restricting their applicability to exploration scenarios.

Some approaches explicitly address uncertainty by developing uncertainty-aware metrics or hierarchical frameworks to manage exploration while minimizing uncertainty. However, these methods rely on oversimplified models that assume consistent feature detection across viewpoints, ignoring the complex perception-awareness, and often being computationally expensive.

In this paper, we present a novel learning-based method that quantifies localization uncertainty and explicitly assesses its risk for safe exploration. Our approach focuses on three objectives: (1) providing real-time estimates of localization uncertainty via predictive localization drift, (2) assessing collision risks based on quantified uncertainties, and (3) integrating uncertainties to enhance exploration efficiency and safety.

To the best of the authors' knowledge, this method is the first to quantify localization uncertainty in terms of drift increment and integrate it into an exploration framework. Our contributions are as follows:

1. A novel learning-based drift increment prediction model to quantify realistic localization uncertainty.
2. Seamless integration of quantified uncertainty with a sampling-based exploration, enhancing risk awareness and improving exploration efficiency.
3. Validation through photorealistic simulations, demonstrating improved state estimation accuracy and reliability in perceptually degraded environments.

2 Problem Formulation

2.1 Sampling-based Volumetric Exploration

A sampling-based method like RRT* can be adapted for exploring unknown space. The tree $\mathcal{T} = (\mathcal{V}, \mathcal{E})$ consists of nodes $\mathcal{V}$ and connectivity $\mathcal{E}$, with the root at the robot's current pose. Each node V_i represents a trajectory τ, information gain g, travel cost c, and value v, while each edge E_{ij} denotes $V_i \rightarrow V_j$

$$V_i = \{\tau_i, g(\tau_i), c(\tau_i), v_i\} \tag{1}$$

The next-best node is selected by maximizing v:

$$\arg\max_{V \in \mathcal{T}} v \tag{2}$$

2.2 Localization Uncertainty-Aware Exploration

The robot's state $\hat{\xi}$ is estimated from a drift-prone estimator like Visual-Inertial Odometry (VIO). Localization drift and its increment are defined as $\tilde{\xi}(k) = \xi(k) - \hat{\xi}(k)$ and $\delta\xi(k) = \tilde{\xi}(k) - \tilde{\xi}(k-1)$ respectively.

Then, the problem of Section 2.1 can be improved by considering localization uncertainty in both information gain and risk. Each node V_i includes risk r, localization drift $\tilde{\xi}$, and drift increment $\delta\xi$, alongside the original quantities:

$$V_i = \{\tau_i, g(\tau_i), c(\tau_i), v_i, r(\tau_i), \tilde{\xi}(\tau_i), \delta\xi(\tau_i)\} \tag{3}$$

The drift $\tilde{\xi}(V_i)$ is the predictive uncertainty of pose of end of the trajectory τ_i,$\xi^*(V_i)$ modeled as a Gaussian random variable. The drift increment $\delta\xi(\tau_i)$ reflects uncertainty during travel from parent node V_h to node V_i. Gain $g(V_i)$

depends on both $\xi^*(V_i)$ and $\tilde{\xi}(V_i)$, while risk $r(V_i)$ accounts for collision risk, considering $\tau(V_i), \tilde{\xi}(V_i)$, and $\mathcal{M}$.

The next-best node is selected by optimizing v with an added risk constraint:

$$\begin{aligned} \arg\max_{V \in \mathcal{T}} \quad & v \\ \text{s.t.} \quad & r < p_{safe} \end{aligned} \tag{4}$$

3 Algorithm Development

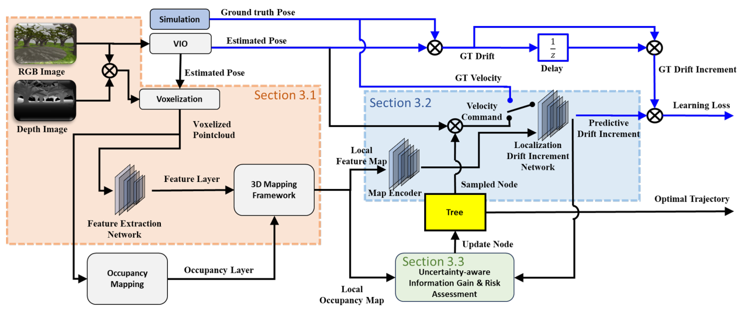


Fig. 1: System overview of the proposed method. Blue lines are for training only; black lines are for both training and deployment.

3.1 3D Feature Mapping

The proposed feature mapping integrates a feature layer $\mathcal{M}_f$ into the volumetric map $\mathcal{M}$ from the Voxblox framework [2]. A colorized point cloud is generated from RGB and depth images, then voxelized. Each voxel's features are extracted using a modified PointNet, which processes 6D colorized point clouds and produces 16-dimensional feature outputs that encapsualte the physical attributes of each voxel.

3.2 Pose Distribution with Localization Drift Increment

The proposed localization drift increment network predicts $\delta\xi$ by leveraging evidential deep learning [1]. Its input consists of two components: 1) The robot's action vector, calculated as the average velocity between nodes V_h and V_i; 2) The encoded local feature map, generated using a map encoder based on VoxelNet. This encoder effectively handles the inherent sparsity in the local feature map by reducing its dimensionality while reserving voxel-wise features.

The local feature map $\mathcal{LM}_f$ is generated using the `Vis()` operator as $\mathcal{M}_f \cap V_{\text{frustum}}$ where the volume of camera frustum V_{frustum} is determined by the estimated state $\hat{\xi}$, the camera's field of view (FoV), and its sensing range.

For given drift distribution $\delta\xi_h$ and predictive drift increment $\delta\xi_i$, drift distribution $\delta\xi_i$ is generated as follows:

$$\tilde{\xi}_i = \tilde{\xi}_h + (\xi^*(V_i) - \xi^*(V_h)) + \delta\xi_i \tag{5}$$

3.3 Uncertainty-aware Information Gain and Risk Assessment

We adopt the TSDF-based 3D reconstruction gain from [4]. Notably, Our gain assessment considers both the nominal state ξ^* sampled from the RRT tree and the predictive localization drift $\tilde{\xi}$. We assess the risk of the sampled node considering localization uncertainty and map occupancy by the collision risk assessment method from [3]. we leverage the predictive localization drift distribution to probabilistically calculate both gain and risk.

3.4 Localization Uncertainty-aware Exploration

The proposed method integrates the uncertainty-aware information gain and probabilistic risk to the existing sampling-based exploration algorithm such as RRT*. The overall process of modified RRT* is depicted in Algorithm 1.

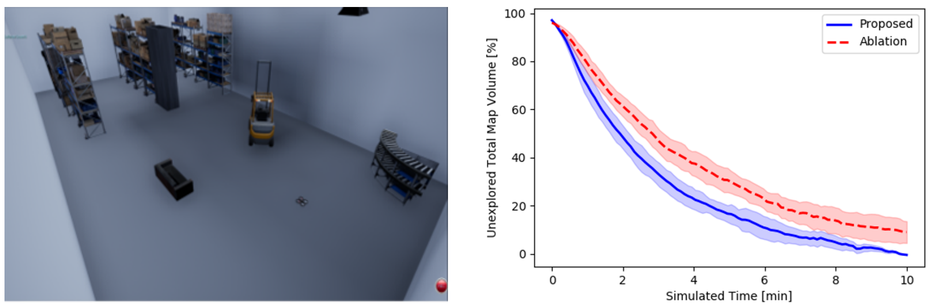
Algorithm 1: Modified RRT* Algorithm

```
T ← (V = {0}, E = ∅) ;                                  // Initialize tree
while Planning do
    V_pivot ← RandomElement(V) ;   // Select pivot node from tree
    ξ*_new ← Sample(ξ*_pivot, l_1) ;  // Sample new pose within range l_1
    LM_f ← Vis(ξ*_new);
    V_near ← Near(V, ξ*_new, l_2) ;   // Find near node within range l_2
    v_best ← 0, V_best ← 0, E_best ← ∅ ;        // Initialize best node
    for all V_i ∈ V_near do
        a_new ← CalAction(ξ*_i, ξ*_new);
        δξ_new ← InferDriftIncrement(a_new, LM_f);
        ξ̃_new ← PropagateDrift(ξ̃_i, δξ_new) ;                // by eq (5)
        r_new ← CalRisk(ξ*_new, ξ̃_new, M)
        if r_new < p_safe then
            g_new ← CalGain(ξ*_new, ξ̃_new, M), c_new ← CalCost(ξ*_i, ξ_new);
            v_new ← CalValue(g_new, c_new);
            if v_new > v_best then
                v_best ← v_new, V_best ← V_i, E_best ← {(V_best, V_new)}
    V ← V ∪ V_best, E ← E ∪ E_best ;             // Add to existing tree
```

Inputs l_1 and l_2 are RRT tree update parameters, and p_{safe} defines the allowed risk for a new node. `CalAction()` and `InferDriftIncrement()` are detailed in section 3.2. `CalCost()` is the positional distance between ξ_i and ξ_j, and `CalValue()` is the gain-to-cost ratio, as described in [4].

4 Numerical Experiments

We compare our proposed uncertainty-aware exploration with its ablation method (i.e., method of section 2.1), using the exploration rate (percentage of environment observed) as the performance metric. If a collision occurs, the simulation is stopped, and the last exploration rate is retained. Experiments in a photorealistic Unreal Engine simulation, repeated 10 times, show that the proposed method achieved a 100% success rate with no collisions, while the ablation method achieved only 60% success with 4 collisions. Overall, the proposed method outperforms the ablation in terms of exploration rate and success rate.



(a) Simulation environment

(b) Exploration rate

Fig. 2: Photorealistic simulation environment and comparison of exploration rates between the proposed method and the ablation method.

5 Conclusion

The proposed method presented an uncertainty-aware exploration that improves exploration efficiency and safety by integrating predictive localization drift into a sampling-based framework. Simulations show it outperforms existing RRT* exploration in terms of exploration rate and collision avoidance.

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