Probabilistic Surfel Fusion for Dense LiDAR Mapping

Chanoh Park[1,2], Soohwan Kim[1], Peyman Moghadam[1,2], Clinton Fookes[2], Sridha Sridharan[2]

[1]Autonomous Systems Laboratory, CSIRO Data61, Brisbane, Australia

[2]Queensland University of Technology, Brisbane, Australia

www.data61.csiro.au

We present a new approach for dense LiDAR mapping using probabilistic surfel fusion. The proposed system is capable of reconstructing a large-scale high-quality dense surface element (surfel) map from spatially redundant multiple views.

Problem Statement

When building the dense surfel map from LiDAR points cloud, there are two main issues. The first issue is surfel degeneracy in a normal direction of a surfel which causes incorrect normal directions. The other issue is that surfel matching is less accurate or not straightforward in the traditional methods. Radius search cannot handle sensor noise efficiently and it is difficult to control the surface resolution in the uncertainty based method.

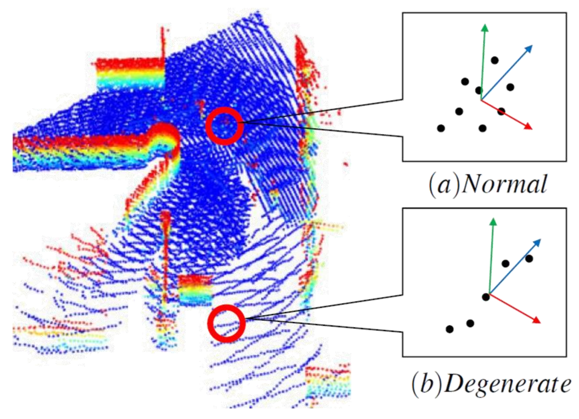


Figure 1: Degenerate surfel normal caused by a degenerate points shape.

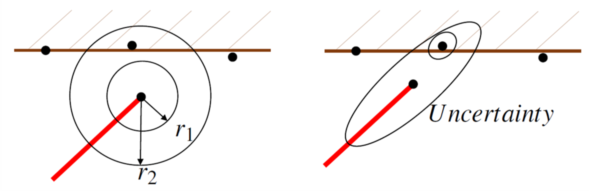


Figure 2: Surfel matching problem in a radius search method(left) and uncertainty based method(right)

Proposed Method

System Overview

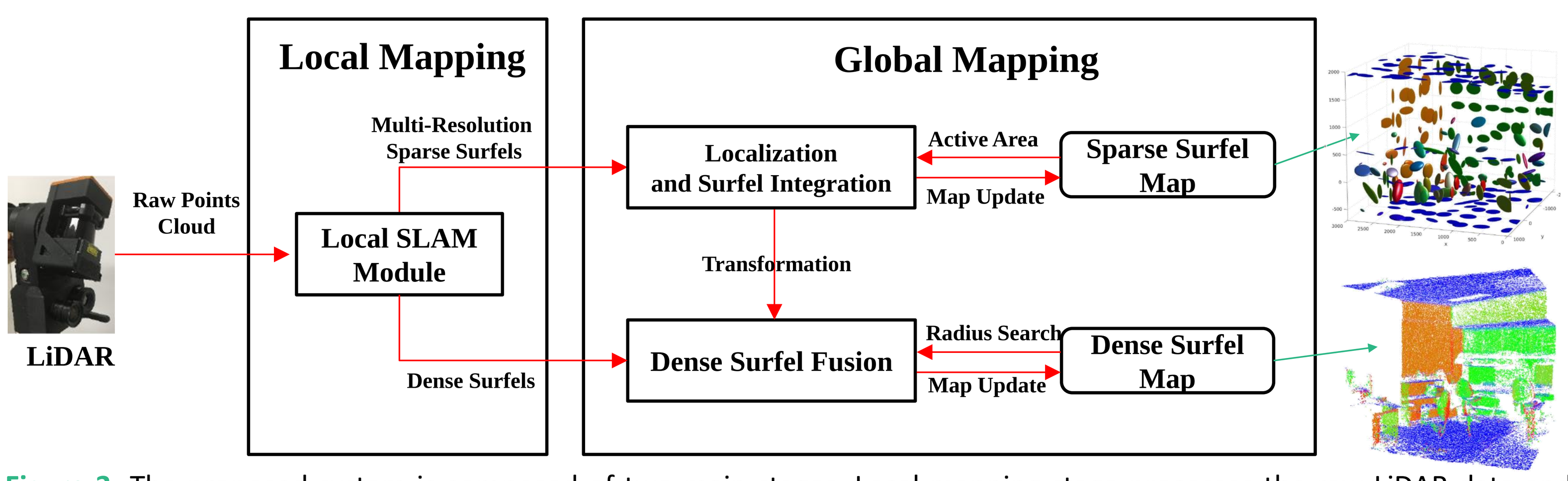
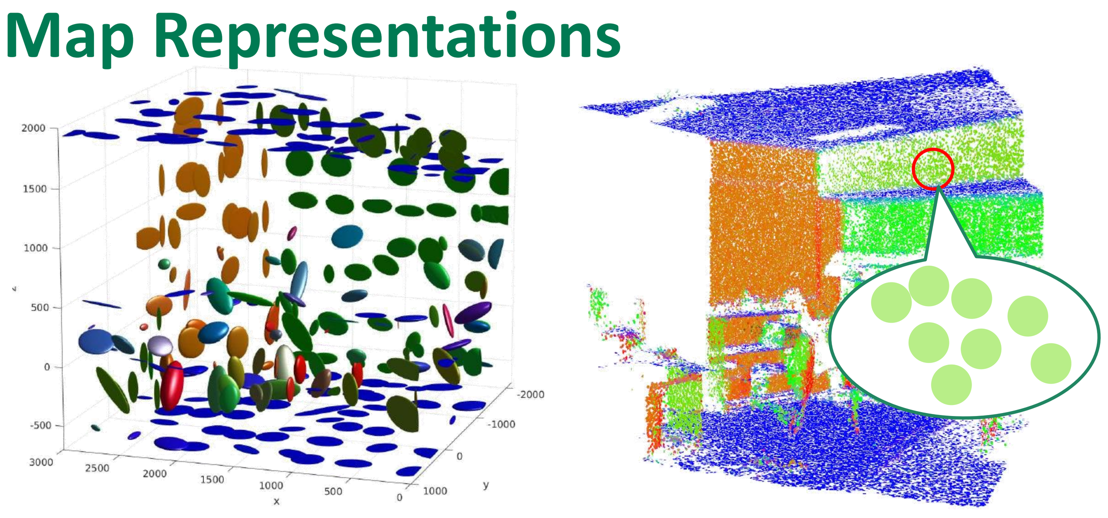


Figure 3: The proposed system is composed of two main stages. Local mapping stage processes the raw LiDAR data and creates local maps. The global mapping stage build a globally consistent map by merging them.

Map Representations



3D Ellipsoidal Surfel Map

from Multi-resolutional Voxel Hassing

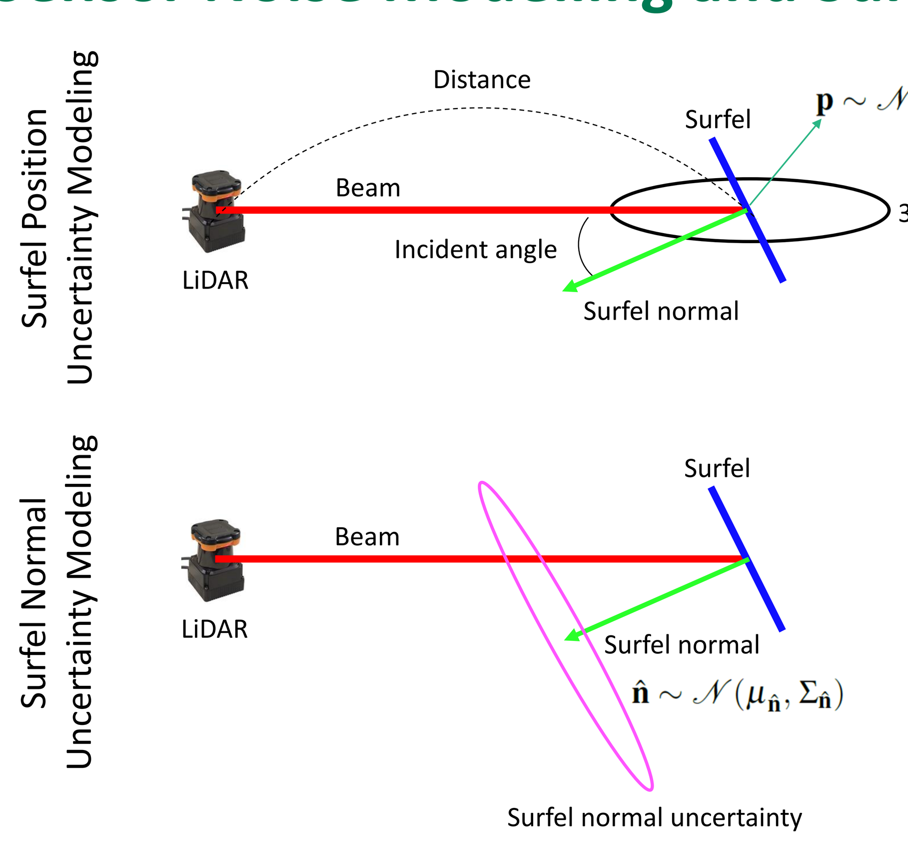
2D Disk Surfel Map

from Nearest Neighbor Searching

3D ellipsoid surfel map is faster and more robust to run localization, and dense 2D disk surfel map is denser and more accurate to 3D reconstruct the environment.

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

Sensor Noise Modelling and Surfel Uncertainty



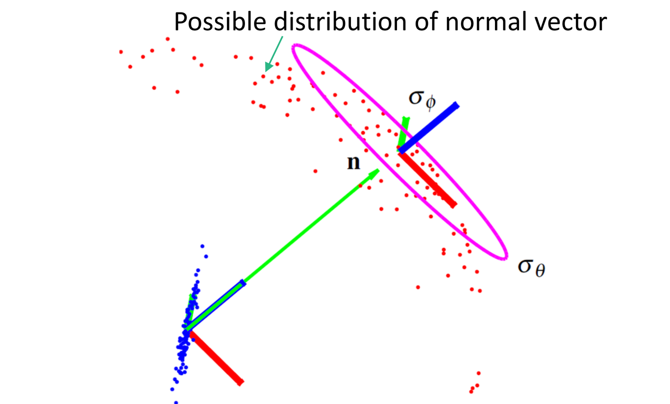


Figure 5: The Illustration of the relationship between the underling points cloud of a surfel and the normal uncertainty

Surfel Matching

The proposed two staged matching algorithm accurately finds the matched surfel of the new input surfel from the local map in the global map.

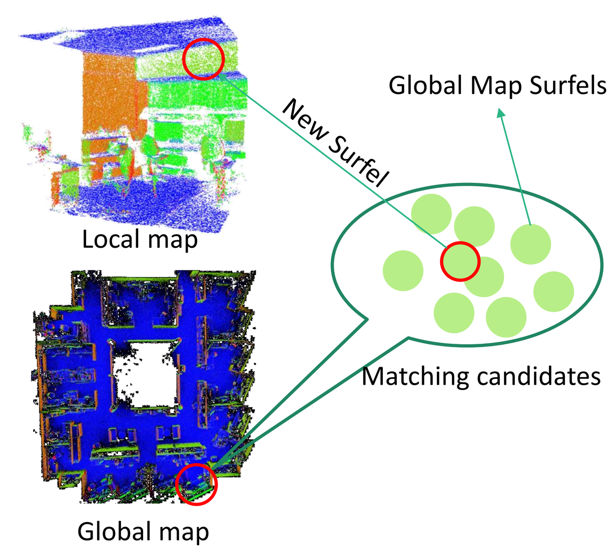


Figure 6: Illustration of surfel matching problem between a local map surfel and the global map surfels.

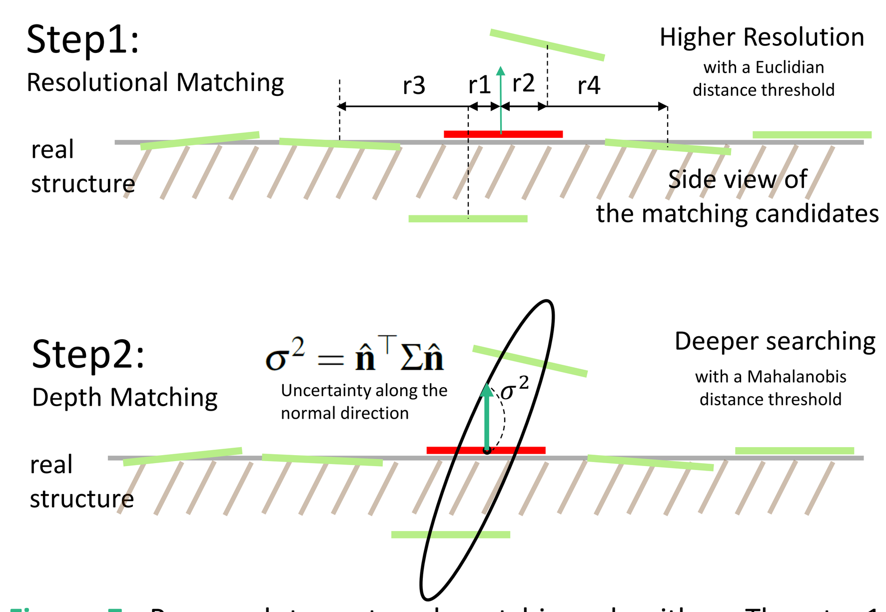


Figure 7: Proposed two staged matching algorithm. The step1 controls map resolution whereas the step2 reduces map noise by searching deeper along the LiDAR beam direction.

Surfel Fusion

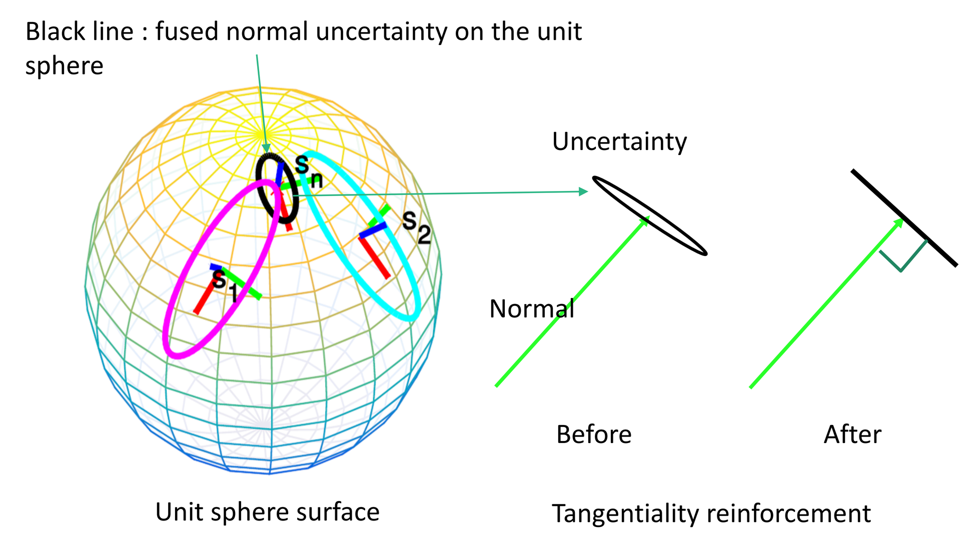
All matched surfels are merged and updated by a Bayesian formula.

Centroid Fusion:

$$\Sigma_d \leftarrow (\Sigma_s^{-1} + \Sigma_d^{-1} + \Sigma_s^{-1})^{-1}$$

$$\mathbf{p}_d \leftarrow (\Sigma_s^{-1} + \Sigma_d^{-1})^{-1} (\Sigma_d^{-1} \mathbf{p}_d + \Sigma_s^{-1} \mathbf{p}_s)$$

For surfel normal update, an additional step for tangentiality reinforcement is required.



Experiment Results

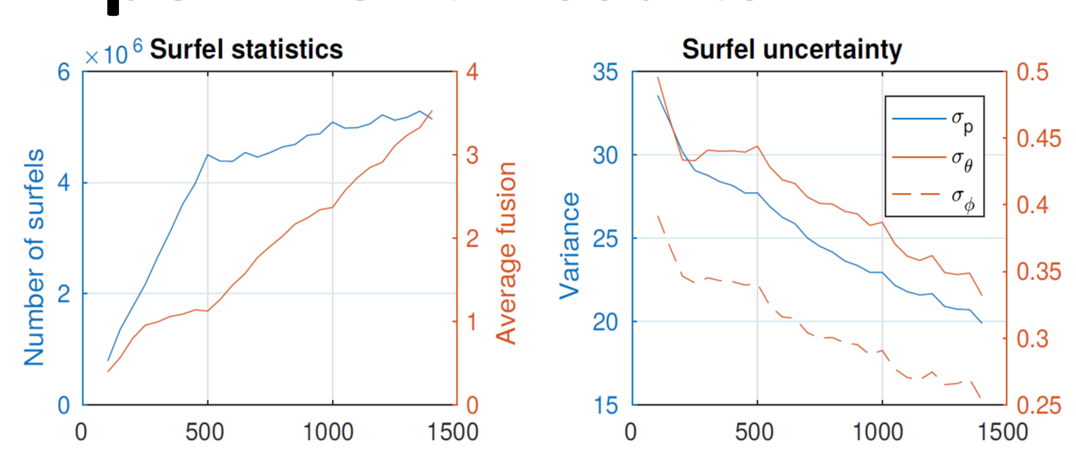


Figure 8: Surfel statistics and uncertainties. [left] The number of surfels and the average number of fusion per surfel, [right] Uncertainties of surfel positions and normal vectors

Figure 9: The experimental handheld 3D spinning LiDAR for mobile mapping.

Figure 10: Reconstructed 3D surfel map of an 20x20 meter office with a color fusion by camera images.

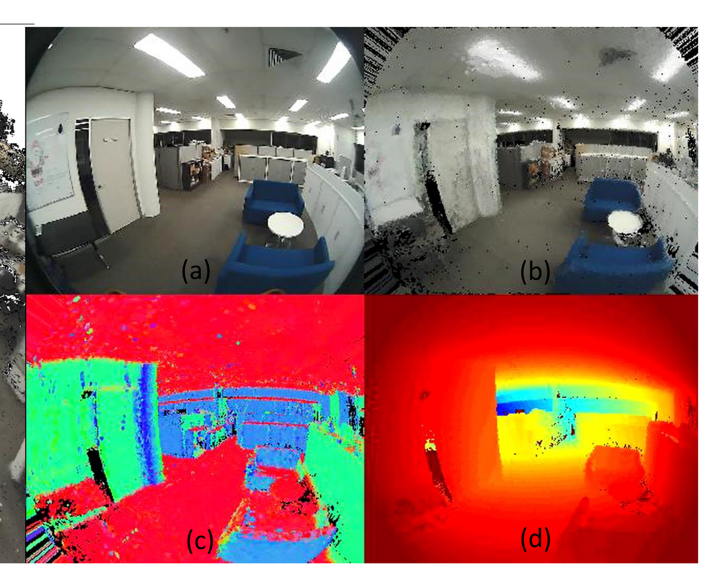


Figure 11: (a) Raw camera image of the office in the red circle. (b) Synthesized image from the surfel map. (c) Surfels map colored with normal direction. (d) Depth image.

Conclusion

Probabilistic dense surfel fusion for LiDAR is proposed. Our method showed denser but lesser noise level in building a dense surfel map. Also, the proposed method has an advantage on long-term SLAM applications.

FOR FURTHER INFORMATION

Chanoh Park

e Chanoh.Park@data61.csiro.au

Peyman Moghadam, Soohwan Kim

e {Peyman.Moghadam, Soohwan.Kim}@data61.csiro.au

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