

Global Bird's Eye View Semantic Mapping

Hefeng Zhou, Ding Zhong, Yiwei Gui, and Yiting Wang
Electrical and Computer Engineering Department, University of Michigan

Abstract

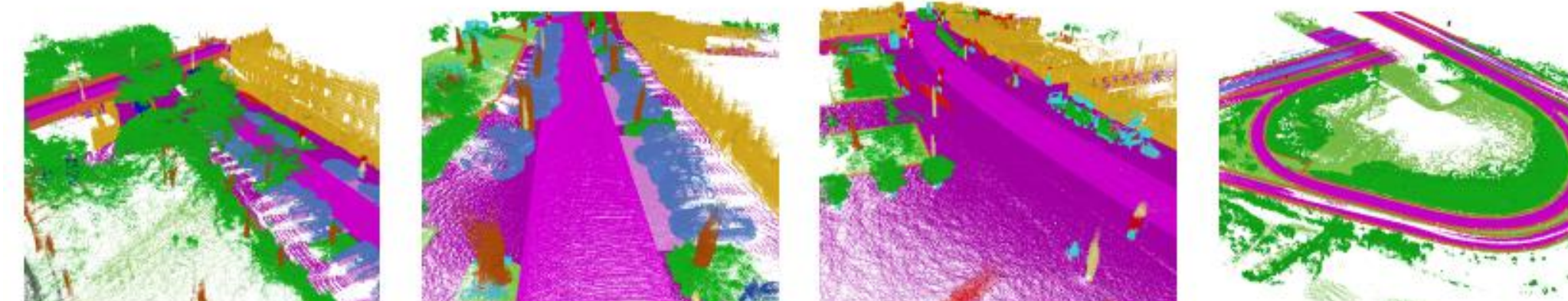
- We integrate AI-IMU[1] and MotionNet[2] to achieve robust localization and semantic scene understanding. AI-IMU dynamically adapts to varying sensor noise and motion patterns. MotionNet generates dense semantic BEV maps and effectively filters dynamic obstacles.
- Experimental validation on the SemanticKITTI dataset demonstrates strong robustness and accuracy in challenging scenarios, including dynamic objects and sensor dropout.

Motivation

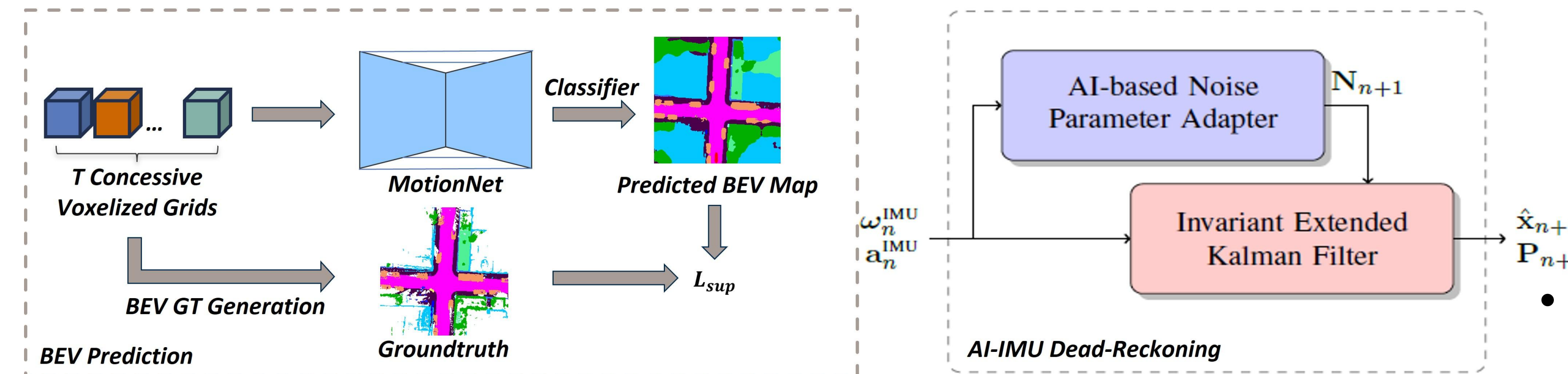
- LiDAR and vision-based SLAM systems tend to degrade significantly in the presence of occlusion, dynamic objects, and sensor dropout.
- IMUs suffer from drift and error accumulation when used in isolation.

Data Sets

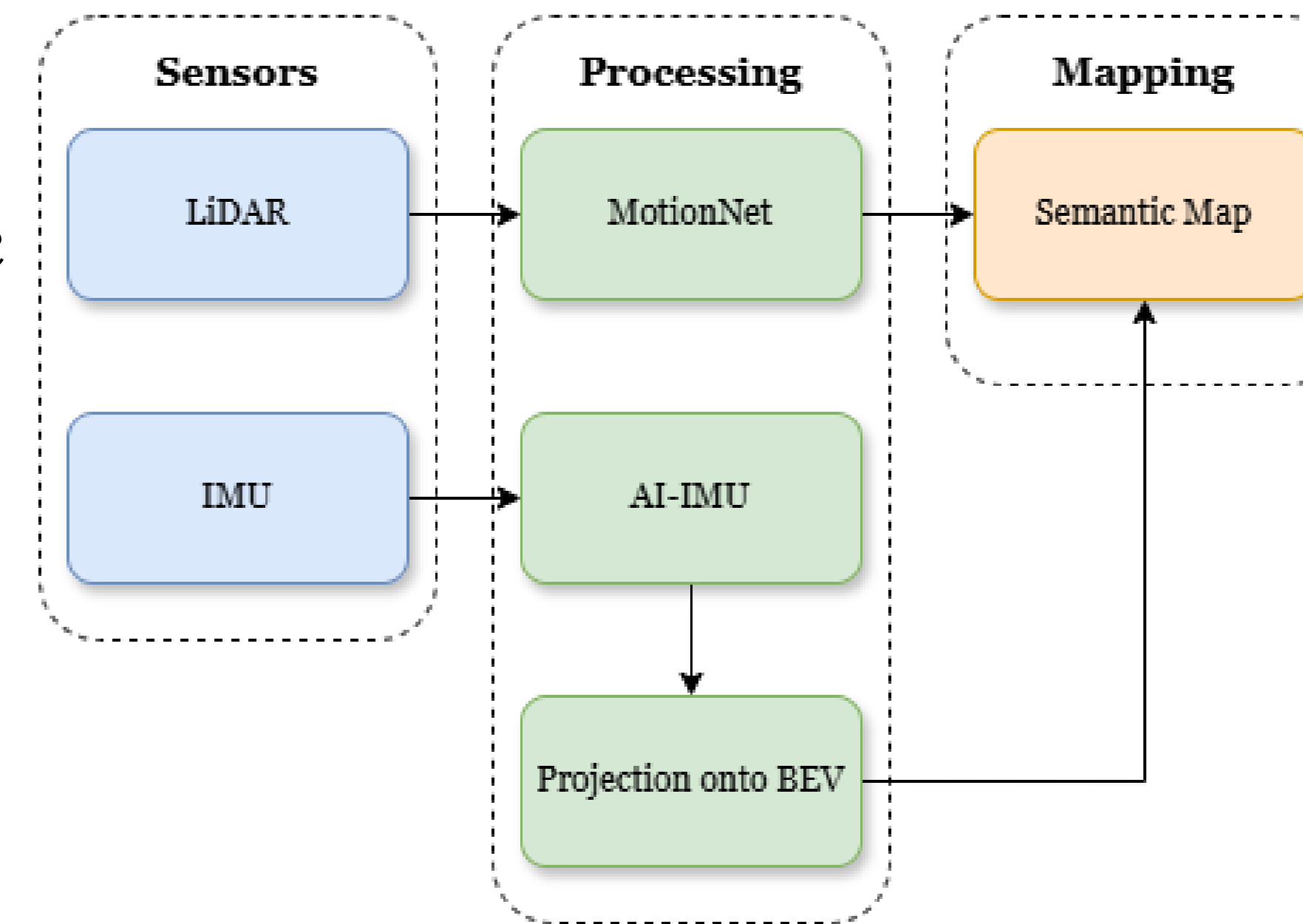
- We evaluate our method on the SemanticKITTI dataset



Methodology



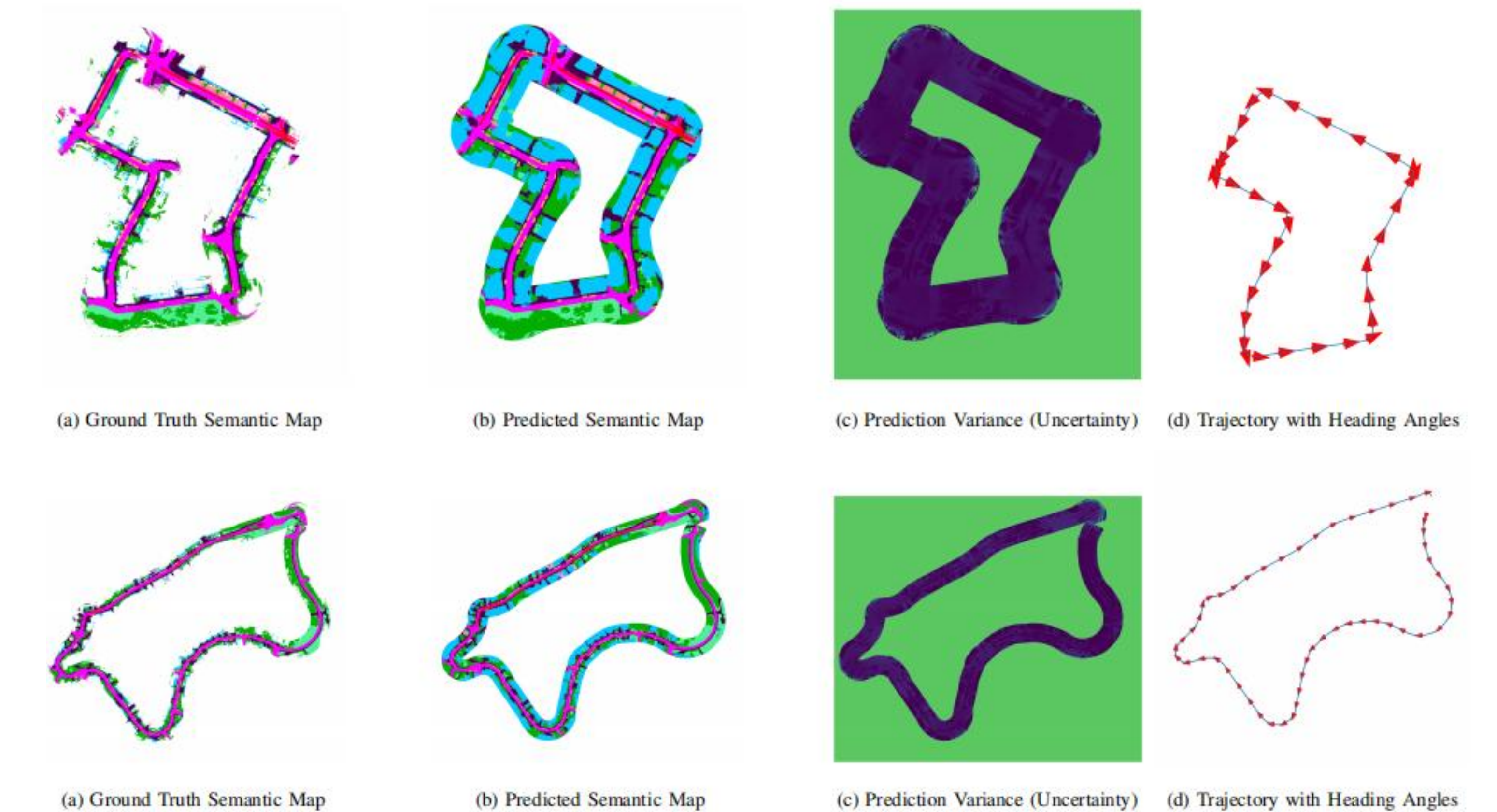
- MotionNet processes LiDAR point clouds to produce accurate semantic BEV maps using a Spatio-Temporal Pyramid Network (STPN).
- AI-IMU employs an Invariant Extended Kalman Filter (IEKF) enhanced by CNN-adaptive pseudo-measurement covariance for precise IMU-based localization.
- Semantic maps from MotionNet are spatially aligned with accurate poses estimated by AI-IMU, enabling consistent semantic mapping.
- Our integrated framework effectively captures dynamic scenes and maintains robustness even when LiDAR or visual data are compromised.



Results

Class ID	car	bicycle	road	parking	sidewalk	building	fence
Baseline IoU (%)	74.8	-	82.8	24.6	53.0	16.0	15.6
Ours IoU (%)	71.59	15.62	87.09	61.32	67.07	19.63	29.63
Class ID	vegetation	terrain	pole	traffic-sign	moving-car	moving-person	
Baseline IoU (%)	49.3	50.3	-	-	-	-	-
Ours IoU (%)	45.91	64.44	22.92	17.98	49.19	20.23	-
mIoU (%)	Ours (13 classes): 44.05				Baseline: 45.80		
mIoU on Baseline Classes Only (%)	Ours: 60.44						

- Our method improved IoU scores on crucial urban classes, such as roads, sidewalks, and terrains.
- Overall mIoU across all 13 classes was 44.05%, slightly below the baseline's 45.80%. When evaluating only classes present in the baseline, our approach notably outperformed, achieving an mIoU of 60.44%.
- These results highlight our model's strong capability in critical urban segmentation scenarios.



[1] M. Brossard, A. Barrau, and S. Bonnabel, "Ai-imu dead-reckoning," IEEE Transactions on Intelligent Vehicles, vol. 5, no. 4, pp. 585–595, 2020.
[2] P. Wu, S. Chen, and D. N. Metaxas, "Motionnet: Joint perception and motion prediction for autonomous driving based on bird's eyeview maps," in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), June 2020.