Elastic LiDAR Fusion

Dense Map-Centric Continuous-Time SLAM

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We present a new approach for LiDAR-based dense 3D mapping by combining map-centric approach with continuous-time SLAM. The proposed system is capable of reconstructing a large-scale high-quality dense surface element (surfel) map from spatially redundant multiple views.

Problem Statement

The concept of Continuous-Time (CT) trajectory representation has brought increased accuracy and efficiency to multi-modal SLAM. However, regardless of these advantages, its offline property caused by the requirement of global batch optimization is critically hindering its relevance for real-time and life-long applications. In this paper, we present a dense map-centric SLAM method based on a CT trajectory to cope with this problem.

Proposed Method

System Overview

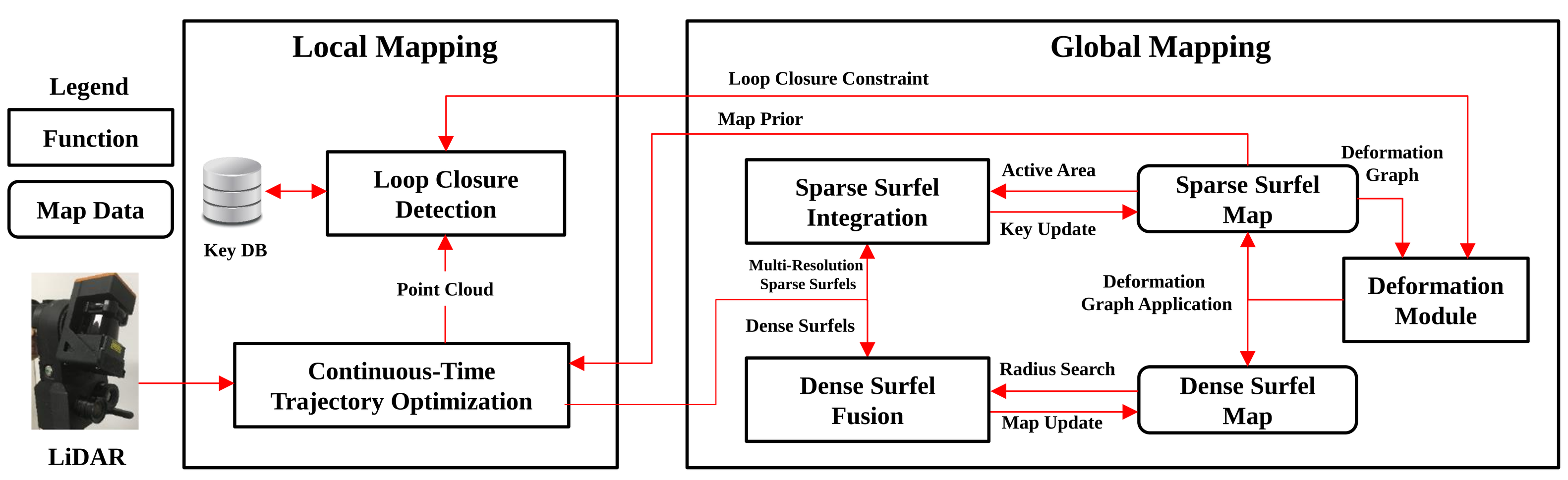


Figure 1: System block diagram of our method. The device local trajectory is tracked in the Local Mapping stage, while the global consistent map is maintained in the second Global Mapping stage.

Windowed Continuous-Time Trajectory Optimization

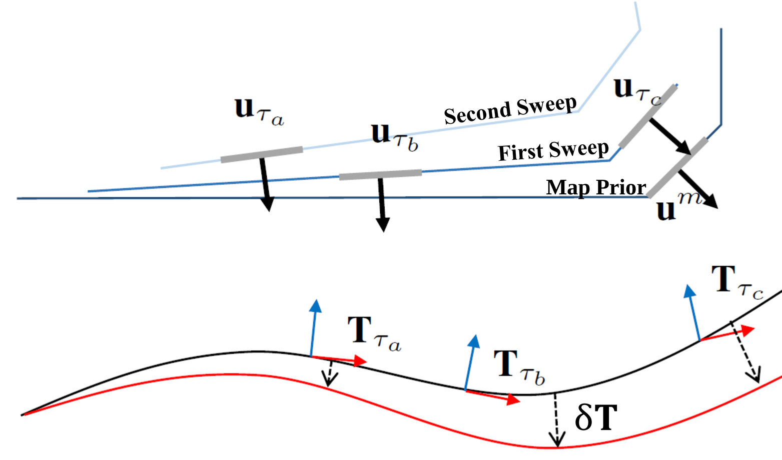


Figure 2: Illustration of geometrical constraints on the local trajectory. Instead of directly optimizing trajectory, we seek for the low frequency correction of the trajectory for efficiency.

We have utilized surfel based trajectory correction proposed in [1]. While removing the global trajectory optimization, we introduced a map prior constraint to be able to bring the model-based localization into the local trajectory optimization. The map prior is achieved from the past windows.

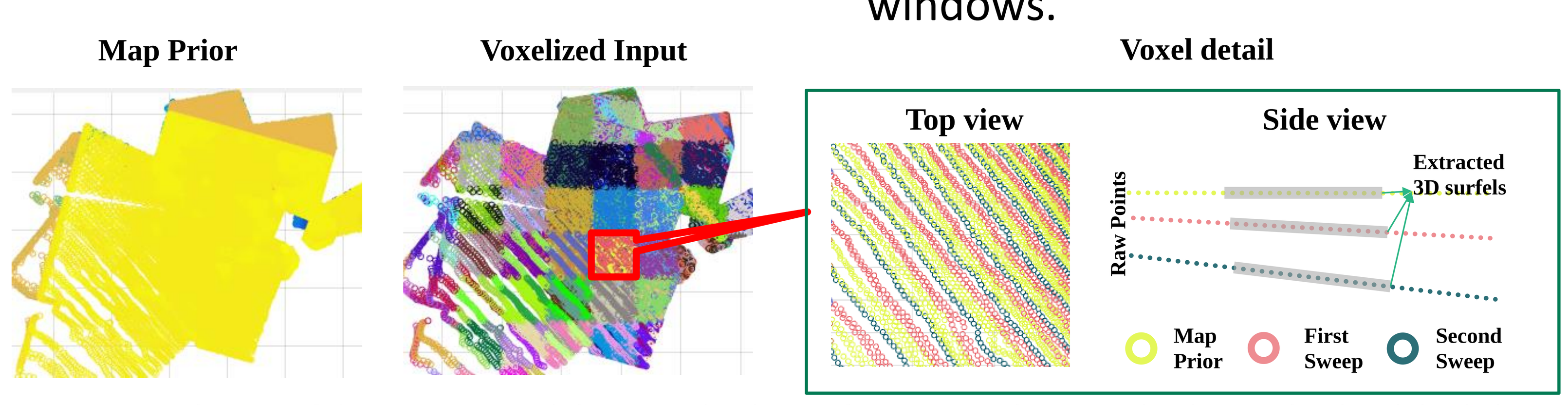
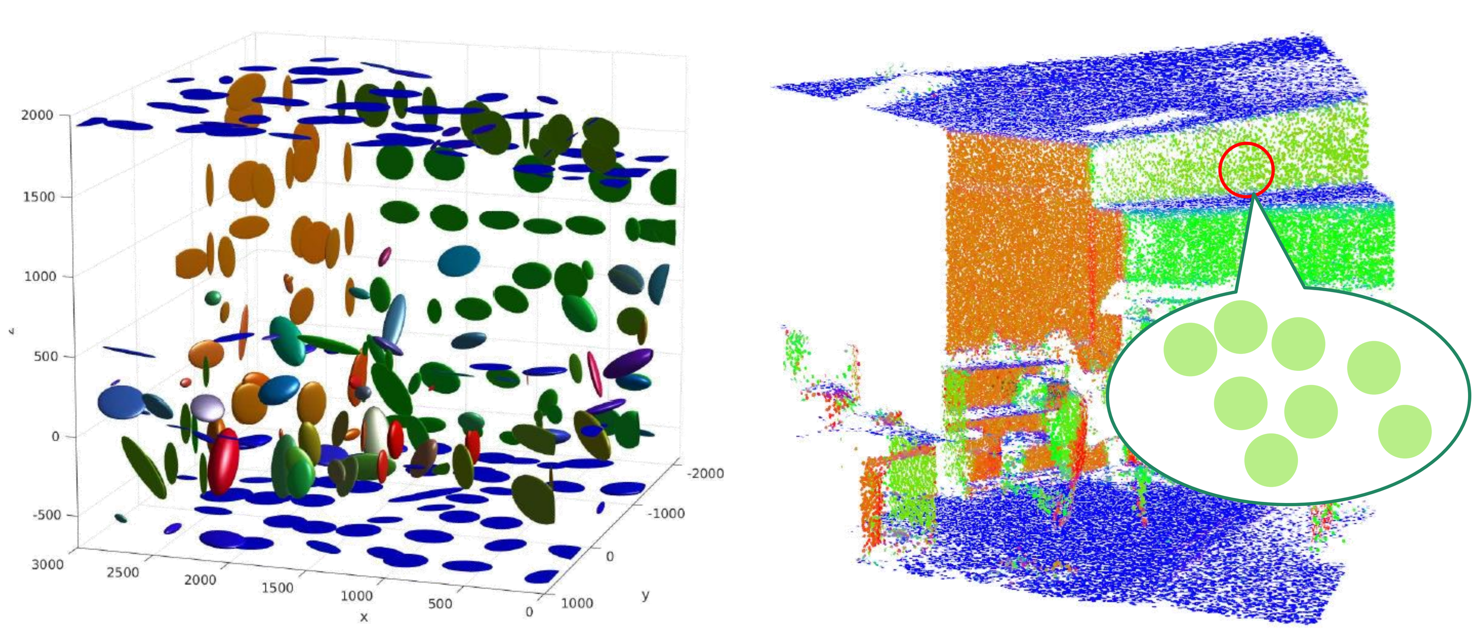


Figure 3: Visualization of the map prior and the point cloud input from LiDAR. The point cloud is voxelized and divided into different groups according to its time of generation. Extracted spatial features by PCA form a surfel and then utilized to find a matched surfels. Third figure shows an example of two pairs of matched surfaces constraints.

Map Representations



3D Ellipsoidal Surfel Map
from Multi-resolutional Voxel Hassing

2D Disk Surfel Map
from Nearest Neighbor Searching

Figure 4: (a) Example of a 3D ellipsoid surfel map with a 60cm resolution which is dedicated for localization and (b) a 2D disk surfel map with a 1cm resolution for dense reconstruction. Both are color-coded by normal directions. Recognize the ceiling and the floor in blue, and objects and walls in orange and green.

Probabilistic Surfel Matching & Fusion

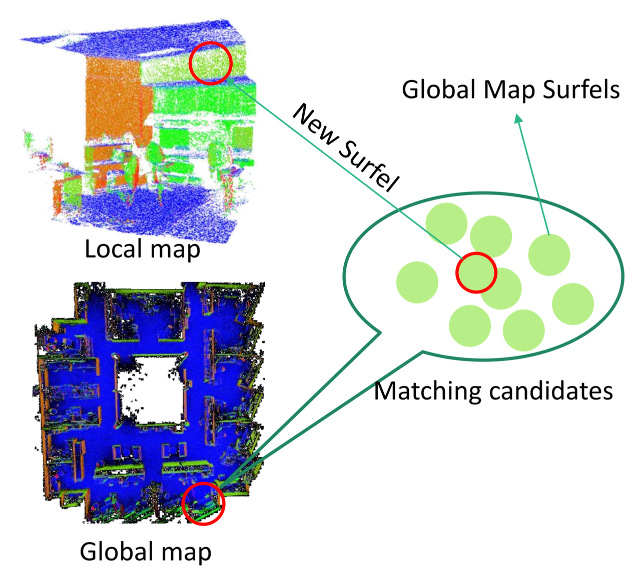


Figure 5: Illustration of surfel matching problem between a local map surfel and the global map surfels. Refer to [2] for more details.

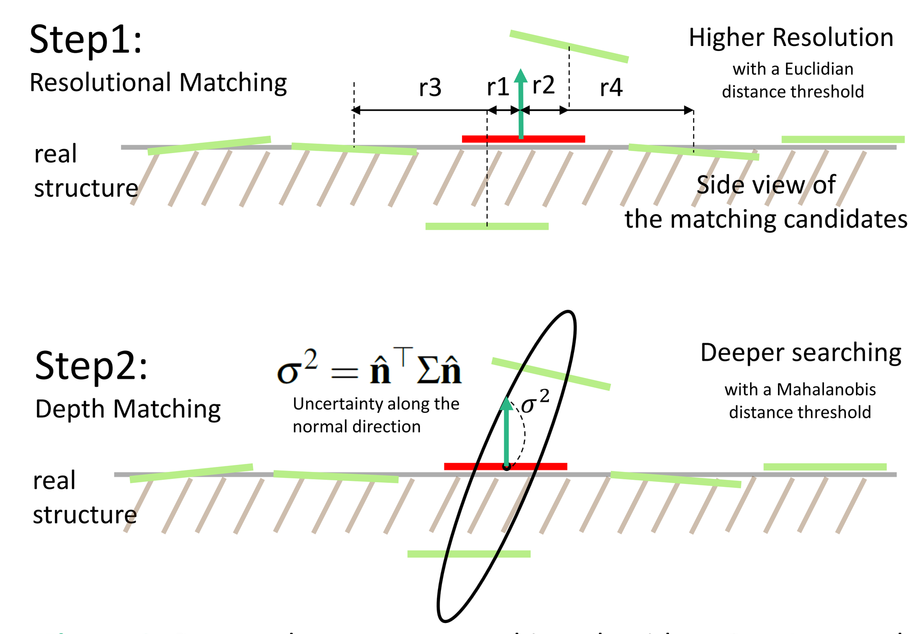


Figure 6: Proposed two stage matching algorithm. Step1 controls map resolution whereas step2 reduces map noise by searching deeper along the LiDAR beam direction.

Loop Closure by Deformation

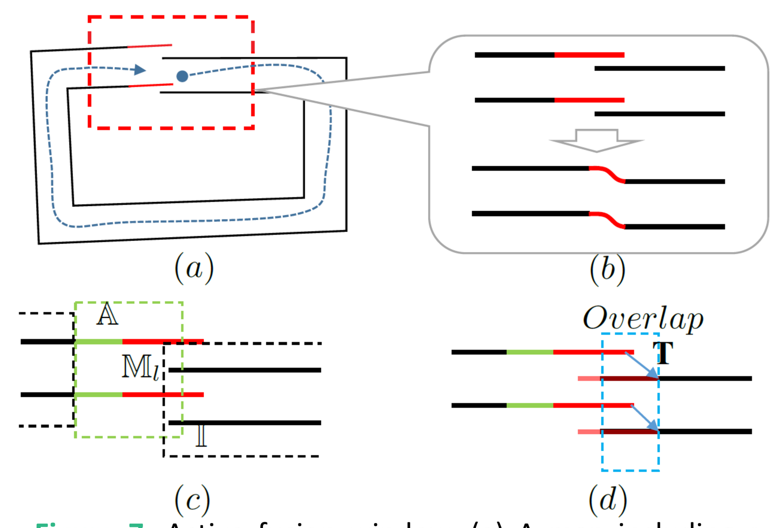


Figure 7: Active fusion window. (a) A map including a loop closure. (b) Fusion at the loop. Before the fusion (upper) and after the fusion (lower) (c) Fusion only within an active window (solid green lines). (d) Misalignment detection between inactive (solid black lines) and active area.

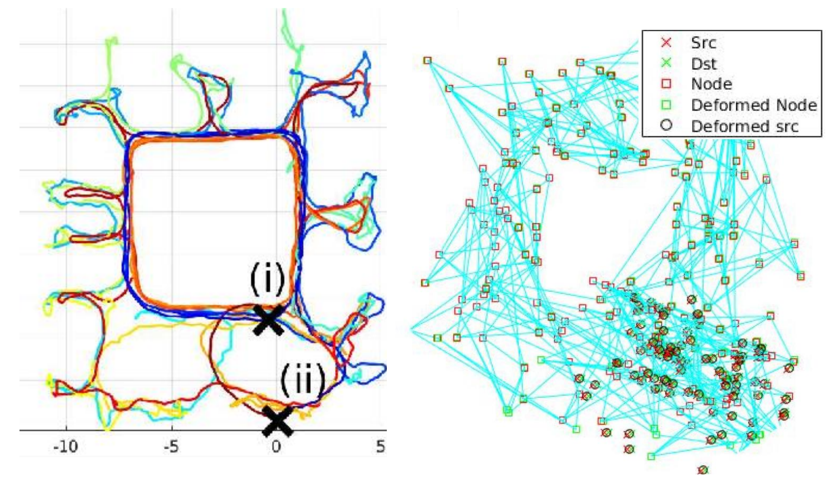


Figure 8: Scanning trajectory and deformation graph of Figure. 11. [left] Scanning path. Our proposed method closes a loop at (i) whereas CT-SLAM does at the end of the trajectory (ii). As the state dimension of the deformation graph is a function of space size, the proposed method is suitable for a long-term operation. [right] Constructed deformation graph.

Experiment Results

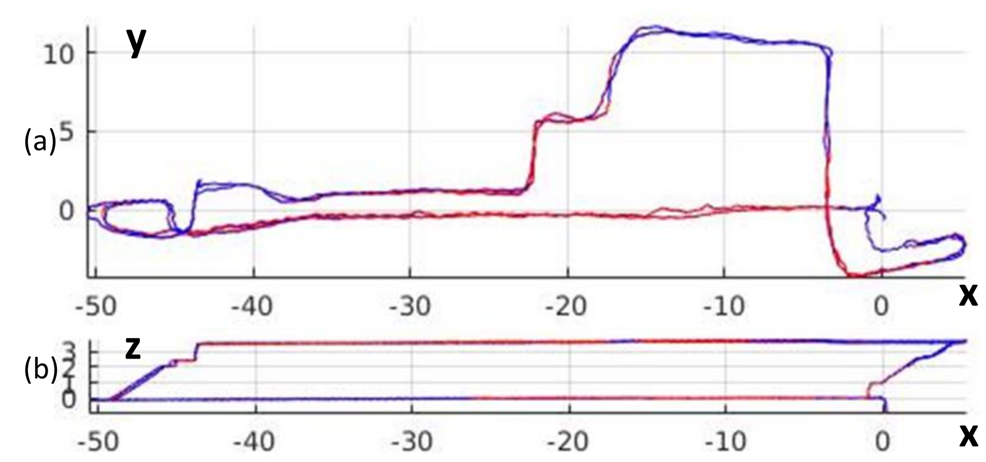


Figure 9: Qualitative trajectory comparison between the global trajectory optimization (blue line) and the proposed method (red line). (a) Top view. (b) Side view. Note that the trajectory includes two traverses.

Figure 10: The experimental handheld 3D spinning LiDAR for mobile mapping.

Figure 11: [Left] Reconstructed 3D surfel map of a 20x20 meter office. The details of the reconstructed map around the circled area is shown on the right side. [Right] (a) Raw camera image of the office around the red circle. (b) Synthesized image from the surfel map. (c) Surfel map colored with normal direction. (d) Rendered depth image from the surfel map.

Conclusion

A new approach for dense LiDAR-based map-centric CT-SLAM was presented. The proposed system utilizes map deformation as a way for maintaining global map consistency instead of conventional global batch trajectory optimization to improve the applicability of the conventional CT-SLAM in long-term operation applications.

FOR FURTHER INFORMATION

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