A Proof-of-Concept Study for LiDAR-Based Traffic Measure Estimation: Traffic Density Estimation and Vehicle Trajectory Extraction

Sungeun Cho*[1], Chiwoo Roh[2], Sungmin Yoo[2], Jaehyun(Jason) So[2]

[1] Master's Student, Department of Data/Network/AI Convergence, Ajou University, Republic of Korea

[2] Master's Student, Ajou University, Republic of Korea

[2] Master's Student, Ajou University, Republic of Korea

[2] Associate Professor, Ajou University, Republic of Korea

SHORT SUMMARY

This study explores the potential of vehicle-mounted LiDAR sensors for road traffic monitoring, focusing on traffic density estimation and vehicle trajectory extraction. Traditional traffic monitoring systems, dependent on fixed infrastructure like cameras or loop detectors, face challenges such as high maintenance costs and limited spatial coverage. LiDAR technology, capable of dynamically collecting high-resolution 3D point cloud data, provides a scalable and efficient alternative. Using the KITTI dataset, this study evaluates three models—PointPillars, PartA2-Net, and PV-RCNN—for vehicle detection and traffic metric estimation. PV-RCNN demonstrated the highest mean Average Precision (mAP) in 3D object detection, excelling in both accuracy and reliability. The results highlight LiDAR's ability to provide detailed and continuous traffic data, addressing the limitations of traditional methods. This approach offers a promising solution for real-time traffic monitoring, with potential applications in adaptive traffic management as automated vehicle technologies advance.

Keywords: Traffic Monitoring, LiDAR, 3D Object Detection, Traffic Density, Vehicle Trajectory

1. INTRODUCTION

The exclusive use of the vast amount of sensor data collected by automated vehicles (AVs) for their operation is not as efficient as it can be in terms of data utility and application. AVs gather data through cameras, radars, and LiDAR (Cao et al., 2024; Göhring et al., 2011), with cameras providing 2D visual data, radars offering distance measurements, and LiDAR generating 3D models (Wu et al., 2024; Yao et al., 2023). This data has potential applications such as creating precise 3D city maps (Yue et al., 2024) and analyzing road surface conditions (Feng et al., 2021; Zhong et al., 2020). Yet, there is a lack of use cases in road traffic monitoring, despite the vast amount of data collected by AVs.

Traditional traffic monitoring systems rely on fixed infrastructure like cameras and loop detectors to estimate metrics such as traffic volume, speed, and road occupancy (Council, 2000; Coifman, 2005). However, these systems face significant limitations, including high installation costs, limited spatial coverage, and reduced reliability during congestion (Lee et al., 2006; Kim & Jang, 2016). Segment-based systems improve data accuracy by calculating vehicle travel times across predefined sections but remain costly and prone to data gaps, making them less scalable for large-scale deployment (Kim & Jang, 2016).

Dynamic methods, such as On-Board Diagnostics (OBD) and GPS-based systems, enable real-time monitoring and reduce dependency on fixed infrastructure (Cristiani et al., 2010; Llorca et al., 2010). These systems capture vehicle-specific data, such as speed and acceleration, as vehicles traverse various conditions (Ahmed et al., 2019; Tanvir et al., 2021). However, their effectiveness depends on widespread adoption, as they primarily collect data from equipped vehicles. This requirement poses significant logistical and cost challenges, as equipping a substantial portion of vehicles with the necessary sensors is essential to ensure reliable and scalable traffic data collection in practice.
LiDAR technology offers a promising alternative, providing high-resolution 3D data in real time and surpassing traditional systems in adverse conditions (Darrah et al., 2022; Seo & Lee, 2018; J. Wu et al., 2020; Hasan et al., 2022). Unlike static systems, LiDAR sensors mounted on AVs or drones can dynamically collect detailed traffic data, enabling advanced monitoring solutions (Zhang et al., 2020; Zhang et al., 2019). Furthermore, LiDAR supports automated vehicle applications and exhibits superior performance in capturing detailed environmental information through 3D point clouds (J. Wu et al., 2020; Hasan et al., 2022). Models like PointPillars (Lang et al., 2019), PartA2-Net (Shi, Wang, et al., 2020), and PV-RCNN (Shi, Guo, et al., 2020) further enhance LiDAR's capabilities by improving object detection and tracking performance.
This study aims to investigate proof of concept for road traffic monitoring by estimating traffic density and vehicle trajectory data based on 3D data collected from vehicle-mounted LiDAR sensors. The first step involves analyzing the 3D point cloud data from LiDAR using various analysis models to detect vehicles. Based on the detected vehicle data, traffic density and vehicle trajectory metrics are derived, enabling an understanding of congestion levels and road saturation (Padiath et al., 2009). Additionally, trajectory data facilitates the analysis of traffic parameters such as vehicle speed, gaps, and delay times (Kashyap NR et al., 2020; Li et al., 2020). This concept of LiDAR-based traffic monitoring enhances sensor data utility and offers a scalable, dynamic solution for modern traffic management systems.

2. METHODOLOGY

Data Collection and Preprocessing

The data used in this study is derived from the KITTI dataset (Geiger et al., 2012), comprising 3D point cloud data, GPS data, and LiDAR data captured using a Velodyne HDL-64E sensor, capable of detecting objects within 120 meters. The dataset includes 7481 training samples and 7518 test samples, with 80% of the training data used for training and 20% for validation, consistent with prior methodologies (Shi, Guo, et al., 2020). Preprocessing involves converting binary point cloud data into NumPy arrays, with 3D coordinates (x, y, z) representing spatial positions. Bounding box parameters, such as center position, size, and rotation angle, are derived for object detection, while reflection intensity is used to adjust visual attributes.

Model selection

This study evaluates three models—PointPillars (Shi, Guo, et al., 2020), PartA2-Net (Shi, Wang, et al., 2020), and PV-RCNN (Shi, Guo, et al., 2020)—for analyzing 3D point cloud data in vehicle detection. PointPillars encodes point clouds as pseudo-images for efficient 2D convolution, balancing speed and accuracy. PartA2-Net refines bounding boxes through a two-stage approach, combining anchor-free and anchor-based methods to achieve high recall rates. PV-RCNN integrates voxel-based and point-based techniques, leveraging RoI feature aggregation with the Furthest Point Sampling (FPS) algorithm for precise detection. Model performance was evaluated using mean Average Precision (mAP), and the most suitable model for traffic monitoring was identified based on these results.

Estimation of Traffic Monitoring Measures

The segment utilized for estimating traffic monitoring measures, like (Figure 1), is located in Karlsruhe, Germany, and comprises two lanes of traffic. The data collected from this segment is characterized by an uninterrupted flow, with no stops observed. Data collection occurred from the start to the endpoint, and the analysis focused exclusively on the direction of travel of the data collection vehicle.

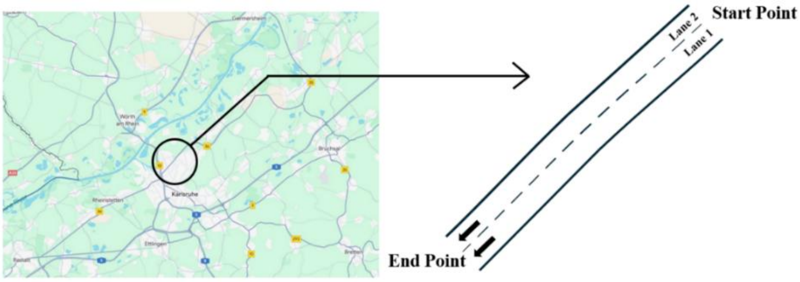


Figure 1: Analysis Segment

The vehicle bounding box information generated by the 3D detection model includes center coordinates, size, and rotation, which are used to accurately position vehicles in the lane area. Using a methodology for measuring macroscopic traffic density, the density of vehicles traveling in the first and second lanes per frame (0.1 seconds) was extracted (vehicles per 120 meters) and converted to a per-kilometer measurement(Kim, 2023).The density for each lane is determined using the (Equation 1), where the number of vehicles in the measurement section and the length of the section are used to calculate density in vehicles per kilometer. The overall segment density is averaged across lanes and frames to estimate density changes per second, as described in the total density (Equation 2).

$$D = \frac{N}{L} \times 1000 \ \ (veh/km) \tag{1}$$

$$D_{total} = \frac{\sum_{i=1}^{n} D_i}{n} \ \ (veh/km) \tag{2}$$

For trajectory extraction, the center coordinates of vehicle bounding boxes detected by LiDAR are initially relative to the data collection vehicle. These coordinates are converted into geographic coordinates by aligning the LiDAR system with GPS data. Using the GPS coordinates of the data collection vehicle as a reference, relative coordinates are translated into latitude and longitude for continuous vehicle trajectory tracking and mapping, following this approach.

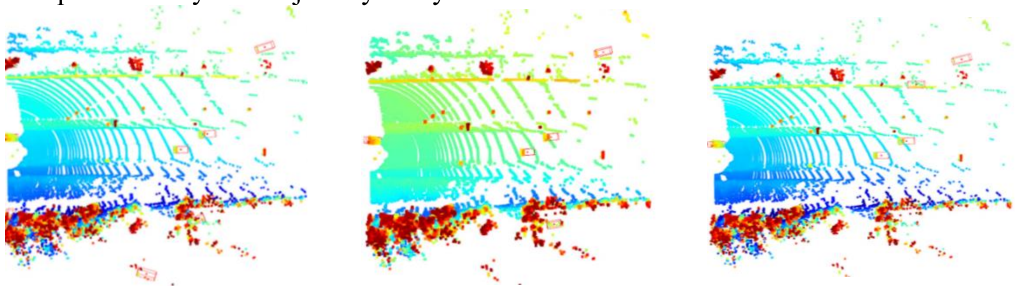
3. RESULTS AND DISCUSSION

The performance of the 3D object detection models was evaluated using mean Average Precision (mAP), a metric that quantifies the accuracy of vehicle detection and recognition. mAP is calculated by averaging the precision-recall curve area for each class, where precision measures the proportion of correct positive predictions, and recall indicates the model's ability to identify actual positive cases. Higher mAP values reflect better model performance in detecting and recognizing objects accurately.

$$Precision = \frac{True\ Positives\ (TP)}{True\ Positives\ (TP) + False\ Positives\ (FP)} \quad (3)$$

$$Recall = \frac{True\ Positives\ (TP)}{True\ Positives\ \ (TP) + False\ Negatives\ (FN)} \quad (4)$$

In this study, PointPillars, PartA2-Net, and PV-RCNN were applied to vehicle detection using the KITTI dataset. As shown in (Figure 2), all three models successfully identified vehicles in various scenarios. Their performance was evaluated using mAP scores at AP40 for bounding box (Bbox), Bird's Eye View (BEV), and 3D detection metrics at thresholds of 0.70 and 0.50. As summarized in (Table 1(a)) and (Table 1(b)), PV-RCNN achieved the highest performance in Bbox, BEV, and 3D detection, as well as the highest Average Orientation Similarity (AOS) scores, demonstrating its effectiveness in handling complex point cloud data. Consequently, PV-RCNN was selected for subsequent density and trajectory analysis tasks.



(a) PointPillars (b) PartA2-Net (c) PV-RCNN

Figure 2: Object Detection Result

Table 1(a): Object Detection Performance at 0.70 Thresholds

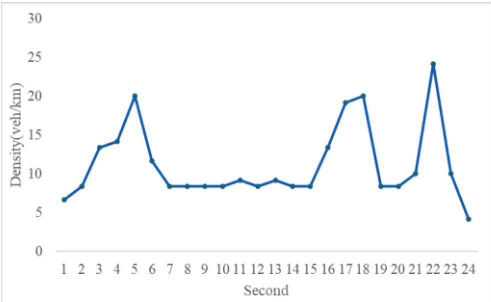
Threshold		0.70	0.70	0.70	AOS
Model		Bbox	BEV	3D	
PointPillars	Easy	95.90	92.58	88.52	95.67
	Moderate	92.58	88.50	79.27	92.09
	Hard	89.86	85.75	76.31	89.14
PartA2-Net	Easy	95.80	92.88	91.85	95.67
	Moderate	93.63	88.69	82.27	93.29
	Hard	91.90	88.40	80.05	91.42
PV-RCNN	Easy	97.82	94.43	91.82	97.78
	Moderate	94.55	90.79	84.54	94.41
	Hard	94.02	88.66	82.42	93.82

Table 1(b): Object Detection Performance for Bbox (0.70) and BEV/3D (0.50)

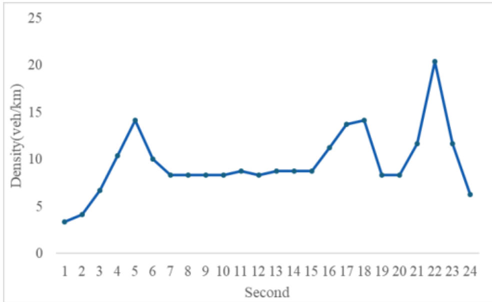
Threshold		0.70	0.50	0.50	AOS
Model		Bbox	BEV	3D	
PointPillars	Easy	95.90	97.56	97.52	95.67
	Moderate	92.58	95.04	94.92	92.09
	Hard	89.86	92.38	92.18	89.14
PartA2-Net	Easy	95.80	95.82	95.80	95.67
	Moderate	93.63	94.31	94.22	93.29
	Hard	91.90	94.20	93.99	91.42

PV-RCNN	Easy	97.82	97.91	97.87	97.78
	Moderate	94.55	96.46	94.63	94.41
	Hard	94.02	94.44	94.34	93.82

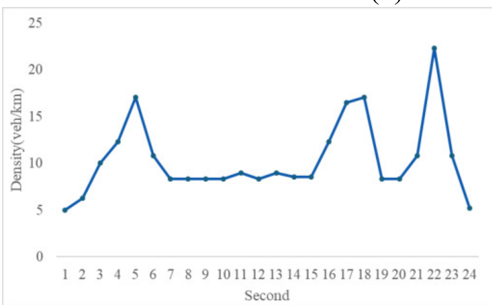
Traffic density variations over time were analyzed for two lanes, with results presented in (Figure 3). The primary lane's density is shown in (Figure 3(a)), the secondary lane's in (Figure 3(b)), and the overall roadway segment's in (Figure 3(c)). Initially, both lanes exhibited increasing density, indicating higher vehicle inflow and occupancy. The middle sections showed relatively stable densities, suggesting steady traffic flow and reduced congestion. In the later sections, density fluctuations were observed, indicating alternating periods of high-speed movement and congestion. While the density trends in both lanes were similar, notable differences were observed, such as higher vehicle occupancy in the primary lane between 15 and 19 seconds.



(a) Traffic density for Lane 1



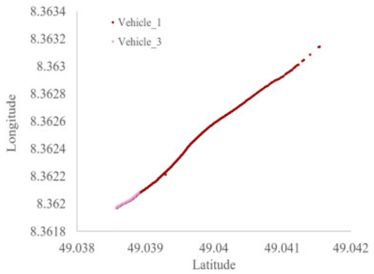
(b) Traffic density for Lane 2



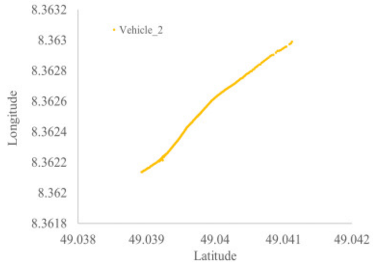
(c) Traffic density for Entire Lane

Figure 3: Results of Traffic Density Estimation

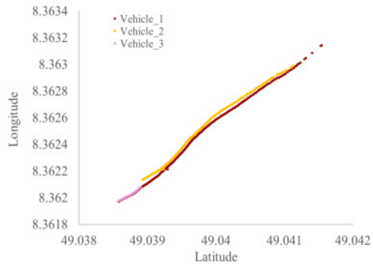
The trajectories of vehicles detected by PV-RCNN within the segment were estimated and visualized for each lane and the entire roadway segment, as shown in (Figure 4). The graphs plot bounding box coordinates of vehicles within a 120-meter LiDAR detection range, with latitude and longitude representing vehicle positions. Trajectories were color-coded to distinguish vehicle movements, showing clear differentiation between lanes and vehicles.
Comparison with the actual road layout (Figure 1) demonstrates a close alignment, accurately reflecting the road's curvature and confirming the system's capability to capture vehicles' adherence to the road's path. The dense recording of trajectory points indicates continuous data collection, and the extracted trajectories successfully represent vehicle movements within the segment, including lane-specific and dynamic patterns.



(a) Vehicle Trajectory for Lane 1



(b) Vehicle Trajectory for Lane 2



(c) Vehicle Trajectory for Entire Lane

Figure 4: Results of Vehicle Trajectory Extraction

4. CONCLUSIONS

This study demonstrates the utility of vehicle-mounted 3D LiDAR sensors for road traffic monitoring by analyzing high-resolution point cloud data. Using detection models such as PointPillars, PartA2-Net, and PV-RCNN, vehicles were identified, and traffic density and trajectory metrics were derived. Among these models, PV-RCNN exhibited the highest performance in mean Average Precision (mAP), particularly for 3D detection and Average Orientation Similarity (AOS), making it the most suitable for traffic analysis tasks.

Traffic density analysis revealed patterns of increasing, stable, and fluctuating densities across road segments, providing insights into road occupancy and congestion. Trajectory analysis compared the vehicle movements to real-world road layouts, highlighting the efficacy of LiDAR sensors in capturing detailed traffic dynamics.

By addressing the limitations of traditional fixed infrastructure systems, this approach offers a dynamic, cost-effective solution for real-time traffic monitoring. However, the study's focus on density and trajectory within a limited road segment emphasizes the need for future research to include diverse traffic indicators, such as speed, acceleration, and lane-changing behavior. Expanding the methodology to complex driving environments will further enhance its applicability, contributing to the development of comprehensive and adaptive traffic monitoring systems leveraging automated vehicle sensors.

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