Ira A. Fulton Schools of Engineering
ARIZONA STATE UNIVERSITY

School of Electrical, Computer and Energy Engineering

MASTERS RESEARCH/THESIS PROPOSAL

An M.S. student must prepare a research/thesis proposal that should be typewritten in a double spaced format and it should be approximately 5-10 pages in length.

The research/thesis proposal should do the following:

- Explain what the student intends to do
- Explain the value of the research
- Outline the research plan
- Define specific criteria for the completion of the research/thesis
- Include a timetable for the completion of the research/thesis
- Include a bibliography relevant to the research/thesis

After the student's faculty advisor is satisfied with the student's research/thesis proposal, the student may submit the proposal to the rest of the research committee. Any member of the committee may establish a requirement for the student to make an oral presentation of the proposal. The research committee evaluates the proposal in terms of:

1. The value of the research
2. The feasibility of the research/thesis plan, and
3. The students' preparation for carrying out the proposed research

The committee will accept the proposal as written, accept it with changes, or reject it. When the committee accepts the proposal, each committee member must sign the approval page given below. Then the student must submit the proposal to the graduate advisor.

A student must have an approved thesis proposal on file with the graduate advisor and an approved MS Thesis form before the student can register for the final 3 hours of research or thesis credits.

Research/Thesis Proposal
for the Master's Degree in Computer

Science

Model-Sync via Selective Mesh Refinement for Bandwidth Constrained Robotic Mapping

Prepared by:

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Date 12/23/2025

Approved by:

Chairperson Dr. Jnaneshwar Das

Committee

Committee

Master's Thesis Proposal:

Model-Sync via Selective Mesh Refinement for Bandwidth-Constrained Robotic Mapping

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1 Introduction

Accurate 3D models are critical for robotic navigation and planning. In planetary missions, coarse terrain models such as DEMs or surface meshes are typically available prior to deployment through orbital sensing. While these models provide useful global context, they often lack the local geometric accuracy required for rover-scale operations, such as hazard avoidance and precise path planning.

Although modern robots can acquire high-resolution geometric data using LiDAR, reconstructing a complete model from scratch is inefficient in bandwidth- and resource-constrained missions. Much of the environment is already adequately represented by existing models, making full remapping unnecessary and redundant.

This thesis adopts the perspective that robotic mapping in such settings should focus on updating an existing model rather than rebuilding it. The prior model is treated as a trusted baseline, and new sensor observations are used to selectively refine only those regions where the prior geometry is inaccurate. Geometric discrepancies are quantified using point-to-surface distance measures, and local refinement is performed only when these discrepancies exceed a defined tolerance, continuing until the local geometry converges.

The objective of this work is to develop and evaluate a framework for selective mesh refinement that improves local geometric fidelity while remaining efficient in sensing and communication.

2 Problem Statement / Research Objective

Pre-existing 3D mesh models provide useful global representations of the environment but often lack sufficient local accuracy for robotic navigation and planning. When new point-cloud observations are acquired, multiple local geometric discrepancies with respect to the prior mesh may be detected. However, updating all such discrepancies is impractical under limited communication bandwidth, and repeated surveying can quickly become redundant.

The problem addressed in this thesis is how to selectively update a prior 3D mesh model using local point-cloud observations. This involves quantifying geometric disagreement between new measurements and the existing surface, prioritizing which local mesh updates are most valuable under bandwidth constraints, and determining when iterative refinement has converged such that additional updates provide negligible benefit.

3 Related Work

3.1 LiSTA: Geometric change detection in 3D maps

LiSTA focuses on detecting geometric changes between multiple 3D maps collected at different times using LiDAR. The method compares point-cloud maps to identify discrepancies while distinguishing meaningful changes from noise or misregistration. LiSTA emphasizes identifying where changes have occurred but does not address surface-level mesh replacement, bandwidth-aware update selection, or convergence-based stopping criteria [1]. This work informs the change-detection aspect of the proposed methodology.

3.2 CAOM: Change-aware online point-cloud mapping

CAOM proposes an online LiDAR-based mapping framework that maintains an up-to-date point-cloud map by comparing online SLAM observations against a high-precision reference map. While CAOM demonstrates selective trust in prior maps, it operates at the point-cloud level and does not perform mesh replacement or consider bandwidth-constrained transmission [2]. The proposed work extends beyond CAOM by operating at the surface level and incorporating convergence-based stopping.

3.3 Woo and Dey: Local mesh updating using point clouds

Woo and Dey present a method for updating triangular mesh models by removing locally invalid surface regions and reconstructing replacement geometry from point-cloud data. Their work establishes local mesh replacement as a valid update primitive but does not address bandwidth constraints, prioritization among updates, or iterative convergence [3]. This thesis adopts local mesh replacement as a primitive and extends it to robotic mapping scenarios.

4 Proposed Methodology / Research Plan

The proposed methodology treats model refinement as an iterative, bandwidth-aware surface update process operating on a pre-existing mesh model.

A Region of Interest (ROI) is first selected based on mission objectives. A robotic platform performs a structured geometric survey of the ROI using onboard range sensors, producing a point cloud

$$P = \{\mathbf{p}_i \in \mathbb{R}^3\}.$$

Let the prior mesh be denoted by

$$M_{\text{prior}}.$$

For each point $\mathbf{p}_i$, the point-to-surface distance is computed as

$$d_i = \min_{\mathbf{x} \in M_{\text{prior}}} \|\mathbf{p}_i - \mathbf{x}\|.$$

Points satisfying $d_i \leq \delta$ are considered consistent with the prior geometry and discarded. The remaining discrepancy points

$$\mathrm{P}_\Delta = \{\mathbf{p}_i \mid d_i > \delta\}$$

indicate regions where the prior mesh is inaccurate.

These points are clustered spatially and used to reconstruct candidate local surface patches $\mathrm{M}^{(k)}_\Delta$ Each candidate patch is evaluated using a geometric importance measure

$$E^{(k)} = \frac{1}{|\mathrm{P}^{(k)}_\Delta|} \sum_{\mathbf{p}_i \in \mathrm{P}^{(k)}_\Delta} d_i.$$

Given a bandwidth budget B, a subset of updates is selected such that

$$\sum_{k \in S} \mathrm{size}(\mathrm{M}^{(k)}_\Delta) \leq B,$$

while maximizing geometric improvement.

At the base station, the prior mesh is updated by removing the corresponding coarse surface regions and inserting the transmitted patches. Iterative surveys are performed until geometric convergence is achieved, defined as

$$|E^{(t)} - E^{(t-1)}| < \epsilon.$$

5 Testing and Simulation

To evaluate the proposed selective mesh refinement framework, both controlled simulation experiments and real-world inspired tests are conducted. Simulation experiments allow precise control over geometric fidelity, sensor resolution, and ground truth, while real-world testing validates the approach under realistic prior model inaccuracies and bandwidth constraints. Together, these experiments demonstrate the effectiveness of local mesh replacement, bandwidth-aware update selection, and convergence-based stopping.

5.1 Simulation

Simulation experiments are conducted using high-quality photogrammetry models of rocks or terrain as ground truth. Coarse prior meshes are generated through decimation to emulate DEM-scale models. Virtual LiDAR sensors with configurable resolution and noise characteristics are used to generate both coarse and fine point clouds representing different sensor ”least counts” (spatial sampling densities).

For each simulated survey, a point cloud P is generated and compared against M_{prior}. The pipeline computes point-to-surface distances d_i, forms P_Δ using the threshold δ, clusters discrepancy points into regions, and reconstructs local surface patches $M_\Delta^{(k)}$. Each patch is serialized in the target encoding (quantized point-patch, reconstructed mesh patch, or heightmap tile) and compressed to estimate transmission size.

Selection policies (e.g., greedy: score = expected improvement / bytes, smallest-first, random) are evaluated under several bandwidth budgets B. The selected patches are applied to produce M_{new}. Metrics such as RMSE, Chamfer distance, p95 residuals, bits transmitted, and bytes-per-RMSE-reduction are recorded. Iterative surveys test convergence behavior until $|E^{(t)} - E^{(t-1)}| < \epsilon$ or a maximum number of iterations is reached.

5.2 Real-World Testing

Real-world testing uses coarse prior meshes obtained from **DeepGIS**. The DeepGIS platform and viewer are available at:

DeepGIS — ROI example

A Region of Interest in DeepGIS is used as the coarse prior M_{prior}. High-resolution local geometry is collected using a rover-mounted LiDAR or an available LiDAR dataset of the same area. The same selective refinement pipeline is applied: discrepancy detection, clustering, local reconstruction, bandwidth-aware selection, transmission, and base-station patch application. Transmission is monitored to ensure the data remains within the chosen bandwidth budgets. Final evaluation compares updated meshes to high-resolution observations using RMSE and percentile distances and reports convergence behavior.

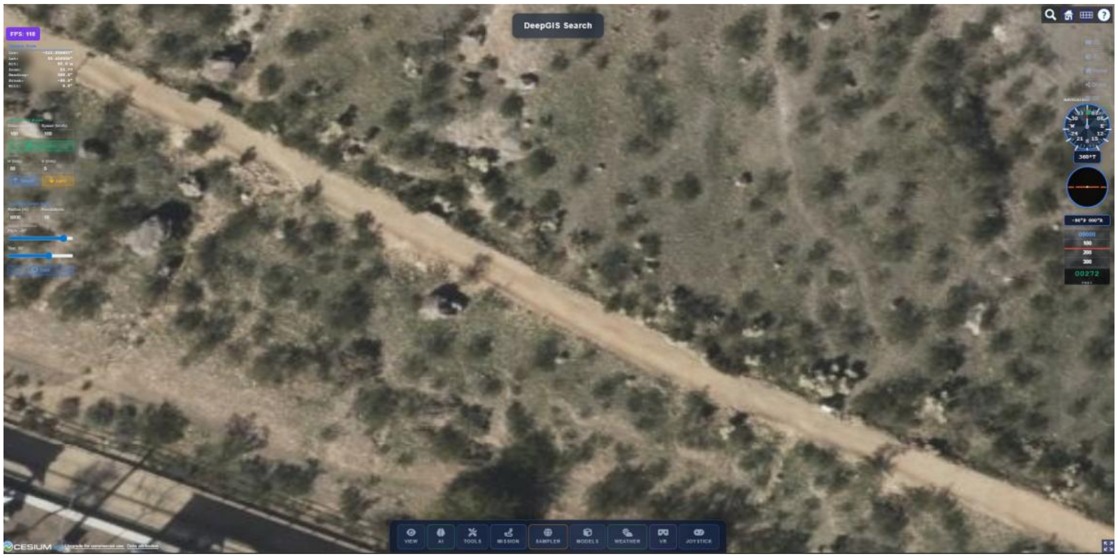

Figure 1: Snapshot of A Mountain as visualized in the DeepGIS platform. This view represents the coarse prior terrain information available before local refinement.

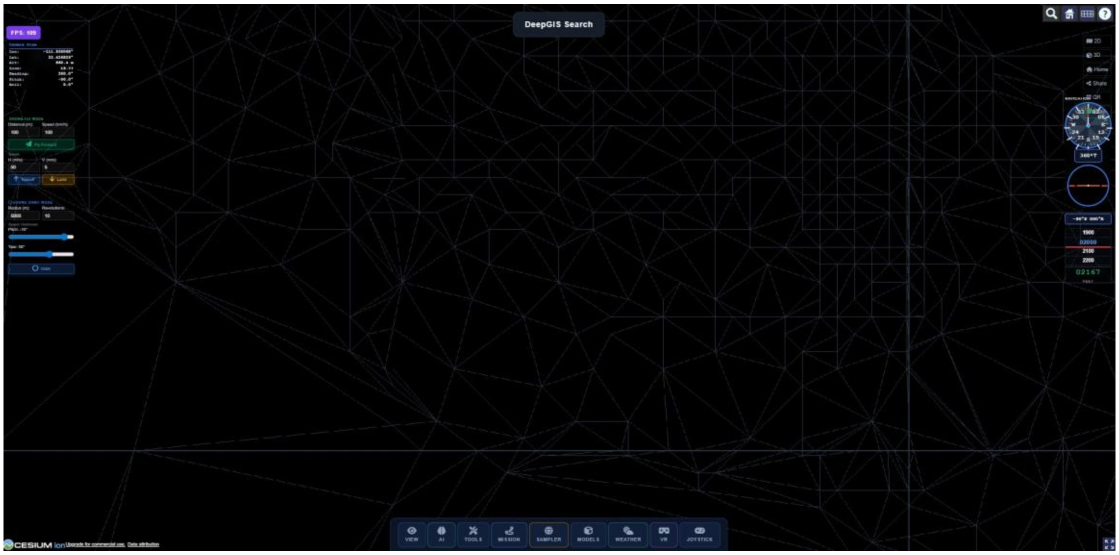

Figure 2: Triangular mesh model of A Mountain derived from the DeepGIS platform. This mesh serves as the initial coarse surface model to be refined using local robotic observations.

6 Criteria of Completion

This thesis will be considered complete when the following criteria are met:

- Successful generation of a high-fidelity geometric model of a selected patch of A Mountain starting from a coarse prior mesh.
- Demonstrated operation within fixed communication bandwidth budgets while achieving significant geometric improvement.
- Verified geometric convergence across iterative surveys.
- Improved model synchronization between a robotic platform and a base station.
- Clear demonstration of generalizability to planetary terrains such as the Moon.

7 Timeline

The proposed thesis work will follow the timeline outlined below:

- **By the end of December:** Set up the complete simulation environment, including generation of coarse and fine mesh models, virtual LiDAR sensor simulation, and integration of the selective mesh refinement pipeline.
- **January:** Perform systematic testing of the proposed algorithm in simulation. Tune key parameters such as the geometric discrepancy threshold δ, convergence threshold ϵ, patch sizes, and bandwidth budgets. Finalize the selection of outdoor test regions (e.g., A Mountain).
- **February–March:** Conduct real-world experiments and validation. Address field-specific challenges, debug data collection and transmission issues, and evaluate geometric convergence, bandwidth efficiency, and model synchronization. Complete final analysis and prepare results for thesis writing.

8 References

[1] J. Rowell, L. Zhang, and M. Fallon, "LiSTA: Geometric Object-Based Change Detection in Cluttered Environments," in *Proceedings of the IEEE International Conference on Robotics and Automation (ICRA)*, Yokohama, Japan, 2024, pp. 3632–3638, doi: 10.1109/ICRA57147.2024.10610102.

[2] Y. Cong, C. Chen, B. Yang, F. Liang, R. Ma, and F. Zhang, "CAOM: Change-aware online 3D mapping with heterogeneous multi-beam and push-broom LiDAR point clouds," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 195, pp. 204–219, 2023, ISSN: 0924-2716.

[3] H. Woo and T. K. Dey, "Updating 3D triangular mesh models based on locally added point clouds," *The International Journal of Advanced Manufacturing Technology*, vol. 30, pp. 261–272, 2006.