

# How Can Aerial Field Robots Use AI to Switch Between Multi-Sensor Navigation Algorithms On the Fly?

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## Introduction

•Multi-sensor navigation algorithms exhibit varying performance in challenging field environments in aerial operations, making reliable algorithm selection critical

•In the absence of ground truth (e.g., GPS), assessing mapping quality is difficult; this work assesses the quality of multi-sensor navigation algorithms using cropped LiDAR point cloud map segments to select the best-performing algorithm at each pose, supporting GPS-resilient navigation

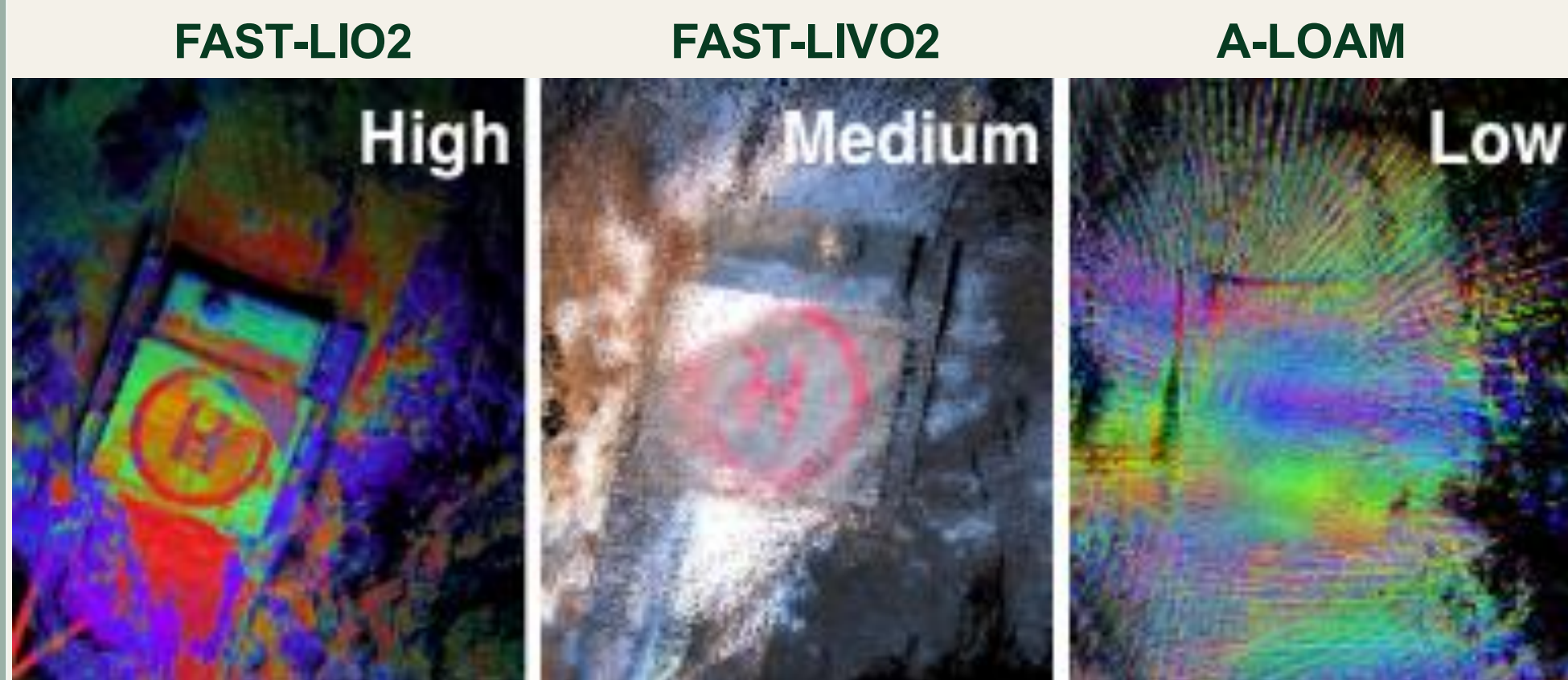


Fig 1: Map segments generated by FAST-LIO2 (LiDAR-Inertial), FAST-LIVO2 (LiDAR-Visual-Inertial), and A-LOAM (LiDAR only) navigation algorithms for Lighthouse dataset sequence from MUN-FRL dataset [1] at the same location, showing High, Medium, and Low map quality, respectively.

## Experimental Setup

- **Datasets** : Four aerial field dataset sequences used
  - **MUN-FRL [1]** : **Author-collected, publicly available** (Lighthouse, and Quarry-2 sequences)
  - **MARS-LVIG [2]** : **Publicly available** (Hkairport\_GNSS02, and AMtown01 sequences)

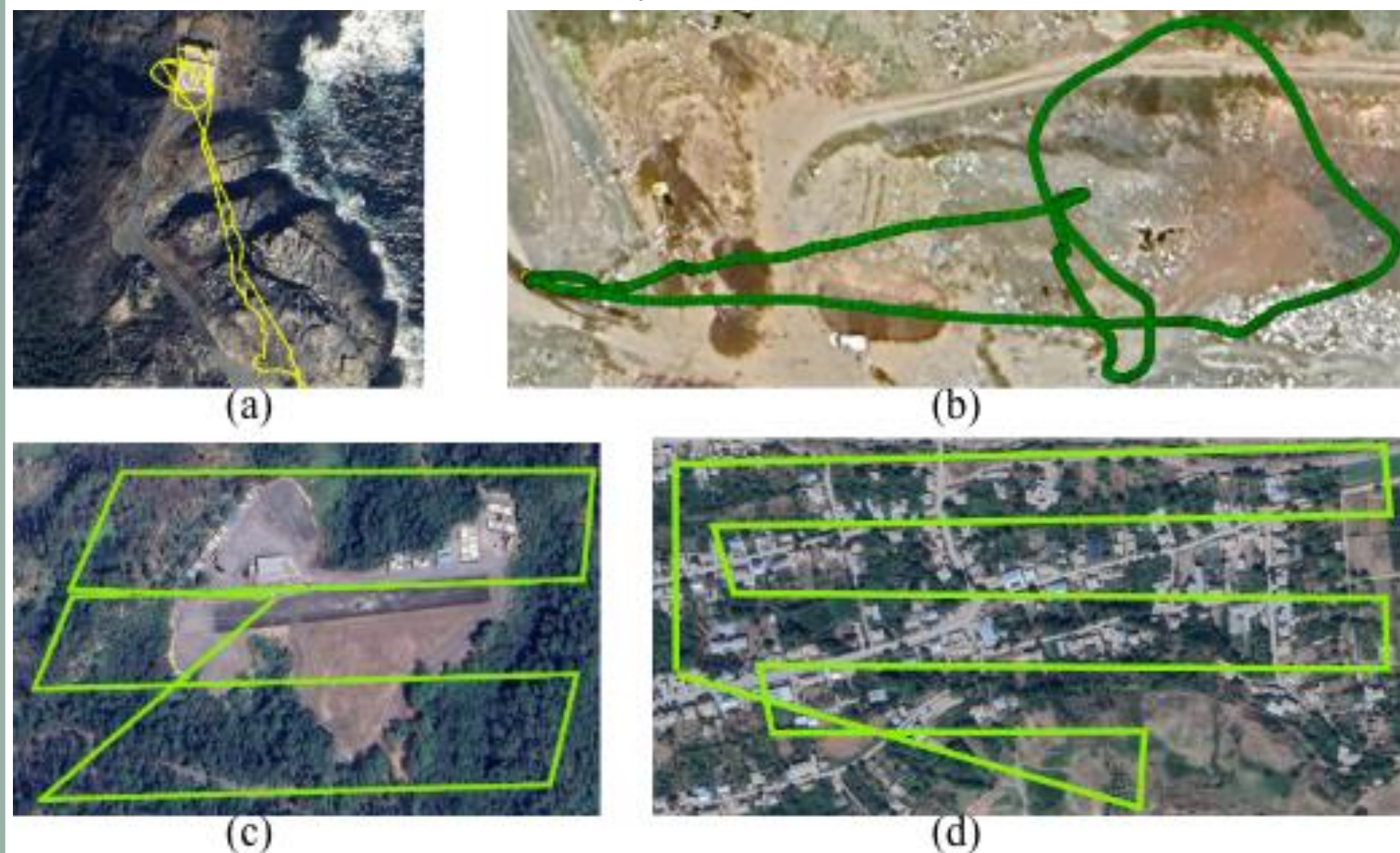


Fig 2: Field datasets used in this work: (a) Lighthouse and (b) Quarry-2 from the author-collected MUN-FRL dataset; (c) Hkairport\_GNSS02 and (d) AMtown01 from the publicly available MARS-LVIG dataset.

- **Multi-Sensor Navigation Algorithms** :

| Dataset Sequence                       | LiDAR-only                    | LiDAR-Inertial | LiDAR-Visual-Inertial | Visual-Inertial |
|----------------------------------------|-------------------------------|----------------|-----------------------|-----------------|
| MUN-FRL (Lighthouse, Quarry-2)         | A-LOAM                        | FAST-LIO2      | FAST-LIVO2            | VINS-FUSION     |
| MARS-LVIG (Hkairport_GNSS02, AMtown01) | LIO-LIVOX (inertial disabled) | FAST-LIO2      | FAST-LIVO2            | N/A             |

- Ground-truth quality of cropped map segments is defined as **RMSE between mapping trajectory and the reference (GPS) trajectory for each pose-wise cropped map segment**

- Smaller quality values indicate higher-quality cropped map segments and larger values correspond to lower-quality cropped map segments

## Proposed Switching Strategy

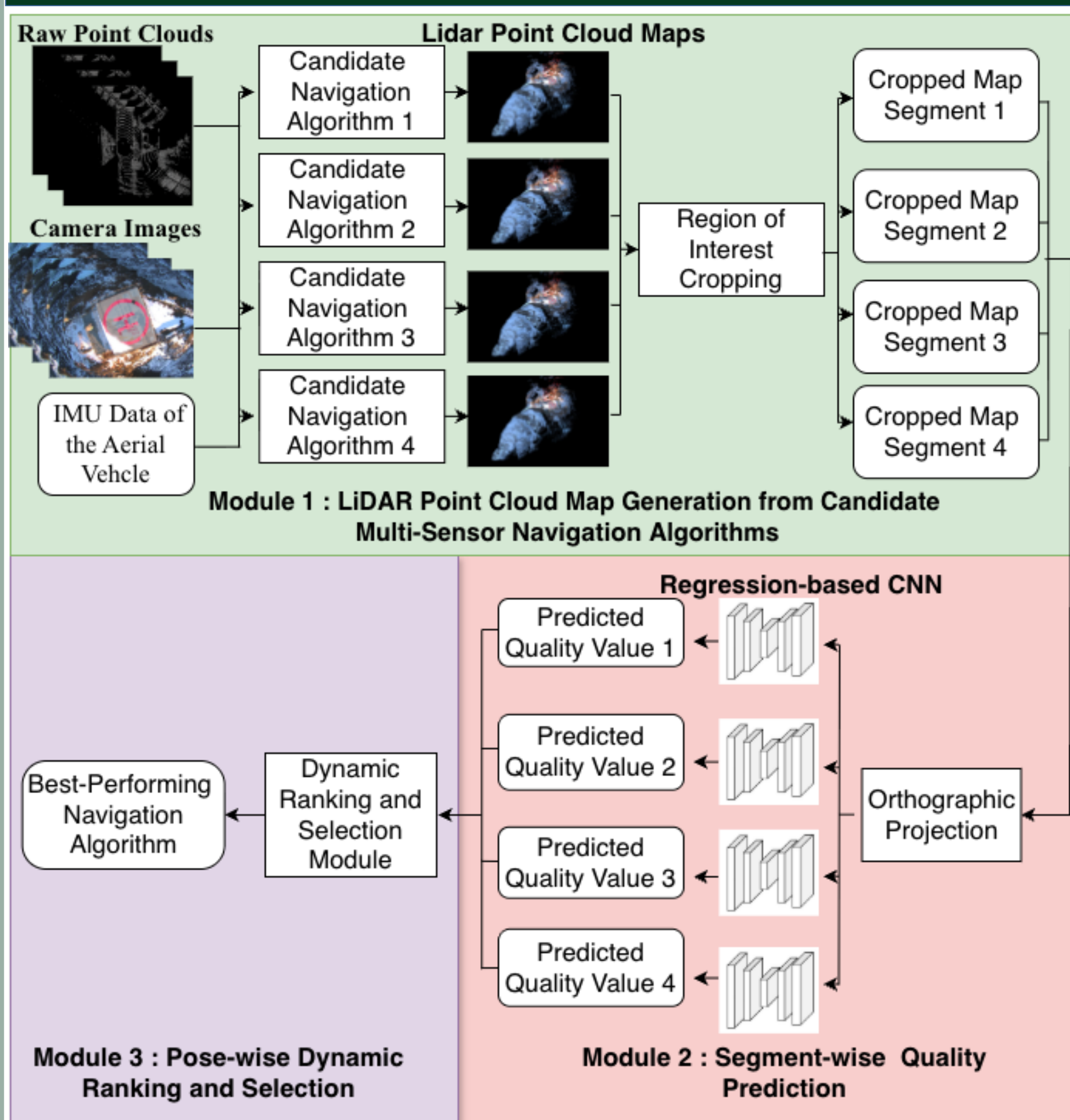


Fig 3: The proposed Switching Strategy

## Proposed Switching Strategy (Cont'd)

### Module 1 : LiDAR Point Cloud Map Generation from Candidate Multi-Sensor Navigation Algorithms

- **Map Generation**: Multiple navigation algorithms generate candidate LiDAR point cloud maps from sensor inputs
- **Region of Interest Cropping**: Pose-wise map segments (50x50x50 m<sup>3</sup>) are extracted from candidate LiDAR point cloud maps. Cropping is performed per pose concurrently with LiDAR point cloud map generation
- **Orthographic Projection**: The cropped map segments are projected to 300x300 pixel orthographic images with *x*, *y*, *z*, *depth* and *remission* channels. These images serve as the inputs for quality prediction

### Module 2 : Segment-wise Quality Prediction

- **Quality Prediction**: Predicts a quality value for each pose-wise cropped map segment for every candidate navigation algorithm.
- **Neural Network Architecture**:
  - Proposed a modified ResNet-34 backbone integrated with **Squeeze-and-Excitation blocks**
  - Input: multi-channel orthographic representations of cropped LiDAR point cloud map segments
  - Ground Truth: log normalized RMSE values
  - Output: predicted mapping quality (log normalized RMSE)

### Module 3 : Pose-wise Dynamic Ranking and Selection

- **Ranking and Selection**: According to the predicted quality values, candidate navigation algorithms are ranked at each pose and best performing navigation algorithm is selected.

## Key Contributions

- Learning-based quality prediction of LiDAR point cloud maps generated from multi-sensor navigation algorithms without using ground truth (e.g., GPS)
- Proposed a light-weight regression-based convolutional neural network architecture for quality prediction of LiDAR point cloud map segments
- Quantitative and qualitative evaluation on multiple real-world challenging datasets sequences, from a **publicly available dataset collected by the authors (MUN-FRL [1])** and an additional publicly available dataset (MARS-LVIG [2])

## Results

### Quantitative Results: Table 2

- The proposed method consistently reduces RMSE and drift across all sequences compared to individual navigation algorithms
- Consistent performance across multiple sequences indicates robustness under varying field conditions.

Table 2 : Validation performance comparison of candidate navigation algorithms and the proposed switching strategy across multiple field datasets sequences.

| Dataset Sequence | Candidate Navigation Algorithm | *Avg. RMSE (m) ↓<br>(Mean ± SD) | *Avg. Drift (%) ↓<br>(Mean ± SD) |
|------------------|--------------------------------|---------------------------------|----------------------------------|
| Lighthouse       | A-LOAM                         | 8.145 ± 1.318                   | 4.509 ± 1.064                    |
|                  | FAST-LIO2                      | 0.635 ± 0.145                   | 0.471 ± 0.119                    |
|                  | FAST-LIVO2                     | 0.650 ± 0.180                   | 0.483 ± 0.091                    |
|                  | VINS-FUSION                    | 5.381 ± 1.079                   | 5.130 ± 2.272                    |
| Quarry-2         | A-LOAM                         | 10.16 ± 0.254                   | 15.22 ± 0.997                    |
|                  | FAST-LIO2                      | 43.27 ± 0.908                   | 14.65 ± 0.571                    |
|                  | FAST-LIVO2                     | 24.5 ± 7.935                    | 15.24 ± 4.034                    |
|                  | VINS-FUSION                    | 6.406 ± 0.361                   | 6.477 ± 0.789                    |
| Hkairport_GNSS02 | A-LOAM                         | 10.16 ± 0.254                   | 15.22 ± 0.997                    |
|                  | FAST-LIO2                      | 43.27 ± 0.908                   | 14.65 ± 0.571                    |
|                  | FAST-LIVO2                     | 24.5 ± 7.935                    | 15.24 ± 4.034                    |
|                  | VINS-FUSION                    | 6.406 ± 0.361                   | 6.477 ± 0.789                    |
| AMtown01         | A-LOAM                         | 10.16 ± 0.254                   | 15.22 ± 0.997                    |
|                  | FAST-LIO2                      | 43.27 ± 0.908                   | 14.65 ± 0.571                    |
|                  | FAST-LIVO2                     | 24.5 ± 7.935                    | 15.24 ± 4.034                    |
|                  | VINS-FUSION                    | 6.406 ± 0.361                   | 6.477 ± 0.789                    |

\*Avg. RMSE and drift are computed by averaging segment-wise values over consecutive pose-wise cropped segments within the validated portion of the trajectory. Values are reported as mean ± standard deviation (SD).

### Quantitative Results: Table 3

- High Top-1 accuracy demonstrates effective selection of the pose-wise best-performing navigation algorithm
- High full-order accuracy reflects reliable ranking of candidate navigation algorithms

Table 3 : Best-performing navigation algorithm selection and full-order accuracy across multiple field dataset sequences

| Dataset Sequence | *No. of CMSs | Top-1 Correct (CMSs, Accuracy %) ↑ | Full-order Correct (CMSs, Accuracy %) ↑ |
|------------------|--------------|------------------------------------|-----------------------------------------|
| Lighthouse       | 200          | 188 (94%)                          | 188 (94%)                               |
| Quarry-2         | 225          | 225 (100%)                         | 192 (85.33%)                            |
| Hkairport_GNSS02 | 287          | 210 (73.17%)                       | 210 (73.17%)                            |
| AMtown01         | 269          | 259 (96.28%)                       | 259 (96.28%)                            |
| All              | 981          | 882 (89.91%)                       | 849 (86.54%)                            |

\*cropped map segments (CMSs)

## Results (Cont'd)

### Qualitative Results:

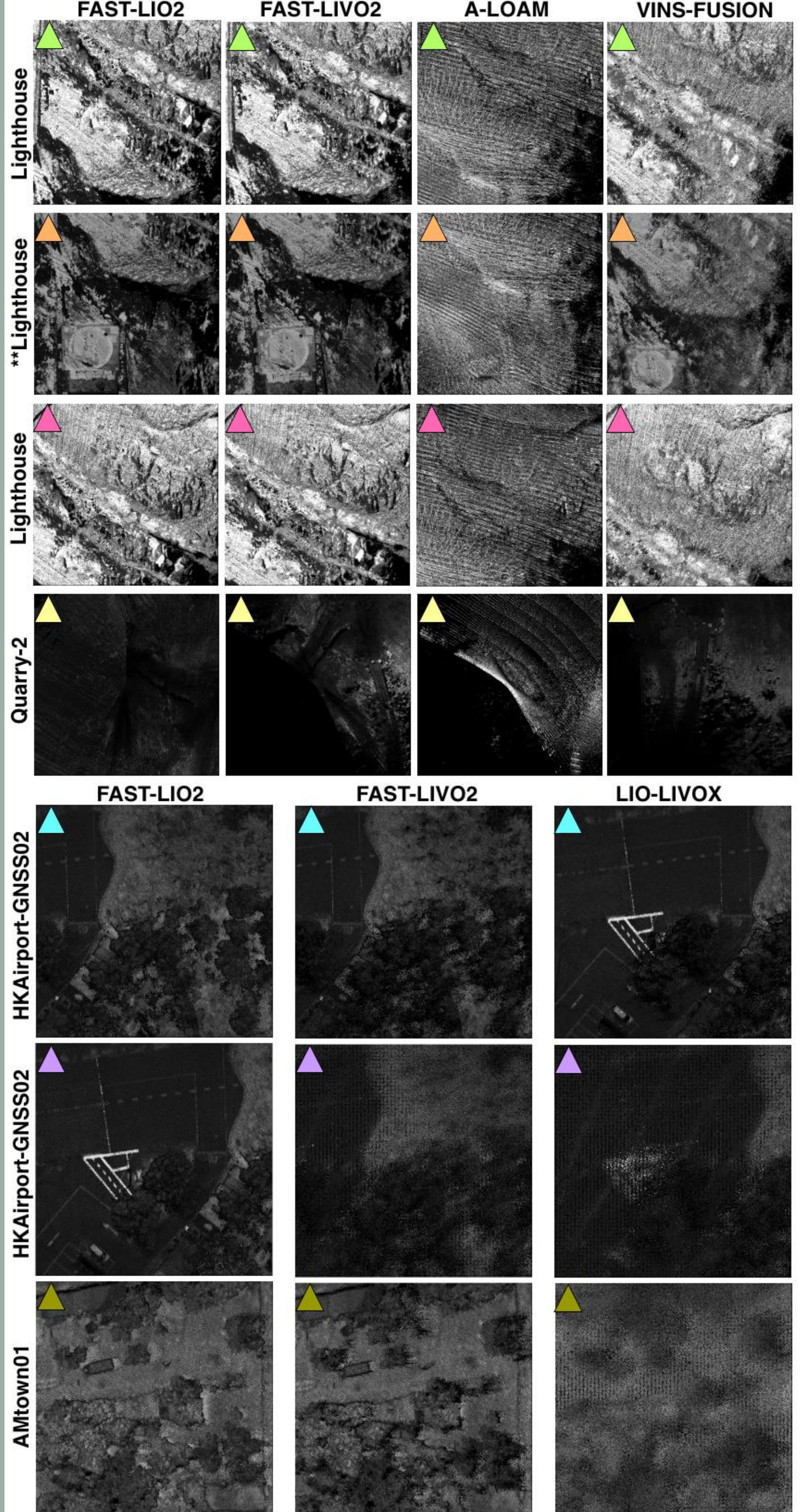


Fig 4 : Qualitative results on MUN-FRL and MARS-LVIG datasets

Table 4 : Ground Truth (GT) vs predicted quality values for validation data across different datasets (\*\* Tie case: Two leading algorithms receive similar predicted quality; Top-1 is considered correct if the ground-truth best-performing algorithm is among them.)

| Dataset Sequence | Gt / Pred | FAST-LIO2 | FAST-LIVO2 | A-LOAM / LIO-LIVOX | VINS-FUSION | Top-1 & Top-2 |
|------------------|-----------|-----------|------------|--------------------|-------------|---------------|
| Lighthouse       | GT        | 0         | 0.00141    | 1                  | 0.9006      | Top-1 Correct |
|                  | Pred      | 0         | 0.00001    | 0.99462            | 0.4842      | Correct       |
| **Lighthouse     | GT        | 0.00445   | 0          | 1                  | 0.63051     | Top-1 Correct |
|                  | Pred      | 0         | 0          | 0.99951            | 0.68359     | Correct       |
| Lighthouse       | GT        | 0.0218    | 0          | 1                  | 0.6384      | Top-2 Correct |
|                  | Pred      | 0         | 0.00002    | 0.9458             | 0.4109      | Correct       |
| Quarry-2         | GT        | 1         | 0          | 0.62535            | 0.52778     | Top-1 Correct |
|                  | Pred      | 0.82861   | 0.09979    | 0.55322            | 0.53955     | Correct       |
| Hkairport_GNSS02 | GT        | 0         | 0.06817    | 1                  | N/A         | Top-1 Correct |
|                  | Pred      | 0.00304   | 0.06222    | 0.98974            | N/A         | Correct       |
| Hkairport_GNSS02 | GT        | 0.0313    | 0          | 1                  | N/A         | Top-2 Correct |
|                  | Pred      | 0.01384   | 0.12988    | 0.99462            | N/A         | Correct       |
| AMtown01         | GT        | 0         | 0.00043    | 1                  | N/A         | Top-1 Correct |
|                  | Pred      | 0         | 0.00005    | 0.00051            | N/A         | Correct       |

- Predicted quality values and rankings for validation data show strong agreement with ground-truth values across different sequences
- Variations in ranking primarily occur between closely performing leading algorithms under low-separability conditions as observed in challenging cases
- Clearly degraded map segments are consistently assigned lower quality values
- Qualitative observations are consistent with quantitative results, supporting pose-wise best-performing navigation algorithm selection

## Conclusion

- The proposed method enables reliable selection of navigation algorithms based on predicted quality
- Consistent performance is achieved across multiple real-world datasets, demonstrating practical applicability in field robotics.
- Results demonstrate improved robustness under varying field conditions

## References

- [1] R. G. Thalagala, O. De Silva, A. Jayasiri, A. Gubbels, G. K. Mann, and R. G. Gosine, "MUN-FRL: A visual-inertial-LiDAR dataset for aerial autonomous navigation and mapping," The International Journal of Robotics Research, p. 02783649241238358, 2024.
- [2] H. Li, Y. Zou, N. Chen, J. Lin, X. Liu, W. Xu, C. Zheng, R. Li, D. He, F. Kong et al., "Mars-lvig dataset: A multi-sensor aerial robots slam dataset for lidar-visual-inertial-gnss fusion," The International Journal of Robotics Research, p. 02783649241227968, 2024.