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# Semantic-Integrated Topological Mapping with Factor Graph Optimization for Small Robots in Unknown Environments

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*Abstract*— **Small, resource-constrained swarm robots require scene understanding that is both semantic and metric, yet most SLAM pipelines either ignore semantics or demand heavy sensors. We propose an online hybrid factor-graph optimisation (FGO) framework that jointly estimates continuous robot poses and discrete terrain labels using only low cost wheel encoder and IMU data. Continuous and discrete variables are modelled as nodes in a single factor graph; maximum-a-posteriori inference is carried out by an alternating optimisation scheme executed inside a fixed-size sliding window, allowing constant-time updates on embedded hardware. The method closes three longstanding gaps: (1) a unified probabilistic formulation for hybrid state estimation, (2) an online solver that scales with mission duration, and (3) automatic construction of a dynamic semantic topological map that captures both spatial layout and label transitions. The resulting graph supports high-level navigation and situational awareness without external infrastructure. We validate the approach in a 2D simulation comprising six terrain regions, random walks of 150 steps, and realistic odometry and classification noise. These results demonstrate that hybrid FGO can endow minimalist robots with robust, semantics-aware mapping capabilities, paving the way for long-duration exploration and cooperative task planning in GPS-denied, sensor-limited environments.**

## I. Introduction

The evolution of robotic systems has facilitated their integration into diverse application domains, with swarm robotics emerging as a particularly promising paradigm for scenarios where traditional monolithic robotic platforms face limitations or where enhanced operational efficiency is desired. This technology has garnered significant attention across multiple domains, including extraterrestrial surface exploration [1], emergency response operations [2], logistics and cargo distribution [3], and microscopic therapeutic delivery systems [4]. Traditional approaches to lunar and planetary surface investigation have predominantly relied on individual, multifunctional rovers operating within relatively benign environments. This methodology has constrained the scope of scientific discovery while introducing substantial mission risk due to the absence of on-site maintenance capabilities. The deployment of robotic swarms offers the potential for comprehensive terrain coverage through distributed exploration strategies. Such systems exhibit inherent fault tolerance, maintaining operational capability despite the loss or malfunction of individual units. However, swarm-based approaches necessitate cost-effective manufacturing of numerous robotic agents, which constrains the sophistication of onboard instrumentation and computational resources compared to their larger counterparts. This limitation renders existing autonomous control strategies, originally developed for high-capability individual robots, unsuitable for swarm applications. Consequently, there exists a critical need for swarm control algorithms specifically designed to leverage the collective behavior of resource-constrained robotic agents with limited individual capabilities.

For autonomous mobile robots to operate stably over long durations, both localization (estimating their own position) and mapping (understanding the surrounding environment) are indispensable technologies. The task of performing these simultaneously, known as SLAM (Simultaneous Localization and Mapping), has been a subject of intensive research. Much of the conventional research in SLAM has focused on handling the geometric information of the environment, such as the location of obstacles. However, for a robot to perform more advanced tasks, it is crucial to recognize semantic information, such as the material of the road surface or the type of vegetation—in other words, "what the place is." Such semantic information is often represented by discrete labels like "sand," "grass," or "rocky." The robot's pose is a continuous state variable in Euclidean space, whereas the terrain label is a discrete state variable. Handling these different types of variables simultaneously is known as a hybrid estimation problem, and its solution presents significant challenges. In this paper, we propose a unified approach to this hybrid estimation problem based on Factor Graph Optimization. The proposed method represents the continuous pose and the discrete terrain label as variable nodes in a factor graph and models the observational information related to both as factor nodes. This allows us to formulate the Maximum a Posteriori (MAP) estimation of the robot's trajectory and the sequence of terrain labels as a minimization problem of a single cost function. Furthermore, we introduce a sliding window to enable online sequential processing, thereby keeping the computational cost within a practical range. The main contributions of this paper are threefold:

1) The formulation of a hybrid factor graph model that handles continuous poses and discrete terrain labels.
2) An online estimation algorithm that combines alternating optimization with a sliding window.
3) A method for constructing a dynamic topological map

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from the estimation results to support a structural understanding of the environment.

## II. Related Works

Early topological approaches such as RatSLAM [5] used appearance cues to generate graph-like maps inspired by hippocampal models. More recent memory–efficient variants, e.g. VineSLAM [6], continue to rely on camera or LiDAR data. These methods, however, struggle in light–deprived or dusty scenes and rarely propagate metric uncertainty.

iSAM2 [7] enabled real-time smoothing of continuous pose graphs, while robust extensions such as switchable constraints [8] and max-mixtures [9] mitigated outliers. Yet they optimise *continuous* variables only. Discrete–continuous FGO theory was generalised by Doherty *et al.* [10], later applied to GNSS integrity monitoring [11]. To date, no study embeds *terrain labels* as explicit discrete nodes within an FGO framework.

IMU-based terrain classifiers have exceeded 90 % accuracy with shallow features [12] or deep FT-LSTM models [13]. Nevertheless, these works treat classification as an end task; labels are neither fused with odometry nor persisted in a map. The TAIL dataset [14] offers varied terrain recordings but leaves algorithmic fusion open.

Existing topological SLAM systems are sensor-heavy and semantic-agnostic; FGO methods rarely handle discrete environmental context; terrain classifiers ignore mapping; and none quantify joint uncertainty across modalities. Our algorithm bridges these gaps by **(i)** operating on *low-cost IMU + wheel encoders alone*, **(ii)** injecting *terrain labels as discrete variables* into a *hybrid FGO* so that poses and semantics are co-optimised, and **(iii)** outputting a *semantic topological map* with unified uncertainty estimates, all in real time on small robots navigating unknown environments.

## III. Problem Formulation

In this section, we define the state variables and observation models for the estimation problem and formulate the estimation task.

### A. State Variables

The state of the robot to be estimated consists of a continuous pose and a discrete terrain label.

- **Robot Pose**: The pose of the robot on a 2D plane at time $t$ is denoted by $X_t \in \mathrm{SE}(2)$. Specifically, it is represented by a vector consisting of the position $(x_t, y_t)$ and the orientation $\theta_t$.
$$X_t = (x_t, y_t, \theta_t)^T \tag{1}$$
- **Terrain Label**: The discrete variable representing the type of terrain where the robot is located at time $t$ is denoted by $L_t$. $L_t$ takes a value from a predefined set of labels $\mathcal{L}$.
$$L_t \in \mathcal{L} = \{\mathrm{label}_1, \mathrm{label}_2, \ldots, \mathrm{Unknown}\} \tag{2}$$
Here, Unknown is a special label representing an unknown region that does not classify as any of the known terrains.

We denote the entire trajectory and the full sequence of labels as $\mathbf{X} = \{X_0, \ldots, X_N\}$ and $\mathbf{L} = \{L_0, \ldots, L_N\}$, respectively.

### B. Observation Models

The robot obtains noisy observations about its movement and the surrounding environment.

- **Motion Model (Odometry)**: The relative displacement $u_t \in \mathrm{SE}(2)$ from time $t-1$ to $t$ is observed from sources such as wheel encoders. This observation is assumed to include Gaussian noise $w_t$.
$$X_t = X_{t-1} \oplus u_t \oplus w_t, \quad w_t \sim \mathcal{N}(0, \Sigma_{odom}) \tag{3}$$
Here, $\oplus$ represents the compounding operator for poses on SE(2).
- **Observation Model (Terrain Label)**: At time $t$, a terrain sensor observes a terrain label $Z_t \in \mathcal{L}$. This observation may be subject to misclassification with a certain probability. We denote the conditional probability of observing $Z_t$ when the true label is $L_t$ as $P(Z_t|L_t)$.

We denote the entire sequence of odometry observations as $\mathbf{U} = \{u_1, \ldots, u_N\}$ and the full sequence of label observations as $\mathbf{Z} = \{Z_0, \ldots, Z_N\}$.

### C. Maximum a Posteriori (MAP) Estimation

Our goal is to perform MAP estimation, which is to find the state sequences $\mathbf{X}, \mathbf{L}$ that maximize the posterior probability given the observation sequences $\mathbf{U}, \mathbf{Z}$.

$$(\mathbf{X}^*, \mathbf{L}^*) = \arg\max_{\mathbf{X},\mathbf{L}} P(\mathbf{X}, \mathbf{L}|\mathbf{U}, \mathbf{Z}) \tag{4}$$

By Bayes' theorem, this is equivalent to maximizing the product of the likelihood and the prior probability.

$$P(\mathbf{X}, \mathbf{L}|\mathbf{U}, \mathbf{Z}) \propto P(\mathbf{U}, \mathbf{Z}|\mathbf{X}, \mathbf{L}) P(\mathbf{X}, \mathbf{L}) \tag{5}$$

Assuming that the state transitions and observations satisfy the Markov property, this probability can be decomposed into a product of factors at each time step as follows:

$$\begin{aligned} &P(\mathbf{X}, \mathbf{L}|\mathbf{U}, \mathbf{Z}) \\ &\propto P(X_0, L_0) \prod_{t=1}^{N} P(X_t|X_{t-1}, u_t) P(L_t|L_{t-1}) \prod_{t=0}^{N} P(Z_t|L_t) \end{aligned} \tag{6}$$

Each term in Equation (6) corresponds to a factor in a factor graph. The MAP estimation problem can be transformed into a problem of minimizing a cost function $J(\mathbf{X}, \mathbf{L})$, which is the negative log-likelihood of the posterior probability.

$$(\mathbf{X}^*, \mathbf{L}^*) = \arg\min_{\mathbf{X},\mathbf{L}} J(\mathbf{X}, \mathbf{L}) \tag{7}$$

The cost function $J$ is defined as the sum of cost terms corresponding to the negative log-likelihood of each factor.

$$J(\mathbf{X}, \mathbf{L}) = \sum_{t=1}^{N} C_{odom}(X_t, X_{t-1}) + \sum_{t=0}^{N} C_{label}(L_t, Z_t) + \sum_{t=1}^{N} C_{trans}(L_t, L_{t-1}) \quad (8)$$

Here, each cost term is defined as follows:

- **Odometry Cost**: From the assumption of Gaussian noise, this is represented by the Mahalanobis distance (squared error).

$$C_{odom} = \|(X_{t-1}^{-1} \otimes X_t) - u_t\|^2_{\Sigma_{odom}} \quad (9)$$

  Here, the operation $(X_{t-1}^{-1} \otimes X_t)$ computes the relative transformation from $X_{t-1}$ to $X_t$.
- **Label Observation Cost**: A penalty for a mismatch between the estimated label and the observed label.

$$C_{label} = \begin{cases} 0 & (L_t = Z_t) \\ c_{\text{incorrect}} & (L_t \neq Z_t) \end{cases} \quad (10)$$

- **Label Transition Cost**: A penalty for a change in the label between consecutive time steps. This improves the stability of the estimation.

$$C_{trans} = \begin{cases} 0 & (L_t = L_{t-1}) \\ c_{\text{transition}} & (L_t \neq L_{t-1}) \end{cases} \quad (11)$$

## IV. Proposed Method: Online Hybrid Factor Graph Optimization

Since the cost function $J(\mathbf{X}, \mathbf{L})$ includes both continuous variables $\mathbf{X}$ and discrete variables $\mathbf{L}$, its direct minimization is difficult. Therefore, this paper adopts an alternating optimization approach, inspired by the EM algorithm. Furthermore, a sliding window is introduced to achieve online performance.

### A. Alternating Optimization Approach

For the data within the sliding window, the following two steps are repeated alternately until convergence.

*1) Step A: Optimization of Discrete Variables (Labels):* With the current pose estimate $\hat{\mathbf{X}}$ held fixed, we minimize the cost function with respect to the label sequence $\mathbf{L}$.

$$\hat{\mathbf{L}} = \arg\min_{\mathbf{L}} \left( \sum_{t=0}^{N} C_{label}(L_t, Z_t) + \sum_{t=1}^{N} C_{trans}(L_t, L_{t-1}) \right) \quad (12)$$

This problem can be viewed as finding the optimal state sequence for a Hidden Markov Model (HMM), where the state is the terrain label $L_t$ and the observation is the sensor's label reading $Z_t$. This can be solved efficiently using the Viterbi algorithm. Let $V_{t,j}$ be the minimum cost for each time $t$ and each state (label) $j \in \mathcal{L}$. The Viterbi algorithm is given by the following recurrence relation:

$$V_{t,j} = C_{label}(L_t = j, Z_t) + \min_{i \in \mathcal{L}} \left( V_{t-1,i} + C_{trans}(L_t = j, L_{t-1} = i) \right) \quad (13)$$

After computing $V_{t,j}$ for all time steps, the optimal label sequence $\hat{\mathbf{L}}$ is obtained by backtracking from the label with the minimum cost at the final time $N$.

*2) Step B: Optimization of Continuous Variables (Poses):* With the label sequence $\hat{\mathbf{L}}$ obtained in Step A held fixed, we minimize the cost function with respect to the pose sequence $\mathbf{X}$.

$$\hat{\mathbf{X}} = \arg\min_{\mathbf{X}} \left( \sum_{t=1}^{N} C_{odom}(X_t, X_{t-1}, u_t) \right) \quad (14)$$

This becomes a standard non-linear least squares problem composed only of odometry factors.

### B. Online Estimation with a Sliding Window

Batch processing, which optimizes over the entire history of data, is impractical for long-term operation as the computational cost continuously increases. Therefore, we introduce a sliding window that considers only the most recent $W$ steps of data. Each time a new observation is received, the window is advanced by one step, and the alternating optimization is performed within it. This allows for the sequential updating of the estimation results while keeping the computational complexity constant.

## V. Dynamic Topological Map Construction

Using the optimized state sequence $(\mathbf{X}^*, \mathbf{L}^*)$ obtained in the previous section, we construct a dynamic topological map that represents the high-level structure of the environment. This map is a graph that shows where each terrain exists and how they are connected.

- **Nodes**: Each estimated terrain label $L \in \mathcal{L}$ becomes a node in the graph.
- **Node Positions**: The drawing position of each node is calculated as the centroid of all poses assigned to that label. The position $P_k$ of the node corresponding to label $k$ is given by:

$$P_k = \frac{1}{|\mathcal{T}_k|} \sum_{t \in \mathcal{T}_k} (x_t^*, y_t^*) \quad (15)$$

  where $\mathcal{T}_k = \{t \mid L_t^* = k\}$ is the set of time steps at which label $k$ was assigned.
- **Edges**: When a label transition occurs in the trajectory (e.g., $L_{t-1}^* \neq L_t^*$), an edge is added between the two corresponding nodes. This represents the adjacency relationship between terrains. The weight of the edge can be determined based on the frequency of transitions.

This topological map is dynamically updated as the robot explores, providing a global understanding of the environment that can be used for tasks such as navigation planning.

## VI. Simulation Study

In this section, we describe the simulation experiments conducted to validate the effectiveness of the proposed online hybrid factor graph optimization method.

### A. Simulation Setup

The simulation environment and robot parameters were configured as detailed below.

*1) Environment Model:* As shown in Figure 1a, we constructed a 2D environment where six different terrain regions (A, B, C, D, E, F), and "unknown" regions outside them are adjacently arranged. The details of each region are as follows:

- **Known Terrains**: Regions A, B, C, and D are known terrains, for which the robot has prior knowledge of their labels and characteristics.
- **Unknown Terrains**: Regions E, F and outside regions are unknown terrains not included in the robot's prior knowledge. When the robot enters these regions, the proposed method is expected to recognize them with the "Unknown" label.

The robot's prior set of labels is only $\mathcal{L} = \{\text{A}, \text{B}, \text{C}, \text{D}, \text{Unknown}\}$; the true labels E and F are not included.

*2) Robot and Sensor Models:*

- **Motion**: The robot moves through the environment in a random walk for a total of $N = 150$ steps with a step length of $\Delta d = 2.0$m. This generates a diverse trajectory that traverses multiple terrain regions.
- **Odometry Noise**: To mimic the uncertainty of a real robot, the motion model includes both a relative error proportional to the movement and an absolute Gaussian noise. The noise parameters were set to a relative error of $\sigma_{rel} = 0.05$ and an absolute error standard deviation of $(\sigma_x, \sigma_y, \sigma_\theta) = (0.3\text{m}, 0.3\text{m}, 2.0°)$.
- **Terrain Sensor Noise**: The sensor observing terrain labels is assumed to operate with an accuracy of 95%. With a 5% probability, it randomly observes a different label from the set of known labels. When in an unknown terrain (E, F, or outside), the sensor always observes "Unknown".

*3) Parameters of the Proposed Method:* The key parameters for the proposed online hybrid factor graph were set as follows:

- **Sliding Window Size**: $W = 50$ steps.
- **Optimization Interval**: Optimization within the window is executed every 5 steps.
- **Cost Function**:
  - Label observation cost (for mismatch): $c_{\text{incorrect}} = 5.0$
  - Label transition cost: $c_{\text{transition}} = 1.0$

These cost parameters are tuned to prioritize maintaining a smooth label sequence (transition cost 1.0) over a single incorrect sensor observation (cost 5.0).

### B. Evaluation Metrics

For the quantitative evaluation of the estimation results, we use the following metrics. The unknown terrains E, F, and outsides are mapped to the "Unknown" label for evaluation.

- **Accuracy**: The proportion of all steps where the estimated terrain label matched the ground truth label.

$$\text{Accuracy} = \frac{\text{Number of Correctly Estimated Labels}}{\text{Total Number of Steps}} \tag{16}$$

- **Precision for Unknown Terrain Detection**: Of all instances estimated as "Unknown", the proportion that were actually unknown terrains.

$$\text{Precision}_{\text{Unknown}} = \frac{TP}{TP + FP} \tag{17}$$

- **Recall for Unknown Terrain Detection**: Of all actual unknown terrain instances, the proportion that were correctly estimated as "Unknown".

$$\text{Recall}_{\text{Unknown}} = \frac{TP}{TP + FN} \tag{18}$$

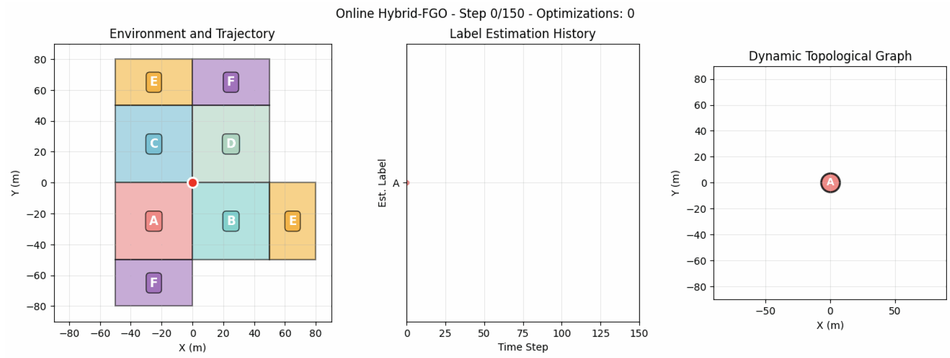
Here, $TP$ is the number of true positives (true unknown estimated as Unknown), $FP$ is the number of false positives (known terrain estimated as Unknown), and $FN$ is the number of false negatives (unknown terrain estimated as known).

### C. Results and Discussion

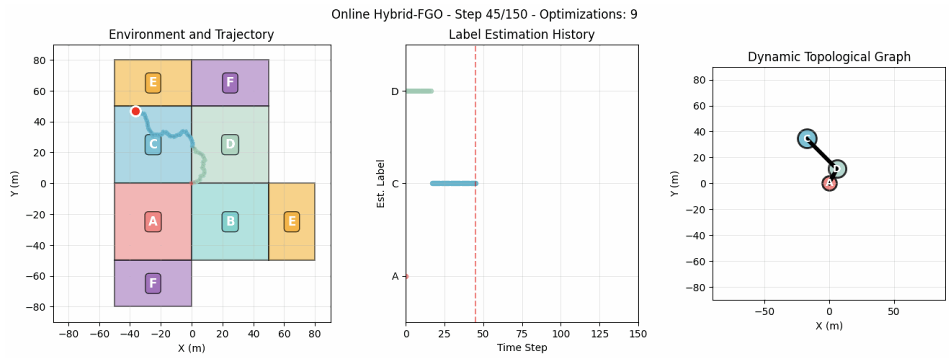
Figure 1 shows an example of the estimation results from the simulation. This figure consists of three panels: left; the environment and the estimated trajectory, center; the time-series evolution of labels, and right; the dynamically constructed topological map.

*1) Pose and Trajectory Estimation (Figure 1 Left):* The left of Fig. 1 shows that the estimated trajectory maintains a smooth and self-consistent path despite the noisy odometry observations. The trajectory is color-coded according to the estimated terrain label at each point in time. When the robot moves through known terrain regions (A, B, C, D), the trajectory is drawn with the corresponding color. Crucially, when the robot enters the unknown regions E or F, the color of the trajectory changes to gray (corresponding to "Unknown"). This suggests that the continuous pose estimation and the discrete label estimation are effectively working together within the proposed factor graph framework.

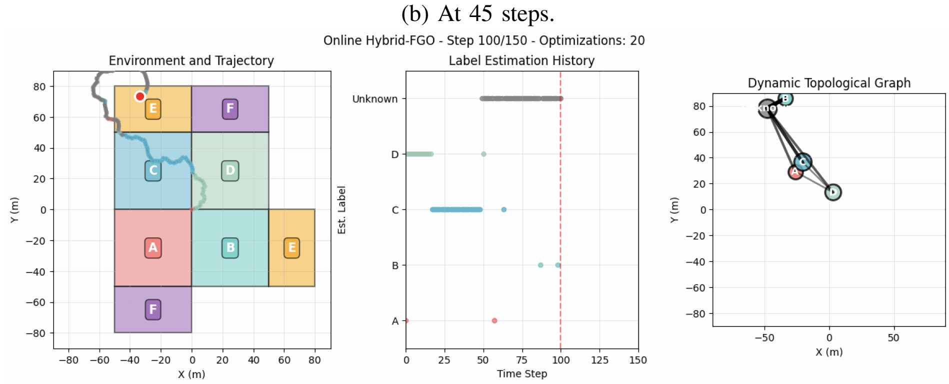
*2) Time-Series Estimation of Terrain Labels (Figure 1 Center):* The center of Fig. 1 displays the history of the estimated labels at each time step. The horizontal axis represents time, and the vertical axis represents the type of label. It can be observed that within each region, the label estimate remains stable despite sensor misclassifications (which occur with 5% probability). This demonstrates that the label sequence optimization using the Viterbi algorithm, which considers both observation and transition costs, functions robustly against sporadic observation noise. When crossing region boundaries, the labels transition cleanly, indicating that the points of environmental change are being correctly identified. In particular, when the robot moves into an unknown region (e.g., from C to E), the estimated label stably switches to "Unknown," demonstrating the capability for unknown region detection.



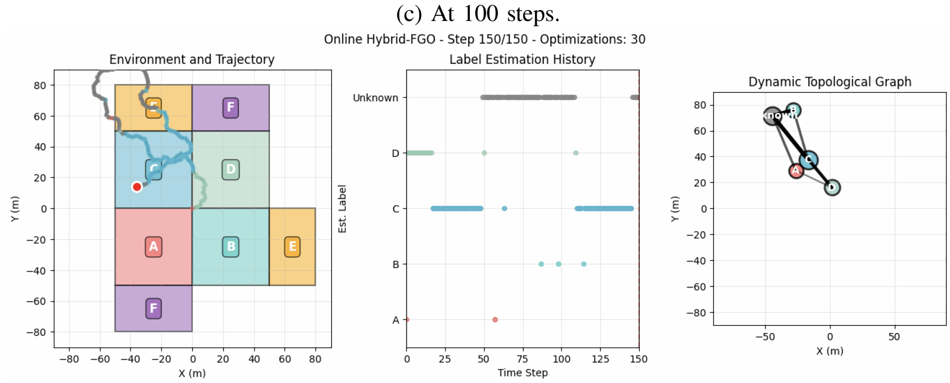

(a) Start.




(b) At 45 steps.




(c) At 100 steps.




(d) At 150 steps.

Fig. 1: Estimation results from the online hybrid FGO. Left: estimated trajectory on the environment map. The color of the trajectory corresponds to the estimated label at each point. Center: history of the estimated label at each time step. Right: the constructed dynamic topological graph, where nodes represent terrain regions and edges represent transitions between them.

*3) Dynamic Topological Map Construction (Figure 1 Right):* The right of Fig. 1 shows the topological map constructed at each step of the simulation. Each terrain visited by the robot (A, B, C, D, and Unknown) is generated as a node. The position of each node corresponds to the centroid of all locations where that label was estimated, reflecting the approximate spatial relationship of the regions within the environment. The edges connecting the nodes indicate that the robot has transitioned between those regions, with the thickness of the edge corresponding to the transition frequency. For example, a thick edge between regions A and D, or C and D of Fig. 1b, would indicate that these regions are physically adjacent and were frequently traversed. Similarly, an edge between C and Unknown of Fig. 1c and 1d suggests a path exists from the known region C to an unknown area. This map demonstrates that the robot can learn not only its pose and geometric information but also the structural connections of the environment, suggesting potential applications in high-level navigation planning.

*4) Quantitative Evaluation:* Table I shows the quantitative evaluation results from the simulation.

TABLE I: Quantitative evaluation of label estimation.

| Metric | Value |
|---|---|
| Overall Accuracy | 95.36 % |
| Unknown Detection Precision | 100 % |
| Unknown Detection Recall | 92.31 % |

The overall accuracy exceeds 95.36%, indicating that the proposed method can classify terrains with high precision. Of particular note are the precision and recall for unknown terrain detection. The high precision signifies that most of the locations identified as "Unknown" were indeed unknown terrains, indicating few false alarms. The high recall signifies that the majority of the existing unknown terrain regions were successfully detected without being missed. These results strongly support the conclusion that the proposed hybrid estimation framework functions robustly even in the presence of unknown environmental elements.

In summary, the results demonstrate that the proposed method can effectively handle hybrid continuous-discrete states, perform online estimation under noise, detect unknown regions, and achieve topological mapping of the environment.

## VII. Conclusion

In this paper, we proposed an online hybrid factor graph optimization method for mobile robots. We simultaneously estimated continuous poses and discrete terrain labels within a unified probabilistic framework and enabled online operation by using a sliding window. We also presented a method for constructing a dynamic topological map from the estimation results. Future work includes validating the effectiveness of the proposed method through experiments in real-world environments and extending the model to handle more complex semantic information, such as static and dynamic objects.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