

Online Map Generation Using Stereo Cameras: A Case Study

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High-definition (HD) maps are essential for advanced driver assistance systems (ADAS) and autonomous driving applications. Conventional HD map generation methods often rely on dedicated measurement vehicles equipped with expensive sensors such as LiDAR (Light Detection And Ranging) and high-precision GNSS/INS (Global Navigation Satellite System/Inertial Navigation System). Although these approaches can generate centimeter-order accurate maps, they require significant data collection and computational costs. Therefore, there is considerable demand for low-cost map generation technologies that can operate using production vehicle sensors. This study proposes an online map generation method that utilizes road landmark observations obtained from a stereo camera together with vehicle trajectory information obtained by GNSS/INS. The method focuses on road landmarks such as lane markings and road boundaries, which generally maintain a consistent spatial relationship with the driving trajectory.

First, road boundary observations detected by onboard sensors are accumulated over multiple frames. To maintain a consistent representation in the current vehicle coordinate system, previously observed landmark points are transformed using the ego-vehicle motion estimated from vehicle velocity and yaw rate. This process enables historical observations to be aligned and integrated over time without requiring immediate projection into a global coordinate system. Next, a landmark existence likelihood distribution is generated from the accumulated observations. Landmark points located within a predefined longitudinal range around the ego vehicle are extracted, and their lateral positions relative to the vehicle are calculated. A histogram of the lateral positions is then constructed, and the frequency of observations is interpreted as the likelihood of landmark existence. Because road boundaries are continuous structures, repeated observations tend to form distinct peaks in the likelihood distribution even in the presence of perception and localization noise. To improve robustness against false detections and temporary observation losses, the likelihood distribution is updated over time using a Binary Bayes Filter. The posterior landmark existence probability is represented in the log-odds form and recursively updated by integrating newly observed likelihoods. This temporal filtering process suppresses spurious peaks while preserving consistent landmark hypotheses, enabling stable tracking of road boundary locations. Finally, landmark positions are estimated from the peaks of the posterior probability distribution. The estimated lateral positions are projected into the global coordinate system using the vehicle position and heading angle obtained from GNSS/INS. By continuously repeating this process, vectorized road boundaries can be reconstructed and stored as map data.

To evaluate the proposed method, road boundaries detected by a stereo camera were mapped into a world coordinate system using GNSS position and heading angle. The proposed likelihood-based tracking approach was applied independently to the left and right road boundaries. Fig.1 shows that the proposed method successfully generated continuous road boundary maps with fewer missing segments than a simple accumulation of raw observations. The method was particularly effective in compensating for temporary detection failures that frequently occur in vision-based perception systems.

However, several limitations remain. The proposed approach may not perform well in complex road structures such as intersections where multiple boundaries merge or diverge. In addition, long-distance observation losses can reduce the reliability of likelihood estimation. Future work includes incorporating confidence measures derived from likelihood values and extending the method to handle complicated road geometries.

Compared with recent deep learning based online HD map generation approaches, such as HDMaNet and MapTR, the proposed method does not require large-scale training datasets or high-performance computing resources. Instead, it exploits geometric consistency between road landmarks and vehicle trajectories, enabling robust map generation with a relatively low-cost sensor configuration.

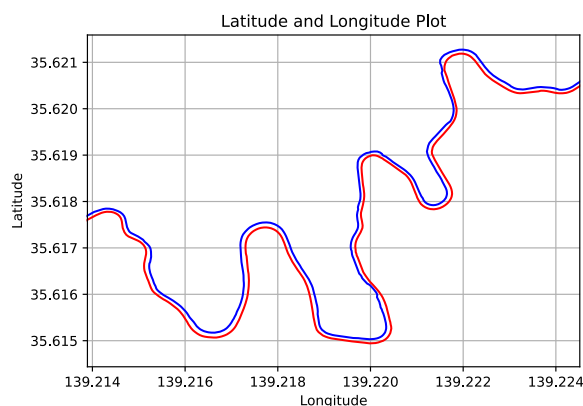


Fig.1 Mapping results