

Cloud-Enabled Lifelong LERF for Semantic Inventory Monitoring

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Abstract—Many environments require a navigating robot to monitor for extensive periods, during which objects in the scene may shift significantly. In particular, inventory monitoring relies on maintaining an up-to-date semantic capture despite objects being swapped, added, removed, or moved. This work introduces Lifelong LERF, a cloud-robotics method that allows a robot with minimal compute to estimate camera poses from a monocular camera and jointly optimize a dense language and geometric representation of its surroundings. We maintain this representation over time by detecting semantic changes and selectively updating these regions of the environment, avoiding the need to exhaustively remap. After updating, a human user can monitor inventory by providing natural language queries and receiving a 3D heatmap of potential object locations. To manage the computational load required, we use Fog-ROS2, a cloud robotics platform, to offload resource-intensive tasks to the cloud, enabling online performance. Experiments in a tabletop environment with 3-5 objects using a Turtlebot with a RealSense camera demonstrate Lifelong LERF can persistently track objects moving over time with overall 91% accuracy.

I. INTRODUCTION

The ability to monitor inventory over time and respond to natural language queries such as “where did I leave my keys?” or “where is the yellow electric screwdriver?” can be useful in homes, retail shops, repair shops, hospitals, and factories. We consider how a mobile robot (wheeled or legged) can navigate using Simultaneous Localization and Mapping (SLAM) [1, 2, 3] to collect images, using cloud computing to build, query, and update semantic 3D models over time. Many indoor scenes — homes, warehouses, factories — evolve over time, with objects moving, changing, appearing, or disappearing. To remain useful throughout these changes, robots must evolve their internal scene representation to keep track of the current environment state.

In this work, we propose Lifelong LERF, a cloud-robotics system that enables a mobile robot with limited on-board compute to *create* a dense representation that supports natural language queries, and *maintain* this representation by automatically detecting semantic differences in 3D as it navigates, updating the reconstruction to reflect these changes. Lifelong LERF leverages DROID-SLAM as its monocular pose estimation backend, and uses these poses to progressively optimize a Language Embedded Radiance Field [4] (LERF) which densely embeds CLIP [5] embeddings within a Neural Radiance Field (NeRF) [6].

Prior work Evo-NeRF [7] demonstrates NeRFs can update a table-top scene by discarding stale images and replacing them with fresh images, similar to how many SLAM models

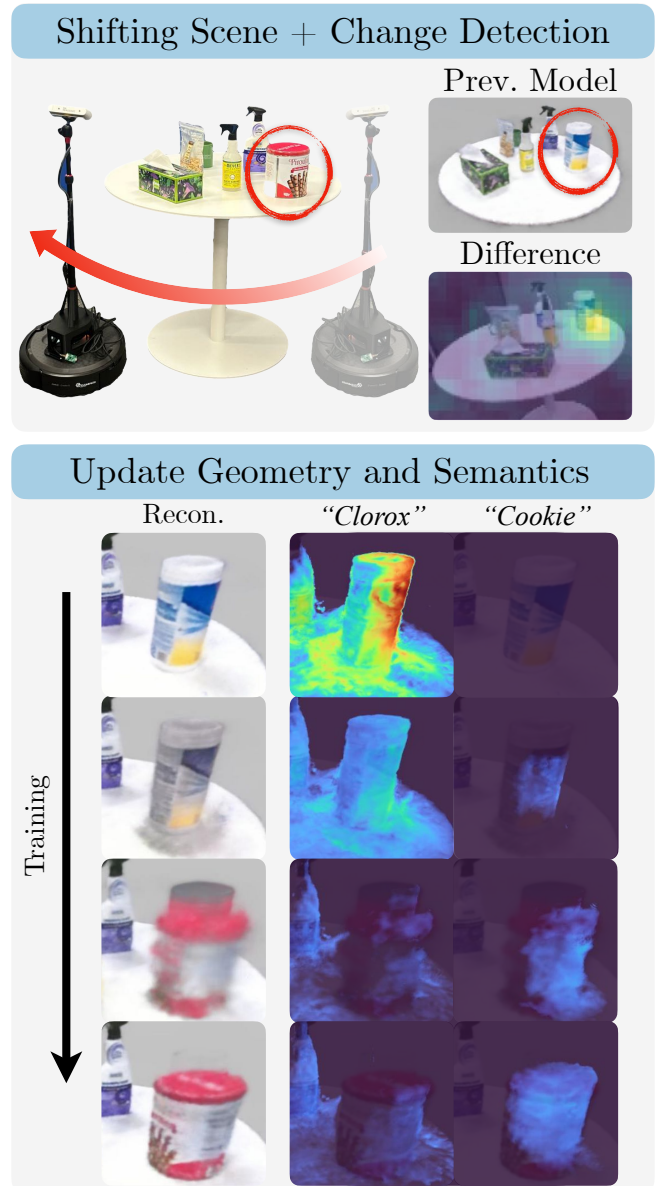


Fig. 1: *Lifelong LERF Example*. **Top**: A mobile robot takes a scan of the scene and builds a Language Embedded Radiance Field (LERF) of the scene. The scene is externally altered, for example the “Clorox” wipes are replaced by a cookie can. The robot periodically rescans the scene and identifies what has changed by rendering semantic features stored in LERF and comparing them against those extracted from the newly captured images. **Bottom**: Lifelong LERF efficiently updates the reconstruction inside the 3D bounding boxes using new images of the scene, progressively changing local geometry and semantics.

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can update an occupancy distribution. However, in a mapping scenario, it is impractical to throw away old images and remap the environment due to the lengthy remapping process. In this work, we instead propose a method for localizing changed regions in an environment to selectively update.

Lifelong LERF detects 3D differences based on the deviation between natural language embeddings computed over a freshly captured image and a view rendered from the LERF at the same pose, leveraging the novel view synthesis capabilities of LERF to generate pixel-aligned difference heatmaps. Given these scene changes, the robot can update the LERF by masking out stale regions of previous input images and ignoring these pixels during future ray sampling. As fresh images are collected to the updated scene, the underlying LERF optimizes to match new observations.

The compute required for running SLAM, optimizing a LERF, and computing semantic differences is too demanding for on-board robot hardware. We address this issue with a cloud computing architecture built on Fog-ROS2 [8]. We conduct experiments on a Turtlebot 4 and evaluate Lifelong LERF’s ability to maintain an updated language representation as changes are made to tabletop and shelf scenes. We find that Experiments in a tabletop environment suggest Lifelong LERF can persistently localize objects through scene changes on average 91% of the time, with the proposed semantic difference method outperforming a depth baseline in robustness to false positives and object swapping.

This paper contributes:

- 1) A novel method for detecting inventory changes in a scene by comparing rendered language embeddings against those calculated from captured images.
- 2) An approach for incorporating detected scene changes progressively into a LERF.
- 3) A cloud architecture that allows Lifelong LERF to function on a robot with lightweight compute (Turtlebot 4 with Raspberry Pi 4).

II. RELATED WORK

A. Semantic SLAM

SLAM algorithms allow robots to localize themselves while building a map of their surroundings. While SLAM primarily focuses on geometric reconstruction, recent variants provide impressive tracking and reconstruction abilities. Several prior systems give robots the ability to model the semantic meaning of the objects in their environment. Many works used explicit scene representations, such as volumes, point clouds, scene graphs, and truncated signed distance functions (TSDF), for semantic scene understanding. McCormac *et al.* [9] proposes an object-oriented online SLAM system to produce semantically labeled TSDF object instances reconstructions and 3D foreground masks. Object segmentation [10, 11, 12, 13, 14] and detection [15] have been leveraged on volume and points clouds for semantic scene understanding. Rosinol *et al.* [16] provides a library for semantic SLAM by constructing 3D semantic meshes from semantic hand labeled images. 3D scene graph has also been

used to describe a static scene either on a given mesh [17] or on the incoming frames of observations [18, 19]. Wu *et al.* [18] incrementally fuses the semantic prediction of the current observation into a global semantic graph. Hughes *et al.* [19] constructs a 3D scene graph incrementally based on topological maps of locally built Euclidean Signed Distance Functions (ESDFs).

Recent research in open vocabulary vision models [20, 21, 22, 23, 24] leads to increasing interest in creating 3D representations that incorporate semantic features. To reconstruct a static semantic SLAM, ConceptFusion [25] combines SLAM and semantic features by projecting CLIP [5] and features into 3D, where the labels are refined by 2D unsupervised segmentation.

B. Dynamic Scene Representation

Environments often undergo changes over time. Extensive study has been done on detecting 2D scene changes [26, 27, 28]. For 3D environments, Rosinol *et al.* [29] represents dynamic scenes with moving agents with 3D dynamic scene graphs by integrating object and human detection and pose estimation model. Looper *et al.* [30] uses the Variable Scene Graph (VSG), an augmentation of 3D scene graph, to represent semantic scene changes. The variability of VSG is estimated in a supervised way. Prior work [31, 32, 33, 34] has shown success using TSDFs in capturing long-term changes. Other works have used 2D point cloud data [35] or spatiotemporal grid [36] to learn the long-term environment changes but don’t provide semantic understanding. These systems also require huge storage overhead.

Neural Radiance Fields (NeRF) [6] are attractive alternative representation for high-quality scene reconstruction from pose RGB images, with an explosion of recent work on visual quality [37, 38, 39, 40, 41, 42, 43], large-scale scenes [44, 45, 46], optimization speed [47, 48, 49, 50], dynamic scenes [51, 52, 53], combining SLAM and NeRF [54, 55, 56, 57, 58] and more.

Most similar to this work are methods which seek to adapt NeRF to a continual framework, such as Evo-NeRF [7], ICNGP [59], Yan *et al.* [60], and CLNeRF [61]. However, prior works either don’t consider changing scenes or naively discard stale images. In Lifelong LERF, we leverage DROID-SLAM [3] to obtain camera poses. We then actively detect changed regions and selectively update them to avoid unnecessarily discarding images.

C. Cloud and Fog Robotics

Cloud Robotics [62] is an emerging computational paradigm for robotics that enables robots with limited on-board computing capability to gain on-demand computing hardware resources. Exemplary cloud robotics applications include SLAM, motion planning [63] and grasp planning [64, 65]. Major Cloud service providers, such as Amazon Web Services (AWS) and Google Cloud Platform (GCP), provide proprietary interfaces for robotics applications to interact with cloud interfaces, such as AWS Greengrass [66] and Google Cloud Robotics Core. Rapyuta [67] is a platform

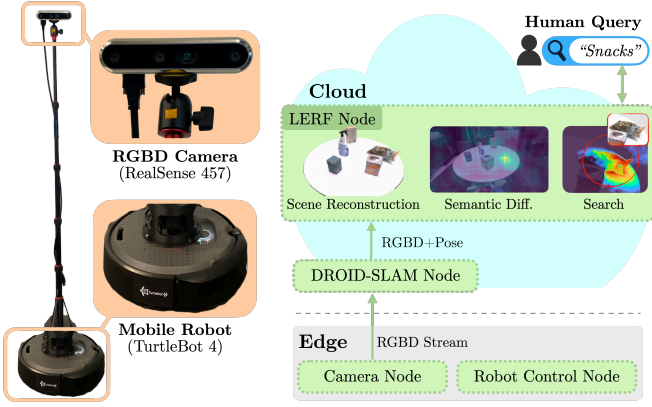


Fig. 2: *Experiment setup and FOG-ROS2 Integration.* **Left:** We use a TurtleBot 4 as the mobile robot. We mount a RealSense D457 RGBD camera on top of the robot via a monopod. **Right:** We use FOG-ROS2 to execute both DROID-SLAM and LERF on a cloud machine. In particular, after the DROID-SLAM node obtains paired RGB and depth observations, it computes the camera pose. The LERF node reconstructs the LERF and calculates if the new observation is semantically inconsistent with the stored representation.

for centralized management and deployment of a pipeline of robotics applications. FogROS [68] is the first open-source cloud robotics platform that offloads robotics applications to public cloud. FogROS enables robots to interact with the Cloud through the Robot Operating System (ROS) interfaces. Ichnowski *et al.* [69] present FogROS2 that supports ROS2 and more major cloud service providers. FogROS2-SGC [70, 8] secure and globally connects distributed robots with a peer-to-peer network. In this work, we extend FogROS2 to a low-powered and inexpensive mobile robot.

III. PROBLEM STATEMENT

For our algorithm, we assume that:

- (i) Objects are distributed on a flat surface with sufficient visibility during a trajectory surrounding them.
- (ii) During any scan of the scene, the objects in the scene are static.

We consider a typical SLAM scenario, with a wheeled, mobile robot equipped with an RGBD camera on a pole mounted on the robot. We consider several time periods: in the first time period, the robot constructs an initial model of the static environment. Between subsequent time periods, a set of objects may have been moved, added, or removed, and the goal of the robot is to detect these unknown changes and update the model accordingly. After each time period, the robot should be able to localize objects specified through natural language queries, even when objects are moved between time periods. The robot should also minimize the amount of time needed to update the LERF, including motion time and computing.

IV. METHOD

Lifelong LERF builds a LERF while the robot moves, updates it through environment changes, and localizes natural language queries. It has three main modules:

- 1) Scene reconstruction takes in a stream of RGBD images and executes DROID-SLAM, concurrently building a

LERF with camera poses from SLAM and RGB image observations.

- 2) The semantic differencing module compares incoming scene observations to the current reconstruction, producing 3D bounding boxes around changed regions.
- 3) The LERF updating module takes in these bounding boxes and masks stale regions of images to ensure the reconstruction adapts to the new scene.

A. Constructing LERF

1) *Camera pose estimation:* To construct the LERF representation, we need accurate camera poses from an RGBD camera stream. To provide these, we use DROID-SLAM [3] to estimate camera poses. DROID-SLAM is a hybrid deep learning and optimization-based SLAM system that takes in monocular, stereo or RGB-D video and outputs per-keyframe disparity maps and keyframe poses. It iteratively updates predicted camera poses and pixel-wise depths through a Dense Bundle Adjustment layer, a differentiable module that computes a Gauss-Newton update to camera poses and pixel-wise depth. We choose to use DROID-SLAM for its strong pose tracking performance, and also for its ability to function without IMU and at lower camera fps (10hz), making it more robust to network latency.

We directly feed the output keyframes and poses into the LERF to use as input views. We first initialize the pose prediction process with 4 RGBD images to ensure DROID-SLAM’s scene scale matches physical scale, then switch to pure RGB estimation, which we find qualitatively drifts less. After adding initial poses, camera poses are additionally refined over the course of NeRF optimization by Nerfstudio’s camera optimization [44], a process which uses the differentiable rendering capabilities of NeRF to fine-tune poses, as proposed in BARF [71].

2) *Scene box determination:* Camera poses generated by DROID-SLAM are not necessarily axis-aligned with real-world coordinates, primarily because they are determined through an optimization process that aims for internal consistency rather than alignment with an external coordinate system. However, the hashgrid encoding [47] assumes all cameras fit within a pre-defined scene box, an important step for ensuring parameters are sufficiently distributed throughout the scene. To account for this, we automatically set the scene scaling based on the first time period of mapping after the whole scene has been traversed.

3) *Concurrency in LERF Computation:* Training for LERF typically takes minutes to complete, which is not sufficient in this context as the robot must actively detect environmental changes and decide whether to update the underlying LERF model. In the standard LERF training process, the input images are first pre-processed by extracting CLIP and DINO features, a process that takes minutes. To enable continual LERF optimization, we introduce two modifications to the LERF training process. First, we continuously optimize the LERF model as the robot scans the scene, dynamically adding images during training as opposed to training on a fixed set. Second, we compute

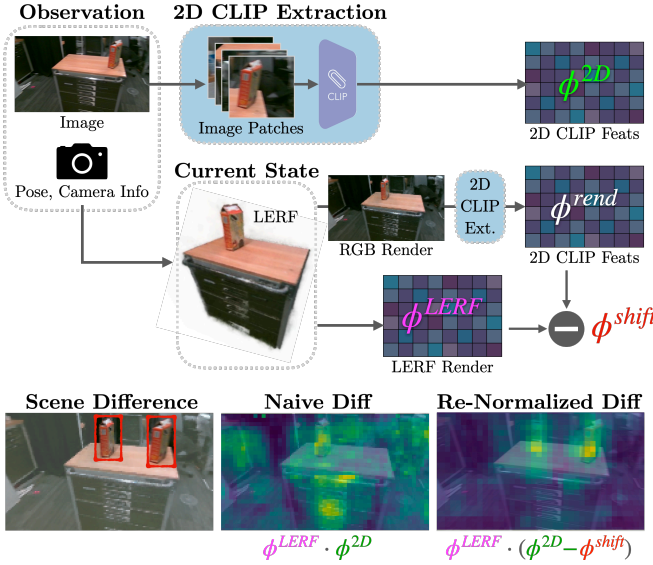


Fig. 3: *Semantic differencing*. The semantic differencing module calculates 2D feature maps from the fresh observation (top), the 3D LERF embeddings (middle), and the 2D CLIP embeddings of a NeRF-rendered image. ϕ^{rend} approximates the distribution shift from 2D to 3D, resulting in higher-quality semantic difference heatmaps (bottom). See Sec IV-B for details.

CLIP and DINO features in parallel with the ongoing LERF optimization, computing features in a callback and offloading completed images lazily within the train loop. This requires significant computation, about 500ms on a 4090 GPU per image, motivating the usage of cloud robotics to offload this process.

B. Scene Change Detection

Motivated by the constantly changing environments in homes and warehouses, Lifelong LERF detects changes in the environment over time so that it can selectively update these regions. Given an image and approximate camera pose as input, the output of this module is a set of 3D bounding boxes of changed regions. We explore a semantic differencing method based on language embeddings rendered from CLIP for computing 3D changed regions. This method leverages the novel view synthesis ability of implicit neural fields for comparing the current reconstruction to new input views.

1) *3D LERF Feature Difference*: Since the primary use case of a semantic map is for semantic queries, this approach uses the underlying language embeddings to identify scene changes. To detect semantic changes, we first render the 3D field from the same camera pose as the new image to obtain a 2D feature map ϕ^{LERF} . Since LERF is a multi-scale representation, we pick an image scale of 0.25 for querying the underlying field with and use the same scale to generate 2D embeddings by sliding a crop over the input image and passing the crops through the CLIP image encoder to obtain ϕ^{2D} .

Naively computing the difference $\phi^{LERF} - \phi^{2D}$ falsely activates on edges of the scene. This is because the CLIP embeddings in 3D experience a distribution shift from their respective input views. To understand this, consider a scene

with a tall narrow object: input views of this object contain primarily the background so their CLIP embeddings are dominated by background features. However, the background is inconsistent between different viewing angles, meaning the average embedding in 3D will be different than each 2D view. To overcome this, we propose a method for estimating this 2D-to-3D distribution shift and apply it to obtain a *semantic re-normalization* of differences obtained. Let ϕ^{rend} be the 2D grid of embeddings obtained by calculating CLIP embeddings of sliding a crop window over a *rendered* RGB image from NeRF. Then, the distribution shift can be quantified as $\phi^{LERF} - \phi^{rend}$. We subtract off this shift from the 2D image embeddings, re-normalize, then compute the dot product with 3D embeddings to find the difference. Mathematically, this is

$$\text{renorm}(\phi^{2D} - (\phi^{LERF} - \phi^{rend})) \cdot \phi^{LERF}$$

This re-normalization is critical; visualizations of an ablation are provided in Fig.3.

2) *3D Box Detection*: We utilize the semantic differencing module while the robot drives to estimate 3D changed regions. To do this, we binarize heatmaps with a threshold of 0.9, with values below 0.9 cosine similarity registering as different. We then run Tarjan’s connected component’s algorithm [72] to parse the heatmap to discrete heatmaps that do not intersect. We then filter out heatmaps with less than 30 pixels and deproject each heatmap into 3D by using the minimum of NeRF depth and RealSense depth, to account for the potential of adding or removing objects. We concatenate point clouds from 15 images at a time, then compute clusters using DBSCAN and fit oriented bounding boxes to each cluster. We constrain boxes’ Z axes to align with the world axis.

C. Updating LERF

Once changes have been identified in 3D, we must update both the language and visual properties of the LERF to match the scene state. To do this, we mask input NeRF views from the previous stage by projecting the 3D bounding boxes into each training view. We then prevent rays from being sampled inside image masks, which effectively prevents the LERF from incorporating information from stale regions of images. During each time period of exploration, we only mask images from prior time periods to avoid over-masking images. NeRF leverages *proposal networks* [39] to accelerate training which represents a low-frequency 3D distribution of where geometry lies in the scene. We modify the proposal sampling procedure by adding a constant probability mass of 0.02 to each ray sample, ensuring that samples are always taken in free space. This is important for the speed of convergence since locations in the NeRF where objects are added would otherwise never receive network samples.

D. Cloud Robotics Integration with Fog-ROS2

Wheeled mobile robots possess limited computation power designed for basic controllers and sensors. Consequently, they cannot execute Lifelong LERF on their single-board

| Difference Method | Add | | Remove | | Replace | |
|---|-----------|-----------|--------|-----------|-----------|-----------|
| | Depth | Semantic | Depth | Semantic | Depth | Semantic |
| Language Query Accuracy (Moved Objects) (%) | 75 | 92 | 89 | 90 | 67 | 92 |
| Language Query Accuracy (Static Objects)(%) | 83 | 90 | 97 | 97 | 63 | 75 |
| Pixel Mask Ratio (%) | 13 | 21 | 20 | 17 | 17 | 24 |
| Change Detection Recall (%) | 92 | 92 | 83 | 92 | 67 | 92 |

TABLE I: **Results:** We evaluate the two scene change detection methods across 8 scenes. Lifelong LERF has on average an 91% language query on accuracy objects moved throughout the trial, highlighting its ability to adapt both geometry and language as the scene changes. Both depth and semantic differencing can detect scene changes with high recall with similar pixel mask ratios, but semantic differencing is more robust against false positives (see Tab II).

| Difference Method | No Change | |
|-------------------|-----------|-------------|
| | Depth | Semantic |
| Decision Accuracy | 0% | 80% |
| Pixel Mask Ratio | 8% | 1.2% |

TABLE II: **False Positive Evaluation:** Depth over-predicts due to SLAM pose drift and NeRF frame misalignment, leading to high false positives. Semantic differencing is more pose-error tolerant.

because of subtle camera pose misalignment between the poses from DROID-SLAM and those that are optimized for LERF training. Any pose misalignment produces false positives in the depth difference and results in a heatmap that over-segments objects.

A. No Changes

Without changes in the scene, Lifelong LERF successfully predicts that there are no changes within the first 15 images 80% of the time. In a mapping scenario, this saves substantial time since the robot does not need to fully remap the environment. In our experiment setup, this amounts to around 30 saved seconds per scene. On the other hand, because depth is sensitive to pose misalignment, the depth difference method decides accurately 0% of the time. The proposed semantic differencing method is more robust to pose misalignment because this language difference is computed at a lower spatial frequency due to the receptive field of CLIP [5].

B. Adding and Removing

When adding objects, Lifelong LERF averages 91% language query accuracy and detects changes in the environment correctly 92% of the time. However, the baseline method using depth averages 79% and 92% respectively. This is because the depth-based baseline severely under-selected the added objects, leading to insufficient updates to the LERF to update the 3D semantic features. In the removal setting, depth-based baseline achieves comparable results with Lifelong LERF in language query accuracy. Prior work [7] has also demonstrated that it is comparatively easier to remove information from NeRF than to add new information. The detection recall differs because, in depth-based methods, it is hard to differentiate small and flat objects from sensor noises. In contrast, CLIP features change more significantly, leading to successful detection.

C. Replacing Objects

The depth baseline suffers significantly because swapping an object largely preserves geometry, while the semantic differencing method is able to capture the differences in the scene since the language embeddings between new and old

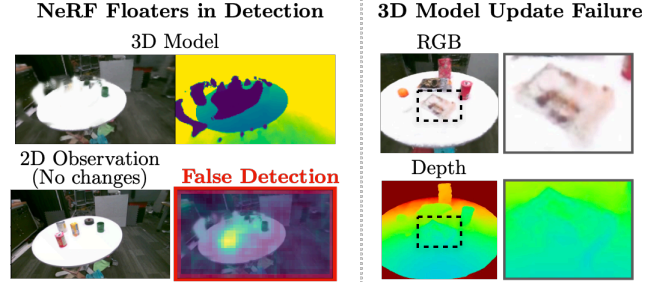


Fig. 6: **Lifelong LERF failure cases:** (Left): NeRF’s spurious density triggers false difference detection and alters CLIP feature differences through incorrect activations. (Right): If semantic changes are not correctly detected, dataset inconsistency will form fuzzy density filled with holes and fail to fully add or remove the object.

objects differ significantly. This is reflected by the semantic differencing’s strong performance on localizing moved objects (92%) vs the baseline (67%).

VII. LIMITATIONS

Some of the failure modes are presented in Fig. 6. Lifelong LERF operates under the assumption of a static scene and uses pre-defined trajectories for mapping. This makes it less practical for dynamic environments and large-scale operations, which would benefit from autonomous exploration and multi-camera setups. The algorithm also shows sensitivity to object size in semantic change detection and has a tendency to over-segment scenes. Our tests were initially run on a private cloud, future work will study using a public cloud server to increase practical scalability.

VIII. CONCLUSION

In this study, we introduce Lifelong LERF, a SLAM algorithm that builds and updates a LERF to dynamically adapt to semantic changes in a scene. By leveraging the dense semantics inside LERF, we propose a method for detecting scene changes that is more robust to pose errors or reconstruction inaccuracy compared to a scene structure baseline. Preliminary results indicate high accuracy in change detection with a minimal rate of false positives in static environments, and the ability to rapidly query the updated LERF with natural language to inventory objects. We offload computation with Fog-ROS2 to enable deployment on an inexpensive Turtlebot robot. Future work will study scaling this method to unrestricted room environments, where more complex mapping and decision-making behavior is necessary. Additionally, future work will focus on real-time performance in public clouds and on improvements in dynamic scene mapping and multi-scale object detection.

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