*Proceedings of the 11th North American International Conference on Industrial Engineering and Operations Management, Milwaukee, Wisconsin, USA, June 9-11, 2026*

*Proceedings of the International Conference on Industrial Engineering and Operations Management*

Publisher: IEOM Society International, USA DOI: 10.46254/NA11.20260271
Published: June 9, 2026

# Lane Feature-Based Localization via ICP Map Alignment

**Briana Popa, Ali Irshayyid and Jun Chen**
Department of Electrical and Computer Engineering
Oakland University
Rochester, MI, USA
bpopa@oakland.edu; aliirshayyid@oakland.edu; junchen@oakland.edu

## Abstract

This paper presents an approach for camera-only localization, by aligning onboard observations to a pre-built reference feature map. By using only lane markings as features, the proposed method provides a lightweight alternative to multi-sensor and dense-map-based approaches. The framework is evaluated on a scaled autonomous vehicle platform in a controlled environment. A drone-based orthomosaic is used to create an aerial reference map. Onboard camera images are transformed into a bird's eye view (BEV) representation to match the perspective of the reference map. Lane features are extracted and represented as point clouds, and alignment between local observations and the global map is performed using the Iterative Closest Point (ICP) algorithm. Experimental results demonstrate the feasibility of lane-based map alignment for localization, while also highlighting sensitivity to initialization.

## Keywords
Localization, Iterative Closest Point, Map Matching, Bird's Eye View (BEV), and Scaled Autonomous Vehicle.

## 1. Introduction
Having robust localization in autonomous vehicles (AVs), especially when certain sensor data is unavailable or degraded, remains a fundamental challenge. Many existing approaches rely on highly detailed prior maps (Asrat and Cho 2024; Chalvatzaras et al. 2023; Liu et al. 2020), referred to as high-definition (HD) maps, which may not always be available. These maps are more commonly used to assist AVs in structured environments such as highways; however, their use in urban environments is often suboptimal due to frequent environmental changes and the low update frequency of HD maps (Chen et al. 2023). As a result, there is a need to explore localization methods that function using more accessible and less complex data. This research proposes a lane feature-based localization approach. Although lane features are not consistently reliable across all environments, they offer a simple and structured representation that can be extracted using vision alone, without requiring multiple sensing modalities. In particular, the objective of this study is to develop and evaluate a map-based localization framework that aligns onboard camera observations with a prior aerial map using lane-based features. Specifically, this work performs cross-view alignment between ground-level camera data and an aerial map representation, implements an iterative closest point (ICP)-based alignment approach (Besl and McKay 1992; Chen and Medioni, 1992), and evaluates the proposed framework using data collected from a scaled AV platform in a controlled indoor environment as a baseline evaluation. The proposed ICP-based approach is demonstrated to offer accurate localization performance, while at the same time may be sensitive to initialization. In other words, the initial guess of the vehicle location needs to be close enough to its true location. The removal of this restriction remains a future work.

The remainder of this paper is organized as follows. Section 2 reviews relevant literature in this area, while Section 3 presents the main algorithm. Section 4 provides details on data collection, and experimental results are discussed in Section 5. Lastly, Section 6 concludes the paper with future work direction.

## 2. Literature Review

This section reviews existing approaches to AV localization, with a focus on map-based methods and feature-based alignment techniques. The goal is to position the proposed approach within the context of current research.

In AV stacks, localization accuracy is critical, as it provides foundational information to subsequent algorithms (e.g. path planning and motion control). There are various approaches to localization. A survey by Chalvatzaras et al. (2023) divides map-based localization into three approaches: map-matching, probabilistic, and deep learning. Map-matching techniques commonly extract only significant features and align them to a prior map using registration algorithms such as ICP. The limitations of map-matching approaches arise from their reliance on accurate alignment; in feature-sparse or dynamic environments, the lack of distinctive features introduces uncertainty in establishing reliable correspondence, resulting in a large number of false positive registrations (Chalvatzaras et al. 2023). Feature-based localization methods have demonstrated increased robustness; however, their performance depends on feature extraction methods, which can be sensitive to environmental variations such as lighting (Durgam et al. 2024).

Map-based localization commonly uses HD maps as prior maps (Chalvatzaras et al. 2023). HD maps are highly detailed, three-dimensional representations of the environment (Liu et al. 2020), constructed through data collection using survey vehicles equipped with various high precision sensors (Asrat and Cho 2024). 2D versions of HD maps have also been explored (Liu et al. 2020). While HD maps are highly detailed, their acquisition and maintenance remain labor-intensive and costly. With satellite imagery being easy to access and regularly maintained, many have resorted to its use for localization with cross-view methodologies (Wang et al. 2023), where ground-level observations are matched to top-down map representations to estimate vehicle position. Existing approaches rely on image-level feature matching, resulting in coarse localization (Wang et al. 2023). Prior work has also explored the use of lane-level data, particularly lane markings, to achieve localization via ICP (Asghar et al. 2020; Gong et al. 2024). These studies demonstrate that lane features can serve as a meaningful and structured feature for localization. However, to improve robustness, additional information needs to be incorporated. For instance, in (Asghar et al. 2020), GPS measurements are used to enhance vehicle pose estimates, while in (Gong et al. 2024), the approach utilizes dense local representation, constructed by aggregating multiple scans. These enhancements help improve the reliability and performance of the alignment, but at the same time they also increase cost as multiple onboard sensors are now required. In contrast, our work investigates a camera-only framework that relies solely on lane features without additional sensing modalities.

On the other hand, most AV development is conducted either in simulation or on full-scale platforms. Simulation environments often lack the fidelity required to capture real-world uncertainties, while full-scale testing can be resource-intensive and limit rapid experimentation (Stocco et al. 2023). Scaled vehicle platforms that preserve key physical characteristics of real vehicles offer a practical and effective compromise.

In summary, existing localization approaches often rely on additions such as sensors or dense maps, which increases system complexity and highlights an opportunity to explore simpler alternatives. The proposed work addresses this gap by investigating a camera-only, lane-based localization method.

## 3. Methods

The proposed methodology consists of several distinct stages, forming a multi-stage pipeline. Each stage addresses a specific component of the localization problem, including feature extraction, representation, alignment, and pose estimation.

This study performs map-based localization by aligning lane features from onboard observations with a prior aerial reference map. A drone-generated orthomosaic, from which lane features are extracted, serves as the global reference, while a front-facing vehicle camera captures local observations of the environment. These images are processed to extract lane features and transformed into a bird's eye view (BEV) representation to remain consistent with the perspective of the aerial reference map. To allow for alignment, the extracted lane line features are converted to point cloud representations. The ICP algorithm is then applied to align the local point cloud with the global reference point cloud, estimating the vehicle's pose.

### 3.1 Bird's Eye View Transformation

For the onboard camera perspective to match that of the aerial reference map, the captured images were transformed into a BEV representation. The BEV transformation was implemented in MATLAB using built-in functions, including cameraIntrinsics, monoCamera, birdsEyeView, and transformImage. The camera intrinsic parameters, such as focal length and principal point, were defined using cameraIntrinsics, while the camera pose, including mounting height and orientation, was specified using monoCamera. Based on this camera configuration, the birdsEyeView function defines the inverse perspective mapping for the top-down transformation, and the transformImage function applies this mapping to generate the BEV image (MathWorks 2026). Figure 1 shows an example of the original onboard camera image, while Figure 2 illustrates the resulting BEV transformation.

Figure 1. Original image from onboard camera

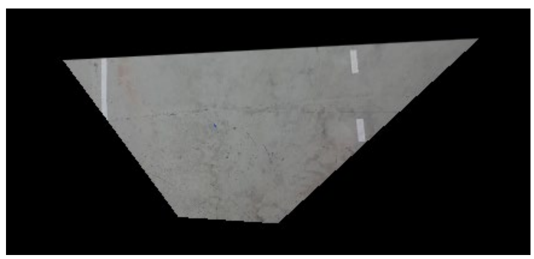

Figure 2. Resulting BEV transformation

### 3.2 Feature Extraction and Preprocessing

To improve the robustness of lane feature extraction, the field of view of the onboard camera was restricted to a region of interest (ROI) corresponding to the ground plane. As a result, a majority of irrelevant image regions, such as the surrounding structures, were removed.

The lane features were extracted using a color-based segmentation approach, as the lane markings were white. The resulting binary mask was further refined through noise reduction, including the removal of small, isolated pixel clusters. Additionally, to remove noise for portions of the track that were near white structures, a second-order polynomial was fitted to the pixels, and pixels outside the estimated boundary were removed. The extracted lane pixels are shown in Figure 3.

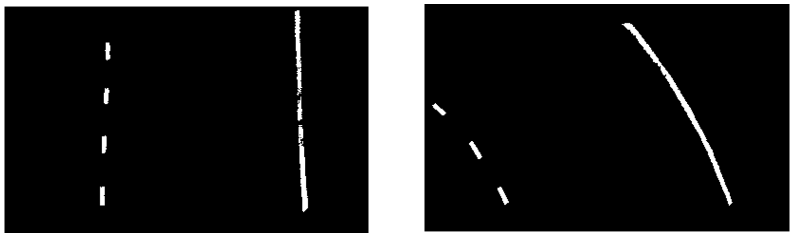

Figure 3. Extracted lane pixels from onboard observations: a) straight track, b) curved track

For the aerial reference map, regions affected by strong light reflections were suppressed prior to white pixel extraction to remove the noise in the lane feature extraction. The detected lane features were converted into a point cloud representation by extracting the pixel coordinates of the binary mask. Each detected pixel was mapped to a 2D coordinate. Figure 4 shows the track, and the resulting reference map point cloud is shown in Figure 5.

Figure 4. Aerial orthomosaic of the test environment

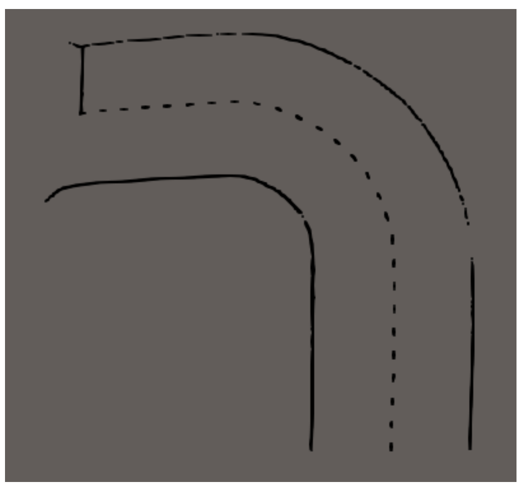

Figure 5. Reference map point cloud

To ensure geometric consistency between the onboard observations and the reference map, a scaling factor was applied such that lane widths were consistent across both datasets.

### 3.3 ICP-Based Map Alignment

To estimate the vehicle pose, the extracted lane features from onboard observations were aligned with the corresponding features from the aerial map using the ICP algorithm. The alignment was performed using libpointmatcher, an open-source library for point cloud registration that includes both point-to-point and point-to-plane ICP variants (libpointmatcher 2026). In this work, the point-to-point variant was used.

To reduce the likelihood of false positive alignments, the registration process was constrained to a local ROI of the reference map, centered around the estimated vehicle pose. By limiting the search space, ambiguity is reduced, helping to mitigate incorrect point correspondences. This design choice is motivated by known limitations of the ICP algorithm, which establishes correspondences between source and target point clouds using a nearest-neighbor strategy before iteratively refining the alignment. Therefore, the initial registration is important; ICP cannot be used as a global registration algorithm, as it will converge to a local optimum, which may not correspond to the globally correct alignment (Liu et al. 2024).

For each frame, multiple initial poses were provided to reduce the sensitivity to initialization. The source point cloud was pre-transformed to each initial position, and ICP was applied to align it with the reference point cloud within the defined ROI. The accuracy of the resulting alignments was evaluated using a nearest-neighbor root mean square error (RMSE) metric, and the alignment with the lowest error was kept.

When propagating to subsequent frames, the vehicle pose and ROI were updated prior to alignment. The vehicle pose for the subsequent frame was estimated using the center of the previous localization result, while the rotation matrix obtained from the ICP transformation was used to orient the ROI for the next alignment step. For the initial frame, an approximate pose was provided to initialize the alignment process.

## 4. Data Collection

Data for this study was collected using a scaled AV platform in a controlled test environment. The platform is shown in Figure 6.

Figure 6. Scaled autonomous vehicle platform

The platform was equipped with a forward-facing camera, which captured the local scene as the vehicle traveled through the track. The dataset consists of sequential image frames captured along the track, including both straight and curved portions of the track.

Aerial imagery was captured using a drone and processed in Agisoft Metashape to generate an orthomosaic of the environment, which was used to create the global reference map. An example of the generated orthomosaic is shown in Figure 4.

## 5. Results and Discussion

The proposed localization framework was evaluated both qualitatively and quantitatively. Qualitative evaluation was performed through visual inspection of the alignment between the source point cloud, derived from BEV lane features extracted from onboard camera images, and the aerial reference map. Quantitative evaluation was conducted using the nearest-neighbor RMSE metric obtained from the ICP alignment.

The results showed that the ICP-based framework can achieve alignment between local observations and the global reference map, resulting in a trajectory that follows the track across the full course. However, the performance was found to be highly sensitive to initialization, ROI selection, and errors introduced during frame-to-frame pose propagation.

## 5.1 Numerical Results

Quantitative evaluation was performed by computing the RMSE of the resulting ICP alignment. Multiple initial poses were tested for each frame, and the alignment with the lowest RMSE was selected. The resulting RMSE values varied across frames, with lower values corresponding to better alignment between the source and reference point clouds.

For the first frame, the best alignment resulted in an RMSE of 13.04 pixels (Figure 7), while the worst alignment resulted in an RMSE of 65.99 pixels (Figure 8). This difference in RMSE corresponds to visually accurate alignment in the best case and clear misalignment in the worst case. These results highlight the sensitivity to the initial location of the source.

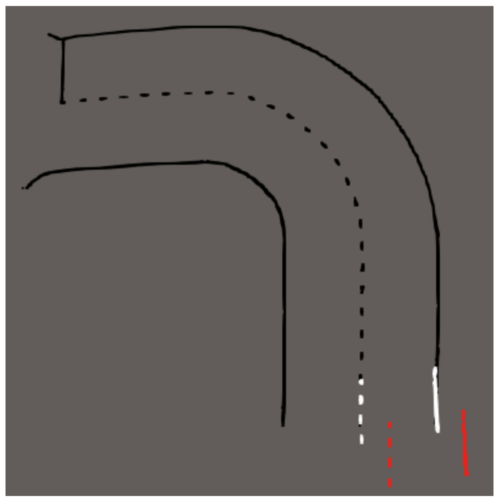

Figure 7. Best alignment result for the first frame: initial position (red), aligned features (white), and reference map (black)

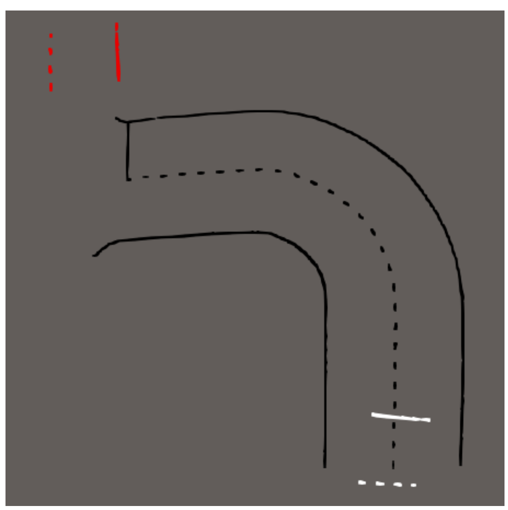

Figure 8. Worst alignment result for the first frame: initial position (red), aligned features (white), and reference map (black)

## 5.2 Graphical Results

Figure 9 shows one of the best alignment results obtained in this study. The onboard lane features (white point clouds) generally follow the curvature of the reference map (black point cloud), demonstrating that the proposed method is capable of following the track shape. Not all frames are shown, although all frames were sequentially aligned automatically, as including every frame would be redundant. Presenting selected frames also allows common false positive alignments to be more clearly observed, without being obscured by sequential overlap.

This failure case is observed at the start and end of the track. The solid lane line aligns with a dashed lane marking in the reference map, while the dashed lane line aligns with the solid marking. This mismatch, or flip of the onboard lane features, indicates that ICP converged to a geometrically convenient local minimum rather than the correct lane correspondence.

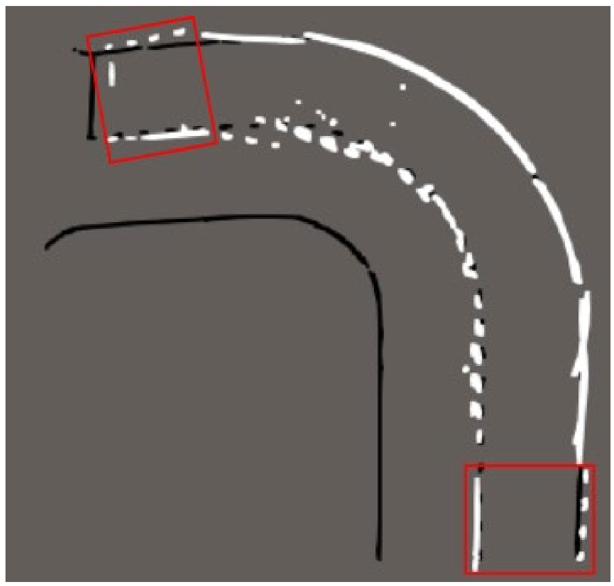

Figure 9. ICP-based alignment between onboard lane features (white) and reference map (black), with red boxes highlighting incorrect alignment

Additionally, in some instances, the alignment may converge to a geometrically consistent solution in which corresponding lane features are correctly matched (e.g., dashed-to-dashed), but the resulting pose is incorrectly oriented. This may not be visually obvious, but can negatively affect subsequent pose propagation. This occurs because lane features provide limited geometric constraints, resulting in degeneracy in certain pose directions (Yue, 2025).

## 5.3 Proposed Improvements

While the proposed method demonstrates the feasibility of lane-based map alignment for localization in a controlled environment using a multi-initialization strategy and ROI constraints, several improvements can enhance its robustness and applicability.

First, to reduce the occurrence of false positive alignments, lane lines could be distinguished between solid and dashed markings. Incorporating such constraints into the alignment process may improve correspondence accuracy and reduce the need for multiple initial poses, thereby decreasing computational complexity.

Second, the integration of additional sensors may enhance robustness. For example, inertial measurement units (IMUs) could provide motion estimates between frames, improving pose estimation.

Finally, exploration of other localization techniques, such as probabilistic localization, may provide insight into their accuracy in similar environments. In parallel, investigating variants of ICP could further improve performance.

## 6. Conclusion

This paper presented a lane feature-based localization approach that aligns onboard camera observations with a global aerial reference map using an ICP-based registration framework. Experimental results demonstrated that the method is capable of maintaining trajectory across the course. Several failure cases were also revealed, including sensitivity to initialization, ambiguity in feature correspondence, and drift during sequential localization. While lane-based localization using ICP is feasible, incorporating additional constraints would likely improve robustness and accuracy.

## References

Asghar, R., Garzón, M., Lussereau, J. and Laugier, C., Vehicle Localization Based on Visual Lane Marking and Topological Map Matching, *Proceedings of ICRA 2020- IEEE International Conference on Robotics and Automation*, pp. 258-264, Paris, France, May 2020.

Asrat, K. T. and Cho, H.-J., A Comprehensive Survey on High-Definition Map Generation and Maintenance, *ISPRS Int. J. Geo-Inf.*, vol. 13, no. 7, pp. 232, 2024.

Besl, P. J. and McKay, N. D., A Method for Registration of 3-D Shapes, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 14, no. 2, pp. 239-256, 1992.

Chalvatzaras, A., Pratikakis, I. and Amanatiadis, A. A., A Survey on Map-Based Localization Techniques for Autonomous Vehicles, *IEEE Transactions on Intelligent Vehicles*, vol. 8, no. 2, pp. 1574-1596, 2023.

Chen, P., Luo, Z., Jiang, X., Yin, Z. and Li, J., Maps for Autonomous Driving: Full-process Survey and Frontiers, Available: https://doi.org/10.48550/arXiv.2509.12632, September 16, 2025.

Chen, Y. and Medioni, G., Object Modelling by Registration of Multiple Range Images, *Image and Vision Computing,* vol. 10, no. 3, pp. 145-155, 1992.

Durgam, A., Paheding, S., Dhiman,V. and Devabhaktuni, V., Cross-View Geo-Localization: A Survey, *IEEE Access*, vol. 12, pp. 192028-192050, 2024.

Gong, Y., Zhang, X., Feng, J., He, X. and Zhang, D., LiDAR-based HD Map Localization using Semantic Generalized ICP with Road Marking Detection, *Proceedings of the 2024 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pp. 3379-3386, Abu Dhabi, United Arab Emirates, 2024.

Liu, R., Wang, J., Zhang, B. and Liu, R., High Definition Map for Automated Driving: Overview and Analysis, *Journal of Navigation*, vol. 73, no. 2, pp. 324-341, 2020.

libpointmatcher, Available: https://libpointmatcher.readthedocs.io/en/latest/, Accessed on April 26, 2026.

Liu, J., Lv, X., Gong, X., Liang, Y. and Hyyppä, J., An Unsupervised Learning Network for Large-scale LiDAR Point Clouds Registration, *IEEE Transactions on Vehicular Technology*, vol. 73, no. 11, pp. 16187- 16200, November 2024.

MathWorks, Available: https://www.mathworks.com/help/driving/ref/birdseyeview.html, Accessed on April 26, 2026.

Stocco, A., Pulfer, B. and Tonella, P., Mind the Gap! A Study on the Transferability of Virtual Versus Physical-World Testing of Autonomous Driving Systems, *IEEE Transactions on Software Engineering,* vol. 49, no. 4, pp. 1928-1940, 2023.

Wang, S., Zhang, Y., Vora, A., Perincherry, A. and Li, H., Satellite Image Based Cross-view Localization for Autonomous Vehicle, *Proceedings of the IEEE International Conference on Robotics and Automation*, pp. 3592-3599, London, UK, May 29 – June 2, 2023.

Yue, H., Xu, Q., Chen, F., Pan, J. and Chen, W., LP-ICP: General Localizability-Aware Point Cloud Registration for Robust Localization in Extreme Unstructured Environments, Available: https://arxiv.org/html/2501.02580v3, May 31, 2025.

## Biographies

**Briana Popa** is an undergraduate student in Electrical Engineering at Oakland University, with a minor in Computer Science and a concentration in Robotics. Her interests include autonomous systems, with a focus on developing skills in perception, planning, and control for real-world engineering applications.

**Ali Irshayyid** received his B.S. degree in Electrical Engineering from Wasit University, Wasit Iraq, in 2016, and Ph.D. in Electrical and Computer Engineering from Oakland University, Rochester, MI, USA, in 2024. He is currently a Postdoctoral Researcher at Oakland University. Dr. Irshayyid's research interests include reinforcement learning, optimal control, and battery management systems for transportation electrification and automotive applications. He served as the Chair of the IEEE Student Branch at Oakland University.

**Jun Chen** received his Bachelor's degree in Automation from Zhejiang University, Hangzhou China, in 2009, and Ph.D. in Electrical Engineering from Iowa State University, Ames IA, USA, in 2014. He was with Idaho National Laboratory from 2014 to 2016 and with General Motors from 2017 to 2020. Dr. Chen joined Oakland University in 2020, where he is currently an associate professor at the ECE department. His research interests include advanced control and optimization, model predictive control, artificial intelligence, and stochastic hybrid systems, with applications in intelligent vehicles, robotics, and energy systems. Dr. Chen is a recipient of the NSF CAREER Award, the Best Paper Award from IEEE TRANSACTIONS ON AUTOMATION SCIENCE AND ENGINEERING, the Best Paper Award from IEEE INTERNATIONAL CONFERENCE ON ELECTRO INFORMATION TECHNOLOGY, the Best Paper Award from IEEE CYBER AWARENESS & RESEARCH SYMPOSIUM, the New Investigator Research Excellence Award and Outstanding Graduate Mentor Award from Oakland University, the Publication Achievement Award from Idaho National Laboratory, the Research Excellence Award from Iowa State University, and the Outstanding Student Award from Zhejiang University. He is currently a Senior Member of the IEEE.