LT-mapper: A Modular Framework for LiDAR-based Lifelong Mapping

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Abstract—Long-term 3D map management is a fundamental capability required by a robot to reliably navigate in the non-stationary real-world. This paper develops open-source, modular, and readily available LiDAR-based lifelong mapping for urban sites. This is achieved by dividing the problem into successive subproblems: multi-session SLAM (MSS), high/low dynamic change detection, and positive/negative change management. The proposed method leverages MSS and handles potential trajectory error; thus, good initial alignment is not required for change detection. Our change management scheme preserves efficacy in both memory and computation costs, providing automatic object segregation from a large-scale point cloud map. We verify the framework’s reliability and applicability even under permanent year-level variation, through extensive real-world experiments with multiple temporal gaps (from day to year).

I. INTRODUCTION

During long-term mapping using light detection and ranging (LiDAR) sensor, we encounter changes in an environment as in Fig. 1. The perceived snapshot of the environment contains both ephemeral and persistent objects that may change over time. To handle this change properly, long-term mapping must solve for autonomous map maintenance [1] by detecting, updating, and managing the environmental changes accordingly. In doing so, the challenges in scalability, potential misalignment error, and map storage efficiency should be addressed and resolved toward lifelong map maintenance.

1) Integration to multi-session SLAM for scalability: Some studies regarded change detection as a post-process of comparing multiple pre-built maps associated with temporally distant and independent sessions. As reported in [2], alignment of multiple sessions in a global coordinate may severely limit scalability. Following their philosophy, in this work, we integrate multi-session SLAM (MSS) and align sessions with anchor nodes [2] to perform change detection in a large-scale urban environment beyond a small-sized room [3]. Our framework consists of a LiDAR-based multi-session 3D simultaneous localization and mapping (SLAM) module, named LT-SLAM.

2) Change detection under SLAM error: Change detection between two maps would be trivial if maps were perfectly aligned. Early works [5][6][7][8] in map change detection relied on the strong assumption of globally well-aligned maps with no error and avoided handling this ambiguity issue. Unfortunately, trajectory error inevitably occur in reality.

3) Compact place management: In addition to change detection, we present and prove a concept of change composition. Once the change is detected, the decision for map maintenance should be followed to determine what to include or exclude. Using this feature, ours not only maintains an up-to-date map such as existing works [1][3], but also extracts stable structures with higher placeness; thereby, we construct a reliable 3D map with authentically meaningful structures for other missions, such as cross-modal localization [9] and long-term localization [10]. This final module, named LT-mapper, manages the changes and enables a central map to evolve in a place-wise manner.

In sum, we propose a novel modular framework for LiDAR-based lifelong mapping, named LT-mapper. Each module in the framework can run separately via file-based in/out protocol. Unified and modular lifelong mapping has barely been made for 3D LiDAR, unlike recently (but partially) delivered visual-based methods [11][12][13][14][15]. To the best of our knowledge, LT-mapper is the first open module framework that supports LiDAR-based lifelong mapping in complex urban sites. The proposed has the following contributions:

- We integrate MSS with change detection and handle
Inconsistent ground-truths over sessions
Noisy points from moving objects
Disappearing objects

Fig. 2: Three challenges for LiDAR-based lifelong mapping in urban sites. (a) Overlaid ground-truth (GT) maps of MulRan dataset DCC 01 and 02. Even with highly accurate sensors (e.g., RTK-GPS), GT maps may not be globally consistent along the temporal axis. (b) Moving objects (red dots) linger on a map as ghost points. (c) Structures or objects may disappear (red dots) or appear anew at a different session. These changes should be updated properly.

sessions resiliently via anchor node. The submodule LT-SLAM can stitch multiple sessions in a shared frame using only LiDAR.

- The submodule LT-removert overcomes alignment ambiguity between sessions with remove-then-revert algorithm along spatial and temporal axes.
- The submodule LT-map can produce both an up-to-date map (live map) and a persistent map (meta map) efficiently, while storing changes as a delta map. By exploiting delta maps, restoration and change detection become memory and computation cost-effective.
- The aforementioned modules are packaged within a single framework, and it is publicly released with readily available console-based commands. Also, we provide real-world experiments with multiple temporal gaps (day to year).

II. RELATED WORKS

1) Multi-session SLAM: In [1, 3], a query scan is assumed to be well localized within the map. However, in the real-world outdoor environment, SLAM error exist and registration between scans may be vulnerable, failing even with small and partial structural variance. Thus, as claimed in [2, 14], jointly smoothing the multiple sessions can improve query-to-map localization performance despite potential motion drift [5].

2) 3D Change Detection: Given well-aligned maps, a set difference operation can be conducted via extracting map-to-map complements [3, 6]. Otherwise, visibility-based scan-to-map discrepancy comparison [1, 7, 8, 16] has been a popular choice, because of the small covisible volume and inherent localization errors. Removert [8] leveraged range images of multiple window sizes. However, it was restricted to a single session and has not treated high and low dynamic points separately.

3) Lifelong Map Management: Lifelong map management should consider two factors: 1) which entity (representation), 2) how to be updated (update unit)?

Representation. The long-term map representation varies from traditional occupancy grid maps [17, 18, 19] to frequency domain representation [20]. For change detection in 3D environments, dealing with a direct raw 3D point cloud may be preferred over the occupancy map-based ones.

Update Unit. With respect to the atomic map update unit, we manage changes at a keyframe level. This contributes to systems scalability, without being restricted to a fixed global frame [1] or room level [3].

4) Modular Design of Lifelong Mapper: The abovementioned exiting modules have been developed individually, whereas a unified system has hardly been discovered for LiDAR. DPG-SLAM [5] combined the full modules but was constrained in SE(2) space and lack of 3D change detection. [1] was also equipped with entire modules, except for MSS.

III. OVERVIEW

LT-mapper is fully modular and supports the three aforementioned functionalities. The overall pipeline is composed of three modules (Fig. 3), which run sequentially and independently. Unlike existing LiDAR-based change detection [21] equipped with expensive localization suites, our system requires only a single LiDAR sensor (optionally IMU for odometry at the initial pose-graph construction).

Accurate alignment between temporarily disconnected sessions is elusive in real-world outdoor environments, as can be seen in Fig. 2(a). In LT-SLAM module, we utilize multi-session SLAM that jointly optimizes multiple sessions accompanied with robust inter-session loop detection from a LiDAR-based global localizer. In this module, a query measurement is registered to the existing central map.

We also need to consider the measurement volatility. For example, in Fig. 2(b) a contracted point cloud map may be noisy, due to surrounding moving objects (red dots) even with the accurate odometry. These volatile objects contribute less to a place’s distinctiveness than stationary points. Thus, these high dynamic (HD) points should be pre-removed before the between-session-differences calculation in LT-removert module.

Fig. 3: A modular pipeline of LT-mapper system. The framework is composed of three modules: LT-SLAM, LT-removert, and LT-map.

The code is available at https://github.com/gisbi-kim/lt-mapper.
After aligning a query and a central session and removing the HD points, we detect changes by applying set difference operation between query measurements and a central map, as in Fig. 2(c). We call the change low dynamic (LD), and it is further divided into two classes: newly appeared points (positive difference (PD)) and disappeared points (negative difference (ND)).

\[
\phi(x_{C,i}, x_{Q,j}, \Delta C, \Delta Q) = \exp \left(-\frac{1}{2} \| (\Delta C \oplus x_{C,i}) \ominus (\Delta Q \oplus x_{Q,j}) \|_2^2 \right),
\]

where \( x \) means a SE(3) pose, \( i \) and \( j \) are pose variable indexes, \( \oplus \) and \( \ominus \) are the SE(3) pose composition operators [33]. \( \Delta \) indicates an anchor node, which is also a SE(3) pose variable. The central session’s anchor node \( \Delta_C \) has very small covariance while the query’s \( \Delta_Q \) has a very large value.

IV. LT-MAPPER

In this section, we give details of the three modules of LT-mapper. We define a session \( S \) as

\[
S := (G, \{(P_t, d_i)\}_{i=1,\ldots,n}),
\]

where \( G \) is a pose-graph text file (e.g., .g2o format) containing a set of pose nodes’ indexes and initial values, odometry edges, and optionally putative intra-session loop edges. This initial pose-graph can be constructed by using any existing LiDAR (-inertial) odometry algorithms [22, 23, 24, 25, 26]. We allow potential navigational drifts and overcome the intra-session drifts via multi-session pose-graph optimization. The \( (P_t, d_i) \) are a 3D point cloud \( P \) and the its global descriptor \( d \) (e.g., [27] [10] [28] [29] [30]) for the \( i \)th keyframe. We assign an equidistant sampled keyframes and \( n \) is the number of total keyframes.

A. LT-SLAM: A Multi-session SLAM Engine

We denote the existing session \( S_{t_c} \) at time \( t_c \) as central (\( C \)), and the newly obtained session \( S_{t_q} \) at time \( t_q > t_c \) as query (\( Q \)). Given a pair of the central and query sessions, LT-SLAM aligns the two sessions.

The incoming sessions’ pose-graphs preserve their own coordinates and LT-SLAM utilizes the anchor node-based inter-session loop factors [2] [31] [32]. As [Kim et al. [2]] reported, the anchor node can successfully estimate a between-session offset, resolving their intra-session drifts. The anchor node-based loop factor for a relative pose measurement \( z \) is

\[
\phi(x_{C,i}, x_{Q,j}, \Delta C, \Delta Q) = \exp \left(-\frac{1}{2} \| (\Delta C \oplus x_{C,i}) \ominus (\Delta Q \oplus x_{Q,j}) \|_2^2 \right),
\]

where \( x \) means a SE(3) pose, \( i \) and \( j \) are pose variable indexes, \( \oplus \) and \( \ominus \) are the SE(3) pose composition operators [33]. \( \Delta \) indicates an anchor node, which is also a SE(3) pose variable. The central session’s anchor node \( \Delta_C \) has very small covariance while the query’s \( \Delta_Q \) has a very large value.

We need to identify a loop-closure candidate \((i, j)\) between sessions \( C \) and \( Q \). For robust inter-session loop detection, we adopt Scan Context (SC) [10] due to their long-term global localization capability and light computation cost. After the inter-session loop is detected, a 6D relative constraint between two keyframes is calculated via Iterated Closest Point (ICP) using their submap point clouds \( P_{C,i} \) and \( P_{Q,j} \). We only accept loops with acceptably low ICP’s fitness scores, and use the score for an adaptive covariance \( \Sigma_z \) in [2]. We also use robust back-end (e.g., [34] [35]) for all inter-session loop factors for safe optimization under inevitable false loop detections. Given the initially aligned sessions using SC-loops, we further refine the graph using radius search loop detection (i.e., based on pose proximity) for non-SC-detected keyframes to finely stitch the sessions.

Finally, each session’s trajectory is optimized within their own coordinates (denoted \( ^C G^*_C \) and \( ^Q G^*_Q \)) as in Fig. 4(a). The optimized maps are then represented in a shared world coordinate \( W \) to be consumed by LT-remover introduced in \( \S IV-B \). To do so, LT-SLAM returns pose-graphs \( ^C G^*_C \) and \( ^Q G^*_Q \) by applying the below transforms for each pose \( x \) in a graph:

\[
^W x_C = ^C x_C ^C G^*_C \text{ and } ^W x_Q = ^Q x_Q ^Q G^*_Q.
\]
B. LT-removert: Two-session Change Detection

As mentioned in §III, the dynamic points are classified into HD and LD. In our second module, LT-removert, we first remove HD without erasing LD points. We denote \( LD_Q^C \) means 3D points that are low dynamic changes detected at a place (keyframe) between the session \( C \) (from) and \( Q \) (to).

1) High Dynamic (HD) Points Removal: We choose Removert [8] for our HD points removal engine. Using range image-based discrepancy, Removert utilizes different sizes of windows to alleviate the pose ambiguity. For example, Fig. 5 (b) and (c) show before and after of applying Removert.

2) Low Dynamic (LD) Change Detection: Once two sessions are aligned and HD points within them were removed, we compare query and central sessions to parse LD points. To do so, we construct a kd-tree for the target map and test whether a source map’s point has \( k \) target map points within a threshold \( r \) m (if not, the point is LD). Then, the ND and PD points are parsed.

3) Weak ND Preservation (Handling Occlusions): Another critical factor to consider is occlusion as argued in [3]. In Fig. 6, an example is given to show the effect of occlusion in determining valid PD and ND. Naturally, the central session A will be compared against the query session B (case 1). However, let us consider the reversed case (case 2) when B occurs prior to A. In this case, some ground points were occluded by walls and became ND points. However, these ground points should not be removed. We name them as weak ND and examine further segregation to avoid falsely removing occluded static points.

For this step, we again employ Removert but with modification. Unlike the original Removert, which removes near map points, the modified Removert removes further points in the raw ND map and reverts them to the static map. The bottom right in Fig. 6 shows the preserved weak ND points (gray) being correctly reverted to the static map.

4) Strong PD for Meta-map Construction: We can consider a similar strong/weak classification for PD that is related to whether it retains permanent static structures. We call strong PD for the points spatially behind. If we only retain strong PD, as in Fig. 7, we can construct a map with maximum volume by carving out the space conservatively. In that sense, we can construct two types of static maps: meta map by removing weak PD and live map by retaining weak PD. The examples of meta map and live map are drawn in Fig. 9.

C. LT-map: Map Update and Long-term Map Management

Given the detected LD, LT-map performs a between-session change update for each keyframe of the central session. The between-session change composition operator \( \odot \) is defined as:

\[
P_C = \tilde{P}_C \odot LD_Q^C = \tilde{P}_C - ND(LD_Q^C) + PD(LD_Q^C),
\]
where $\tilde{P}_C$ is a keyframe’s HD removed point cloud. The function $ND(\cdot)$ and $PD(\cdot)$ return ND and PD points near the keyframe and represented in the keyframe’s local coordinate. The $-$ and $+$ are set difference and union operation on 3D point space. This delta map containing only differences benefits compared to the snapshot-based methods that up/download the whole map. For example, in Fig. 5, transmitting the whole new map to a server requires 11 M points, whereas only 0.47 M points are needed when using delta maps (only 4.3% of the entire map).

V. EXPERIMENTAL RESULTS

A. Implementation Detail and Dataset

1) Implementation Detail: Our entire modules are written in C++, and are designed to be readily used with handy commands as in §III. LT-SLAM’s pose-graph optimizer is implemented using iSAM2 [36] of GTSAM [37]. We adopted publicly available sources of Scan Context [10] and Removert [8]. We refer the readers our open source codes 2 for the specific parameters of the system. For the initial graph construction to be fed as an input of LT-mapper, we provide keyframe information saver 3 as add-ons of existing LiDAR odometry open sources (e.g., LIO-SAM [25]).

2) Datasets: For the validation, MulRan [4] and our own LT-ParkingLot dataset were selected. Both datasets have multiple sequences and repeated coverage on fixed sites. MulRan dataset: We leveraged this dataset to evaluate the feasibility of our LT-SLAM. Recently, we have acquired and released an extended sequence for KAIST that is suitable for long-term change detection research. We used the KAIST and DCC sequences to identify long-term changes. LT-ParkingLot dataset: A parking lot would be a typical place to witness LD changes. We collected six sessions at different times over three days. The sessions’ origins are all different and their global alignments are initially unknown as in the middle of Fig. 4(b).

B. Multi-session Trajectory Alignment

Both qualitative and quantitative results for LT-SLAM are shown in Fig. 4 and Fig. 8. We used the RPG trajectory evaluation tool [38]. The intra-session translation and rotation (particularly yaw) errors are noticeably reduced via the inter-session anchor node-based loops. Two sessions with different origins successfully suppressed each other’s drifts.

C. Lifelong Mapping

LT-mapper can update the world representation in two ways, as shown in Fig. 9. First, LT-mapper can efficiently maintain a live map via sending only LD changes to a central server, instead of whole snapshots. For the second representation, meta map, LT-mapper extends spatial volumes without adding weak PDs. This elaborates a meta representation of a 3D scene, which is independent of short-term stationary or periodic changes.

D. Change Composition

Because there exist no point-wise ground-truth for the 3D changes over time, we propose an implicit way to
qualitatively evaluate our LD change detection performance via composing changes (Fig. 10). We have pre-calculated LD changes from LT-removert between KAIST 01 and 02, 02 and 04, except for 01 and 04. If the calculated LD_{01} and LD_{04} are reliable, then the composed virtual LD change LD_{01} should match the actually obtained LD_{04}. In other words, P_{04} \circ LD_{01} should be equal to P_{04}. As can be seen in Fig. 10, the restored KAIST 01 from 04 is well-matched to the real map of KAIST 01. This delta map chaining process is identical to map rollback, and we can restore a map at any timestamp without saving all memory-consuming snapshots.

**Accuracy:** To quantitatively evaluate the consistency between the restored 01 and 01, we use Chamfer distance [39]. First, we divide the aligned maps in Fig. 10 into 5 m^3 cubic patches and calculate the distance for each pair of corresponding patches having more than at least 25 points in a cubic. Table I shows the positive pair (i.e., restored 01 and 01) had lower distances and less inconsistent patches for a given target map 01 than the negative pair (e.g., 04 and 01) are reported.

**Efficiency:** For spatial change analysis, our change composition has also an advantage in computational efficiency. The time cost of conducting LT-removert once is \( O(nm) \), where \( n \) is the number of keyframes and \( m \) is the number of map points. Running LT-removert for a pair of consecutive sessions (i.e., between time \( t \) and \( t+1 \)) is required only once. Later when we aim to compare two arbitrary sessions, we need only to perform the lightweight change composition (empirically 0.05 sec per keyframe) which is linear to the number of keyframes.

**TABLE I: Accuracy evaluation of Fig. 10 using Chamfer distance and its statistics to summarize the structural inconsistency. Among the number of patches (NP) containing at least 25 points (NP_{valid}), we count NP having the distance value larger than a threshold (\( \tau \)).**

| Chamfer Distance (CD) | Max | Avg | Var | NP_{CD>\tau}^{\text{Pos. Par. (01 \leftrightarrow 04)}} | NP_{CD>\tau}^{\text{Neg. Par. (02 \leftrightarrow 04)}} |
|-----------------------|-----|-----|-----|---------------------------------|---------------------------------|
|                       | 34  | 9   | 1   | 1424                           | 1306                            |

**TABLE II: Efficiency evaluation of Fig. 10 LT-mapper efficiency against the snapshot-based method.**

|                          | Memory Usage [MB] | Computation Time [sec] |
|--------------------------|-------------------|-------------------------|
| Baseline (saving whole snapshot) | 213.6             | 87.0 (w/o HD removal)  |
| Ours (LT-map, delta map chaining) | 85.7              | 9.8                     |

**Fig. 10:** An example of change composition. By chaining delta maps, LT-map can restore the map at any timestamp. After the rollback with change compositions, the unmatched wall in KAIST 04 (red) correctly disappears and the original wall in KAIST 01 is successfully recovered.

**Fig. 11:** Automatically parsed object examples. Top: the strong ND points in the scene of Fig. 6. Bottom: examples from the scene of Fig. 1. Colors were arbitrarily selected for clear visualization. All objects are parsed with simple Euclidean distance-based clustering.

only from consecutive changes, we can efficiently make any combinatorial pair of sessions’ changes without re-performing LT-removert for the pair. The quantitative report is summarized in Table II. Compared to maintaining entire sessions, our LT-map representation with delta map saved nearly 60% of the amount of memory and yielded a performance 8.9 times faster than computing LD changes from scratch.

**E. Automatic Parsing of Ephemeral Objects**

From our PD and ND maps, we can easily segment ephemeral objects’ points, as in Fig. 11. We expect this to promote understanding of the relationship between the ephemeralization of an object and its 3D shapes. If we proactively assess the ephemerality of a 3D object, we also expect this to improve LT-removert performance via serving it as prior information.

**VI. CONCLUSION**

In this work, we presented an open, modular, and unified LiDAR-based lifelong mapping framework, LT-mapper. We tackled three challenges to build a reliable long-term (day to year scale) map update system: 1) no or inconsistent ground-truths over sessions, 2) noisy points from high dynamic objects, and 3) new/disappeared structures. As shown in our extensive evaluations of real-world changing urban environments, our open framework can be a core engine for multiple applications for urban spatial understanding by efficiently maintaining live/meta maps, composing changes, and automatically sorting ephemeral shapes.
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