Integrating Learned Map Completion with Uncertainty-Aware planning for Autonomous Robot Exploration

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Abstract—**Autonomous mobile robots depend on complete and accurate environmental maps for efficient navigation and exploration in unknown environments. While LiDAR-based SLAM systems are effective for building local maps, coverage tends to remain sparse over time and localization uncertainty can accumulate due to drift. Recent advances in deep-learning inpainting models, such as LaMa, provide a data-driven means to predict unobserved map regions, with the potential to accelerate exploration by inferring plausible environmental structure. In this work, we present a framework that combines ensemble-based LaMa map completion (as implemented in the MapEx system) with uncertainty-aware frontier-based exploration planning. Our systematic evaluation, conducted in simulated environments, analyzes how model uncertainty and localization drift affect both map prediction quality and overall exploration performance. Experimental results demonstrate that ensemble predictions (visvarprob) can enhance frontier selection and coverage efficiency under accurate localization; however, their reliability significantly degrades in the presence of odometry drift, leading to lower map overlap and increased prediction errors. We further discuss the challenges associated with model generalization across domains, highlight the pronounced impact of localization errors on occupancy grid alignment and inpainting output, and underscore the need for robust domain adaptation and explicit uncertainty estimation in learned completion models for reliable real-world robotic exploration.**

Index Terms—**Autonomous exploration, SLAM, deep learning, map completion, uncertainty, LaMa, probabilistic robotics, active mapping**

I. Introduction

Autonomous exploration of unknown indoor environments represents a fundamental challenge in robotics, with critical applications spanning search and rescue operations, industrial automation, and environmental mapping. Traditional frontier-based exploration algorithms have long relied on geometric heuristics while typically assuming perfect localization capabilities [1], [2]. However, real-world deployments consistently encounter significant challenges including odometric drift, limited sensor coverage, and pervasive map uncertainty [8], [9].

While Light Detection and Ranging (LiDAR)-based Simultaneous Localization and Mapping (SLAM) systems can produce high-fidelity occupancy grids, these maps remain fundamentally incomplete until sufficient environmental coverage is achieved. The ability to predict unobserved regions could enable more efficient path planning and accelerate the exploration process. Recent advances in deep generative models, particularly inpainting networks such as Large Mask Inpainting (LaMa) [5], have opened new possibilities for robots to generate plausible completions of partially observed maps.

The MapEx framework [4] introduced the groundbreaking concept of leveraging predicted maps for active exploration, demonstrating significant improvements over classical exploration methods. However, most existing approaches continue to make strong assumptions about perfect localization and treat neural network predictions as deterministic outputs, thereby overlooking crucial uncertainty information that could be exploited to improve exploration efficiency.

This work systematically addresses three critical research questions that remain underexplored in the current literature. First, we investigate how localization noise, specifically odometry drift, affects both LaMa predictions and frontier selection. Second, we examine whether LaMa ensemble uncertainty can be effectively leveraged to improve exploration efficiency beyond current deterministic approaches. Third, we evaluate whether LaMa networks generalize effectively from synthetic training data, such as those from KTH and MapEx datasets, to novel simulated domains and real-world environments.

Our main contribution consists of a comprehensive systematic analysis of LaMa-ensemble-driven exploration under controlled uncertainty conditions in simulation environments, with careful attention to practical limitations and considerations for future field deployment.

II. Related Work

A. Frontier-Based and Information-Theoretic Exploration

Classical exploration methodologies have historically employed frontier detection techniques [1], [2], which direct robots toward the boundary regions between known free space and unknown areas. While these methods offer computational efficiency, they inherently lack global environmental awareness and fail to account for information value beyond simple geometric properties. Yamauchi [1] provided the foundational formalization of frontier-based exploration, establishing the theoretical framework that continues to influence modern approaches. Building upon this foundation, Burgard et al. [2] extended the methodology to multi-robot scenarios, addressing coordination challenges in distributed exploration tasks.

The limitations of purely geometric approaches led to the development of more sophisticated information-theoretic methodologies. González-Baños and Latombe [3] were among the first to introduce information-theoretic considerations to the exploration problem, recognizing that not all regions provide equal informational value. Advanced information-theoretic approaches [6], [7] subsequently reformulated exploration as an optimal sensing problem, seeking to maximize the mutual information between robot observations and map estimates. These methods represent a significant theoretical advancement by explicitly modeling the expected information gain from potential robot actions.

Despite their theoretical elegance, information-theoretic approaches often assume perfect map structure and localization capabilities, which significantly limits their practical applicability in real-world scenarios where uncertainty is pervasive. The computational complexity of these methods also presents challenges for real-time implementation in resource-constrained robotic systems.

B. Deep Learning for Map Prediction

The emergence of sophisticated neural networks has revolutionized the field of map completion and prediction. Modern deep learning architectures have demonstrated remarkable capabilities in extrapolating plausible geometric structures from partial observations. The MapEx framework [4] represents a particularly significant advancement, utilizing LaMa [5] networks to predict unobserved map regions and demonstrating substantial improvements in exploration efficiency compared to classical planning approaches.

LaMa networks, originally developed for image inpainting tasks, have proven surprisingly effective when adapted to occupancy grid completion. These networks can generate coherent spatial structures that respect geometric constraints while filling in missing regions of partially observed maps. The success of such approaches suggests that learned priors about indoor environments can significantly enhance exploration performance beyond what is achievable through purely reactive or geometric methods.

However, current deep learning-based exploration methods typically treat neural network predictions as deterministic outputs, potentially missing valuable uncertainty information. While these networks can extrapolate plausible geometry based on learned patterns, the reliability and confidence of such predictions remain largely unexplored in the robotics literature. This deterministic treatment represents a significant limitation, as uncertainty quantification could provide valuable information for exploration planning and decision-making.

C. Uncertainty Quantification in Robotics and Deep Learning

Uncertainty quantification has long been recognized as a critical issue in robotics applications [8], [9]. Probabilistic SLAM frameworks explicitly model the pose and map uncertainty through sophisticated statistical representations, enabling principled decision-making under uncertainty. These approaches recognize that both robot localization and environmental mapping are inherently uncertain processes, requiring careful statistical treatment to ensure robust performance.

In contrast, most deep learning-based planning systems do not explicitly account for model uncertainty, potentially leading to over-confident predictions and suboptimal exploration strategies. Recent advances in deep learning have begun to address this limitation through various uncertainty quantification techniques. Bayesian neural networks [10] provide a principled framework for modeling parameter uncertainty, while deep ensembles [11] offer a practical approach to estimating prediction uncertainty through multiple model instances.

Despite these advances in uncertainty quantification techniques, the integration of such methods into exploration planning remains limited. Most current approaches either ignore uncertainty entirely or treat it as a secondary consideration rather than a fundamental component of the planning process. This represents a significant gap in the current literature, as uncertainty information could potentially guide exploration strategies toward regions where model confidence is low, thereby improving overall mapping efficiency.

Our work builds upon these established research threads by critically evaluating the complex interplay between model-driven map completion, localization uncertainty, and information-theoretic exploration principles within realistic simulated robotic environments. We aim to explore the gap between uncertainty-aware map completion and practical robotic exploration, providing insights that could inform future real-world deployments.

III. System Overview and Methodology

This section details the methodology underpinning our uncertainty-aware robotic exploration framework, as illustrated in Figure 1. Our work builds directly upon the MapEx [4] system, which integrates deep learning-based map prediction and frontier-based planning, but originally assumes perfect localization. Here, we extend this pipeline by investigating the role of pose uncertainty, evaluating how accumulated odometry drift affects both map prediction and exploration efficiency, and discussing how additional localization correction (e.g., EKF and scan-to-map registration) can be incorporated.

The original MapEx [4] system employs a four-stage pipeline: **SENSING**, **MAP PREDICTION**, **PLANNING**, and **EXECUTION**. A simulated 2D LiDAR provides environmental perception, with occupancy grids updated via ray-casting. Map prediction leverages the LaMa ensemble, where five parallel inpainting networks (with distinct initializations) complete the observed partial map, producing both a mean prediction and pixel-wise uncertainty estimates via ensemble variance. The frontiers are then detected and prioritized using

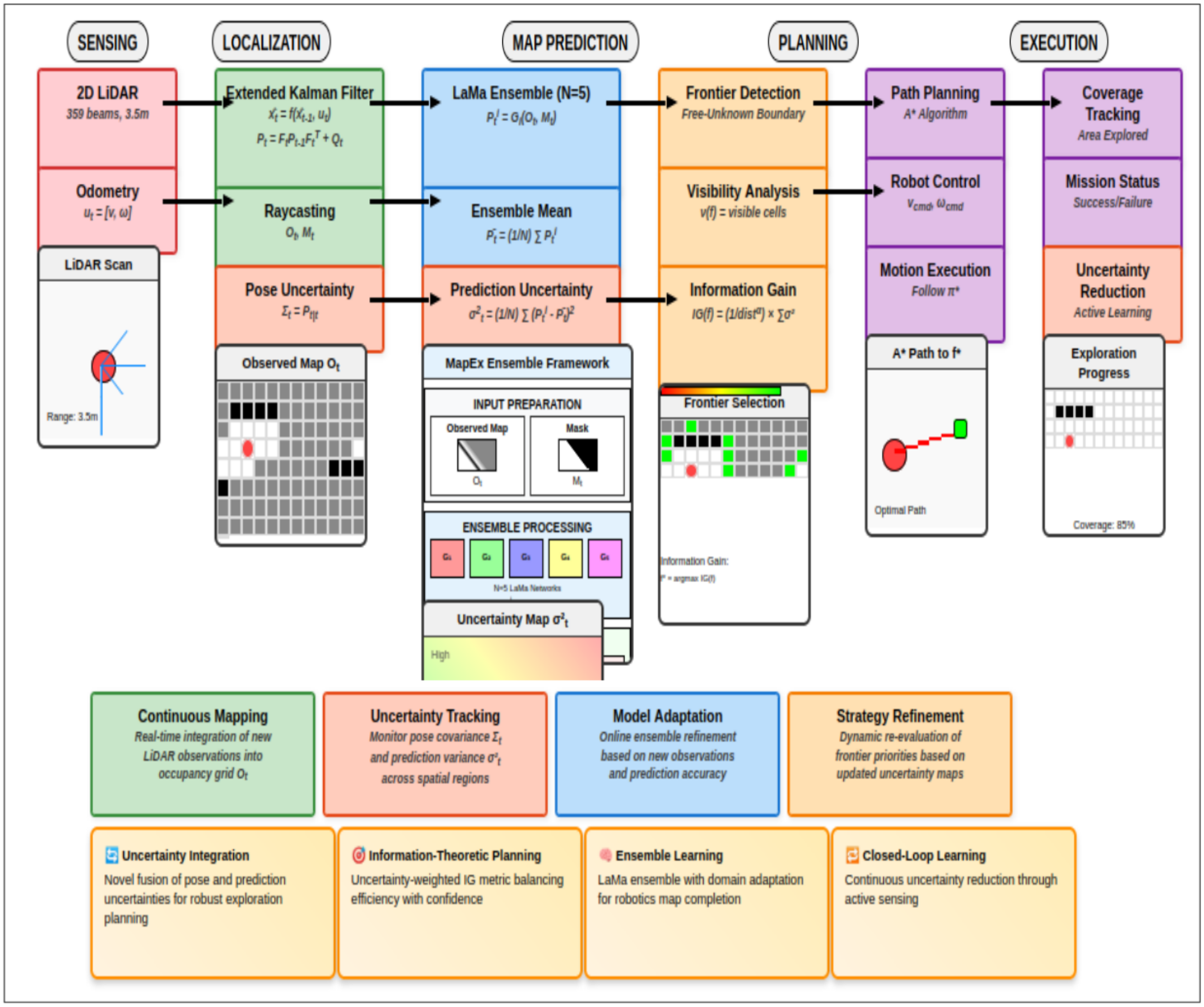

Fig. 1. Complete system architecture of our uncertainty-aware exploration framework. The pipeline includes SENSING, LOCALIZATION, MAP PREDICTION, PLANNING, and EXECUTION stages, with explicit uncertainty tracking. The center highlights the MapEx ensemble with LaMa for map completion and frontier selection.

an information-theoretic score that combines the expected information from both the mean prediction and the cost of the trip. This pipeline assumes access to an accurate robot pose at all times, allowing reliable spatial alignment of sensor data and robust prediction.

A. SENSING Stage: Multi-Modal Data Acquisition

The **SENSING** stage, illustrated in the leftmost section of Figure 1, encompasses our carefully designed multi-modal sensor configuration optimized for indoor robotic exploration. The primary perception system employs a simulated 2D LiDAR scanner configured with realistic operational parameters, including 359 individual laser beams that provide comprehensive angular coverage within a 3.5-meter detection range. This configuration ensures detailed environmental perception while maintaining computational efficiency suitable for real-time autonomous operation. The LiDAR scan visualization within the diagram demonstrates the sensor's radial measurement pattern, showing how individual laser beams extend from the robot's position (depicted as a red circle) to detect environmental obstacles and free space boundaries. The comprehensive angular coverage enables the system to maintain situational awareness across the full 360-degree field of view, critical for safe navigation and accurate mapping in unknown environments.

B. MAP PREDICTION Stage: Domain-Adapted LaMa Ensemble Architecture

The **MAP PREDICTION** stage is the central innovation of the MapEx framework, enabling robust completion of partially observed occupancy maps through a domain-adapted LaMa ensemble architecture. This stage comprises three phases: input preparation, ensemble processing, and ensemble statistics computation, as detailed below.

1) Input Preparation: The system receives the current partial occupancy grid O_t and its corresponding observation mask M_t. These are preprocessed into a unified two-channel input, where the first channel encodes spatial occupancy (free, occupied, unknown) and the second channel encodes observation confidence. To standardize network input, the data are resized to 256×256 and normalized to match the domain of training data. This step ensures consistent network behavior and leverages domain adaptation for better generalization from simulation to real-world-like environments.

2) Ensemble Processing: At the core of the MapEx approach is an ensemble of five independently initialized LaMa inpainting networks, each denoted as G_i for $i = 1, \ldots, 5$. Given the same input (O_t, M_t), each network produces a distinct plausible map completion $P_t^i = G_i(O_t, M_t)$. The use of independent random seeds in ensemble members induces diversity in the predictions, effectively capturing epistemic uncertainty in regions lacking direct observation. The LaMa models employ Fast Fourier Convolutions (FFC) for efficient global context aggregation and were pre-trained on simulated KTH test maps, with input data preprocessed as RGB and occupancy-normalized images.

3) Ensemble Statistics Computation: For each time step, the ensemble predictions are aggregated to compute both the mean map and spatial uncertainty. The ensemble mean $\bar{P}_t = \frac{1}{N}\sum_{i=1}^{N} P_t^i$ is used as the final predicted map for planning, while the pixel-wise variance $\sigma_t^2 = \frac{1}{N}\sum_{i=1}^{N}(P_t^i - \bar{P}_t)^2$ quantifies model uncertainty at each location. The mean prediction captures consensus free/occupied space, whereas the variance highlights areas of high ambiguity—usually near unexplored frontiers or ambiguous map regions. This spatial uncertainty is directly exploited in subsequent planning.

C. PLANNING Stage: Uncertainty-Aware Frontier Evaluation

The **PLANNING** stage operationalizes the information provided by the map prediction and uncertainty maps to guide efficient exploration. This stage consists of three principal components: frontier detection, probabilistic raycasting, and uncertainty-weighted information gain computation.

1) Frontier Detection: Frontiers are extracted as the boundaries between known free space and adjacent unknown cells within the occupancy grid. These frontier cells represent candidate targets for exploration, as their observation would increase map completeness.

2) Probabilistic Raycasting: For each detected frontier f, the system performs probabilistic raycasting to simulate the field of view the robot would acquire upon reaching f. This generates a visibility mask $\nu(f)$—the set of map cells expected to be observable from that frontier, considering realistic sensor range and occlusions as predicted by the ensemble mean map.

3) Uncertainty-Weighted Information Gain: The final frontier selection combines travel cost and expected reduction in map uncertainty. Specifically, each frontier is scored by:

$$\mathrm{IG}(f) = \frac{1}{\mathrm{dist}(\mathbf{x}_t, f)^{\alpha}} \sum_{(x,y)\in\nu(f)} \sigma_t^2(x,y) \tag{1}$$

where $\mathrm{dist}(\mathbf{x}_t, f)$ denotes the planned path distance from the robot's current position $\mathbf{x}_t$ to the frontier f, and α controls the trade-off between information gain and travel efficiency. The summation term captures the total map prediction uncertainty visible from f. This approach favors frontiers whose exploration is expected to provide the greatest reduction in model uncertainty per unit of travel effort.

The optimal frontier f^* is selected as the one maximizing $\mathrm{IG}(f)$, ensuring that the robot prioritizes both exploration efficiency and uncertainty reduction, as visualized in the corresponding planning module of Figure 1.

D. Extending MapEx: Modeling Pose Uncertainty

To better reflect real-world deployment, we investigated the effects of **pose uncertainty** by simulating odometry drift within the same pipeline. In this setting, the robot's pose estimate accumulates error over time, leading to misalignment between observed sensor data and their true spatial locations. This directly impacts both the observed occupancy grid (potentially distorting obstacles and free space) and the subsequent map completion and frontier selection processes. Notably, frontiers detected on a misaligned map may not correspond to unexplored regions in the true environment, and sensor observations used for map inpainting may be incorrectly registered, reducing prediction fidelity.

E. Addressing Pose Uncertainty: EKF and Scan-to-Map Registration

Given these challenges, we propose augmenting the baseline with explicit localization correction, namely **extended Kalman Filter (EKF) localization fused with scan-to-map registration**. In this scheme, EKF predicts the robot's pose using odometry and incorporates corrections from aligning incoming LiDAR scans with either the latest LaMa-predicted map. This fusion aims to bound pose drift over time and propagate improved pose confidence to refine mapping and planning stages. While the theoretical integration of Extended Kalman Filter (EKF) localization with scan-to-map registration is well established in the robotics literature, we were unable to fully realize this pipeline within the available time frame of our project. Our primary technical barrier was not related to the scan-matching methodology itself, but rather to practical issues of data compatibility and computational resources. Specifically, obtaining robust LaMa pretrained weights for our own simulated Gazebo environments proved infeasible due to the extensive data requirements, high computational cost of large-scale inpainting model training, and challenges in achieving consistent reproducibility across simulation runs. As a result, our experimental evaluation relies on the KTH test maps and the official MapEx pre-trained weights, which limited the opportunity to fully prototype and benchmark scan-to-map registration, especially with ray casting and predicted map alignment on custom map domains.

Furthermore, integrating scan-to-map registration in this setting introduces additional challenges: it requires reliable feature extraction from both partial observed maps and predicted maps (which may exhibit hallucinated regions or ensemble-driven uncertainty), as well as robust raycasting algorithms capable of accommodating the spatial uncertainty inherent to neural inpainting outputs. Addressing these challenges and implementing a tightly-coupled EKF with scan-to-map loop closure, using predicted maps as registration targets, remains an important direction for future work. Overcoming the practical limitations of model training and simulation environment adaptation will be critical for advancing toward a fully uncertainty-compensated, real-world-ready exploration system.

F. Summary of Methodological Contributions

In summary, our methodology:

- Re-implements and extends the MapEx system to examine the impact of localization errors on deep map prediction and exploration.
- Simulates pose uncertainty via controlled odometry drift, enabling direct comparison of performance under both ideal and uncertain conditions.
- Motivates the integration of EKF+scan-to-map registration for future work to mitigate the observed degradation due to pose uncertainty.
- Adopts an ensemble-based inpainting and uncertainty-aware frontier selection, preserving the core MapEx pipeline and rigorously evaluating its robustness.

IV. Results and Analysis

We evaluated the performance of the proposed map prediction and frontier-based exploration framework on a benchmark indoor environment using the *visvar* and *visvarprob* strategies. For each approach, experiments were conducted under two conditions: (i) perfect localization (no odometry drift) and (ii) simulated odometry drift to model accumulated localization uncertainty. Evaluation metrics include Intersection over Union (IoU), true positives (TP), false negatives (FN), and false positives (FP), summarized in Table I. The visual and quantitative results are illustrated in Figures 3, 2.

TABLE I
Map Prediction Metrics for visvar and visvarprob Methods (No Drift vs. Drift)

Method	Drift	IoU	TP	FN	FP
visvar	No	0.202	15466	17924	43046
visvar	Yes	0.183	14523	18867	45828
visvarprob	No	0.230	18252	15138	46092
visvarprob	Yes	0.194	15315	18075	45371

In the absence of drift, the *visvarprob* approach achieves the highest IoU (0.230), indicating a greater map prediction completeness compared to *visvar* IoU (0.202). However, both

Fig. 2. Qualitative comparison of predicted maps (top: no drift, bottom: with drift) based on *visvarprob* Method.

Fig. 3. Qualitative comparison of predicted maps (top: no drift, bottom: with drift) based on *visvar* Method.

methods experience a decrease in IoU when odometry drifts are present, with increased false negatives and persistent false positives. For instance, *visvarprob* under drift achieves an IoU of 0.194, with a reduction in TP (from 18,252 to 15,315) and an increase in FN (from 15,138 to 18,075). This decline is further illustrated by the qualitative error maps in Fig. 3, where larger red regions signify missed ground truth areas due to misaligned robot pose and uncertainty.

Examining the robot trajectories (Fig. 4), the detrimental impact of odometry drift on exploration and map prediction becomes evident. In the absence of localization errors, the robot is able to follow a smooth and efficient trajectory, systematically covering the environment, and reliably reaching a diverse set of frontiers. This results in high coverage efficiency and accurate alignment between the collected sensor data and the ground truth map, allowing the inpainting model to generate high-quality map predictions.

However, when localization uncertainty is introduced, the situation changes markedly. The robot's estimated pose be-

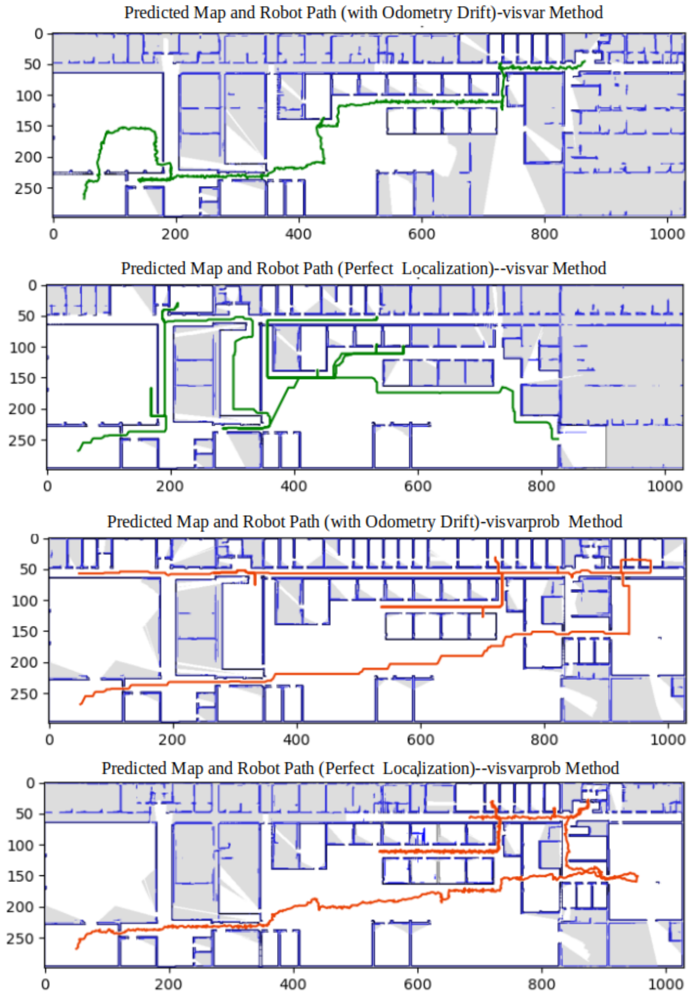

Fig. 4. Predicted maps and robot paths for bot vivarprob and visvar Methods.

comes progressively misaligned with its true position due to the accumulation of drift. As a consequence, the reliability of frontier detection and selection is significantly reduced; the robot may select frontiers that are, in reality, already explored or even unreachable, while failing to discover unexplored areas. This manifests as inefficient and redundant trajectories, with the robot repeatedly visiting previously mapped regions and missing critical frontiers, as clearly shown by the increased path looping and deviation in the drift scenario. Furthermore, the observations accumulated along this misaligned trajectory are spatially inconsistent, meaning that the sensor data fed to the inpainting model do not correspond correctly to the actual environment structure. This misregistration leads to further degradation in map prediction accuracy, with higher rates of missed and falsely predicted regions.

To address these challenges, it is crucial to explicitly compensate for localization uncertainty within the exploration pipeline. One effective approach is to incorporate pose-graph SLAM or loop closure techniques, which interestingly correct the robot's estimated trajectory and reduce the accumulation of drift. Alternatively, the exploration strategy itself can be made uncertainty-aware: by representing both the mean and variance of the robot's pose estimate, planners can bias frontier selection towards regions where uncertainty is lower or where revisits can help reduce accumulated error. In addition, uncertainty information can be explicitly integrated into the mapping process; for example, inpainting models could be trained or conditioned on probabilistic inputs that reflect pose uncertainty, thereby making their predictions more robust to spatial misalignment.

Ultimately, these results underscore that robust frontier-based exploration depends not only on the accuracy of map prediction but also on the fidelity of localization. To achieve reliable exploration and mapping in real-world scenarios, it is imperative to develop tightly coupled systems that jointly consider both mapping and localization uncertainty, using techniques such as SLAM, uncertainty-aware planning, and probabilistic map completion.

V. Discussion

The simulation results clearly indicate that localization uncertainty manifested here as odometry drift significantly degrades both map completeness and exploration efficiency. The drop in IoU and the increased number of missed ground truth cells highlight the system's sensitivity to pose errors. This is especially relevant in frontier-based exploration, where the selection of new frontiers heavily depends on the robot's estimated position; uncertainty here can result in suboptimal or redundant exploration paths, as seen in the drifted robot trajectories. In particular, the *visvarprob* method is more robust than *visvar* in the presence of drift, still achieving mission completion, while *visvar* failed under high uncertainty. This suggests that probabilistic approaches to map prediction and frontier evaluation are better equipped to tolerate pose inaccuracies, likely due to their inherent uncertainty modeling.

From a mapping perspective, the LaMa inpainting architecture was able to reconstruct plausible map completions when provided with accurate, well-aligned observations. However, under pose drift, the input observations are spatially misaligned, resulting in more pronounced artifacts and unobserved regions in the final map predictions. This underlines the critical need for tightly integrated mapping and localization: improvements in SLAM or loop closure, uncertainty-aware mapping (e.g., probabilistic occupancy grids) and post-processing alignment (such as scan registration) may all serve to mitigate the negative impact of drift.

In addition, mission-level metrics, such as the number of unique frontiers reached, total path length, and coverage rate over time, also reflect the performance drop under drift conditions. The frontier-based planner is susceptible to systematic bias in frontier selection when localization uncertainty is not properly handled, causing repeated visits and incomplete exploration. These effects can be partially alleviated by employing uncertainty-aware frontier selection or by incorporating active loop closure strategies to correct for accumulated pose errors.

The present study demonstrates that while AI-based exploration frameworks, such as MapEx and LaMa offer considerable advantages—including semantic spatial reasoning, global prediction capability, and principled uncertainty quantification, their robustness is fundamentally limited by localization accuracy. Our experiments show that in low-drift regimes, ensemble predictions (visvarprob) guide exploration more efficiently and with greater map completeness than conventional frontier-based approaches. However, as odometry drift accumulates, both the plausibility of map completions and the informativeness of uncertainty maps deteriorate, resulting in increased coverage gaps and inefficient, redundant trajectories. The root cause of this brittleness is the disconnect between training conditions - where observations are spatially consistent - and deployment scenarios, where accumulated drift produces severe misalignment. We recommend several strategies to address this gap: rigorous input filtering, hybrid SLAM-AI mapping, uncertainty-aware exploration policies, and domain-adaptive training regimes. Ultimately, practical deployment of deep learning-driven exploration will require tightly integrated systems that fuse both geometric and learned representations, enabling safe and robust operation even under significant uncertainty.

VI. Conclusion

In summary, this study demonstrates the importance of accounting for localization uncertainty in autonomous exploration and map prediction. Quantitative and qualitative evaluations show that while advanced map-completion models such as LaMa can generate accurate predictions from partial observations, their performance is heavily dependent on the reliability of the underlying pose estimates. The proposed *visvarprob* method outperforms standard approaches in case of drift, but there remains significant room for improvement, particularly in environments with challenging geometries and prolonged missions.

Future work will explore tighter coupling of mapping and localization, including online correction of robot pose, integration of SLAM and loop closure, and more robust uncertainty modeling within both the frontier planner and the map prediction network. Ultimately, reducing the adverse effects of pose uncertainty will be key to achieving reliable, efficient, and complete map exploration in real-world scenarios.

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