An Automated Framework for Analyzing Vehicle Passing Distances to Cyclists

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Abstract
The safety of cyclists in urban environments remains a critical concern in sustainable urban planning. A primary factor affecting this safety is the passing distance maintained by motor vehicles when overtaking cyclists. This study aims to use current technology to provide an affordable and robust framework, integrating several distance measuring sensors with an AI camera system, to collect and analyze vehicle-cyclist passing distances. Preliminary deployments in Singapore have demonstrated the system's efficacy in capturing high-resolution data under varied traffic conditions. Our setup, using a LIDAR distance sensor, OAK-1 AI camera, and the DBSCAN clustering technique, had a 100% success rate for correctly identifying the number of close vehicle passes for distances between 1 to 1.5m. The insights garnered from this integrated setup promise not only a deeper understanding of vehicle-cyclist interactions but also a roadmap for data-driven urban safety interventions.

1. Introduction

The shift towards cycling is a global phenomenon, not just restricted to Singapore. Driven by environmental concerns, health advantages, and economic factors, urban centers worldwide have seen an uptick in the use of bicycles. The projected growth of the global bicycle market from USD 110.38 billion in 2023 to USD 228.90 billion by 2030 (Fortune Business Insights, 2023) underscores this trend. In urban hubs like Singapore, where car ownership costs are soaring (Hamzah, F., 2023), cycling offers both an eco-friendly and financially sound alternative.

Modern urban planning champions sustainability, and a significant part of this entails prioritizing cycling. Cities, including Paris with its ambitious plan to be 100% cyclable by 2026 (Reid, C., 2022), are aggressively developing infrastructure to ensure bicycles and motorized vehicles coexist safely and efficiently.

With the rise in cycling, there has been an unfortunate increase in related accidents. The World Health Organization reports that 41,000 cyclists face fatal accidents annually during commutes (World Health Organization, 2020). In Singapore, the growth of food delivery services necessitates more cyclists on the road, further escalating the risk. Data reflects a 62% increase in average monthly spend on food deliveries from 2019 to 2020, which corresponds with a 25% rise in cycling-related accidents during the same period (Abdullah, A. Z., 2021).

To address the safety concerns, some cities, including Singapore, have set a 1.5m passing distance guideline (Toh, T. W., 2021). However, studies like the one from Germany show variable adherence levels, where cars meet the legal passing distance of 1.5m only 30% of the time (Stülpnagel et al., 2022), emphasizing the need for consistent monitoring. Table 1 shows different countries and their different MPD (mandatory passing distance) rules.

Table 1

Countries With a Minimum Passing Distance Guideline or Law.

Country	MPD Advised	MPD Mandated
Austria	Yes - 1.5m	No
Belgium	No	Yes - 1m
Chile	Yes - 1.5m	No
France	No	Yes – 1m on roads with ≤50km/h speed limit, and 1.5m on roads with >50km/h speed limit.
Germany	No	Yes - 1.5m in urban areas, and 2m out of town.
New Zealand	Yes - 1.5m	No
Singapore	Yes - 1.5m	No
United States	Yes -Varies by state	Yes - Varies by state

Note. Table containing the mandatory passing distance rules for various countries. Adapted from Road Safety Authority. (2018). Examining the international research evidence in relation to minimum ... Examining the International Research Evidence in relation to Minimum Passing Distances for Cyclists. . https://www.rsa.ie/docs/default-source/road-safety/r4.1-research-reports/safe-road-use/examining-the-international-research-evidence-in-relation-to-minimum-passing-distances-for-cyclists.pdf?sfvrsn=bf8ed37c_5

Despite guidelines, adherence remains an issue. Uncertainty about distance measurements from motorists and a lack of quantifiable evidence from cyclists create complications. Current methods to measure passing distances are labor-intensive, error-prone, and often costly. Some studies, like the one in Australia, relied on GoPro devices paired with ultrasonic sensors, necessitating manual data extraction post-collection (Beck et al., 2019). Another study from Spain featured a complicated setup including three video cameras, 2 speed sensors, 2 distance sensors, a VBOX data logger, PC and batteries (Llorca et al., 2017). Moreover, several studies lack a comprehensive evaluation of sensor reliability, indicating a need for improved methods.

This study investigates the potential of an automated data collection method that reduces manual effort, offering a solution for policy-makers, researchers, and consumers. We leverage modern technology for cost-effectiveness. Our system is mounted on a bicycle and identifies vehicles passing within 1.5m or closer without requiring manual logging or video cross-referencing. The total cost of our setup is around USD$200. Through the integration of a distance sensor, microcontroller, and an AI camera with computer vision capabilities, we ensure automatic and precise data recording. Post-collection, clustering analysis identifies vehicle passes, providing a clear count of close encounters.

2. Methodology

We start by reviewing various distance measuring sensors: laser, LIDAR, and ultrasound. These were assessed for accuracy, range, and reliability through tests against a stationary wall at varying distances. From this evaluation, we selected the most suitable candidates for outdoor experiments. In our outdoor test, the sensors were attached to a stationary bike on the roadside to gauge their proficiency in detecting passing vehicles. Our preferred choice was then integrated with the OAK-1 AI camera, simulating real-world data collection as the bike navigated actual roads with traffic. The system was programmed using the Raspberry Pi, employing modules like Pyserial and Smbus to facilitate communication between the sensors and the Pi. The AI camera was programmed through the DepthAI API by Luxonis. Post-data collection, noise was filtered out to emphasize clusters indicative of vehicle passes. Finally, a machine learning clustering method was employed to auto-detect vehicle passes, the accuracy of which was validated using GoPro footage.

3. Sensor Selection

To ensure a robust and accurate data collection system, our study employed an iterative process of selection, testing, and deployment of three types of measuring sensors. The methodology consisted of preliminary indoor and outdoor tests, followed by on-road stationary and mobile tests.

Table 2 shows a general comparison between the different types of sensors available. From this comparison alone, it is difficult to determine which type or model of sensor is the most appropriate. Hence, the tests aim to guide our selection.

Table 2

General Comparison Between Different Types of Sensors

	LiDAR	Laser	Ultrasonic
Working Principle	Uses laser beams to measure distances	Uses a laser beam to measure distance based on reflection	Uses sound waves to measure distances based on echo timing
Range	Typically 100m - 300m, but can go up to 1km for some models	Shorter, often less than 100m	Typically 2 cm - 5m, though specialized models can go further
Accuracy	±2cm to ±10cm depending on model and conditions	±1mm to ±5mm	±1cm for close range but can vary based on conditions
Resolution	Fine; can be sub-cm in some models	Fine, often sub-mm	Coarser, often in the cm range

Pros	High resolution, long-range, works in various lighting conditions	High precision, works in many lighting conditions	Simple, cheap, works in the dark and through many materials
Cons	Expensive, can be affected by atmospheric conditions and reflective surfaces	Range limited, can be affected by reflective surfaces or ambient light	Affected by sound-absorbent materials, less accurate at longer distances

3.1 Indoor and Outdoor Fixed Distance Tests

To determine the compatibility of the sensors with our project's specific needs, we executed a comprehensive set of tests. Our benchmarks necessitated the precise measurement of distances up to 3 meters in outdoor daylight and the capability to detect high speed vehicular movements.

We tested each sensor at fixed intervals of 0.5 meters, spanning a range from 0 to 5 meters. These tests took place in both internal and external environments to assess the sensor performance under varying conditions. At every interval, around 500 distance data points were gathered. The sensors were either operated using their default software or integrated with a Raspberry Pi for control.

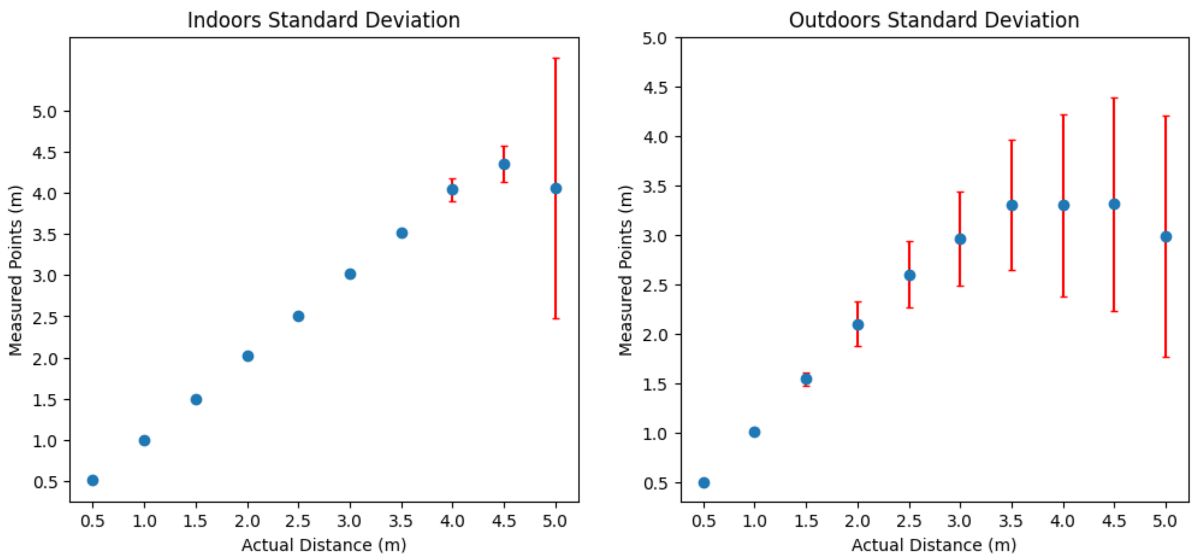

Fig. 3. Depicts the mean distance measured by the TOF sensor across distances of 0.5m to 5.0m. The red bars represent the standard deviation of the measurements at each interval.

Table 3

Standard Deviation of Measurements at Different Intervals for TOF Laser Range Sensor

	0.5m	1.0m	1.5m	2.0m	2.5m	3.0m	3.5m	4.0m	4.5m	5.0m
Indoors	0.01	0.01	0.01	0.01	0.01	0.02	0.03	0.14	0.22	1.58

Outdoors	0.00	0.01	0.07	0.23	0.34	0.48	0.66	0.92	1.08	1.22

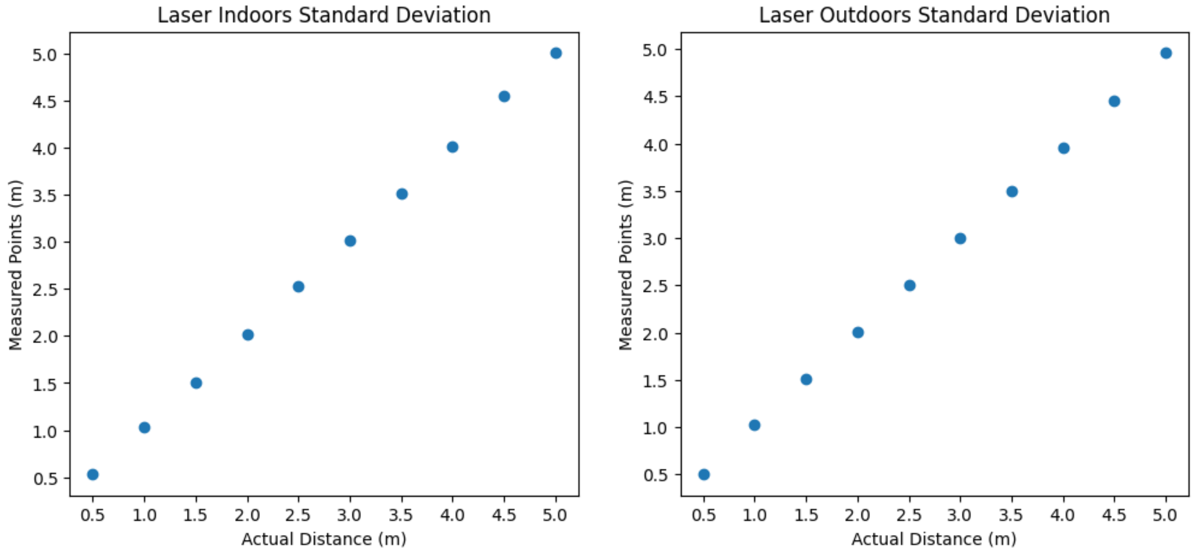

Fig. 4. Illustrates the mean distance measured by the laser across distances of 0.5m to 5.0m. The red bars represent the standard deviation of the measurements at each interval.

Table 4

Standard Deviation of Measurements at Different Intervals for JRT Laser Distance Module

	0.5m	1.0m	1.5m	2.0m	2.5m	3.0m	3.5m	4.0m	4.5m	5.0m
Indoors	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Outdoors	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

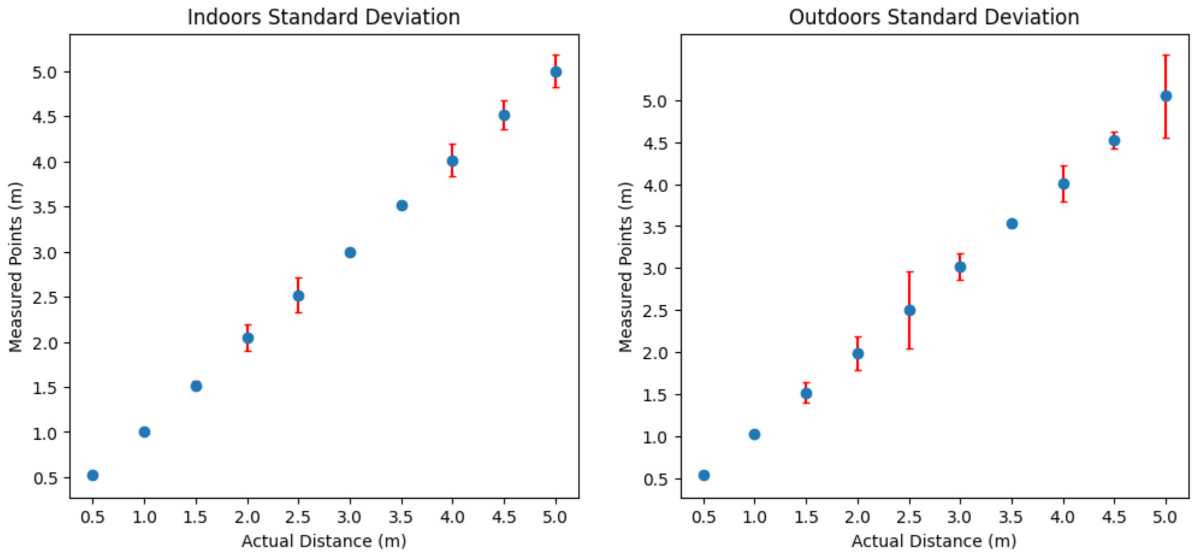

Fig. 5. Depicts the mean distance measured by the LIDAR sensor from the 0.5m to 5.0m range. The red bars represent the standard deviation of the measurements at each interval.

Table 5

Standard Deviation of Measurements at Different Intervals for LIDAR Lite V4

	0.5m	1.0m	1.5m	2.0m	2.5m	3.0m	3.5m	4.0m	4.5m	5.0m
Indoors	0.01	0.02	0.05	0.15	0.19	0.03	0.03	0.18	0.16	0.18
Outdoors	0.02	0.02	0.12	0.20	0.46	0.16	0.04	0.21	0.10	0.49

Note. We noticed an anomaly where the standard deviation for the LIDAR sensor around 2.0m to 2.5m spikes. This could be due to an internal algorithm in the sensor.

Each graph uses solid dots to show the average distance recorded by the sensor at specific intervals. The red bars showcase the standard deviations. As per Figure 3, the TOF sensor was dependable up to 4.5m indoors. However, its outdoor performance exhibited significant inconsistencies and inaccuracies as seen from Table 3 which sees the standard deviation increase from 0.34m at 2.5m to 1.22m at 5.0m. Conversely, both the laser and LIDAR sensors demonstrated good accuracy in all settings. The laser sensor was so precise that its standard deviation was almost negligible. Although the LIDAR sensor was accurate, it lacked the same level of precision as the laser sensor. Table 5 shows the highest standard deviation for the LIDAR sensor to be no more than 0.5m, which is significantly better from the TOF Laser Range Sensor. Based on this preliminary data, the laser sensor emerged as the top contender due to its reliability, closely followed by the LIDAR.

3.2 Stationary Bike Test

We mounted the sensors onto a stationary bicycle positioned beside a road with moderate traffic. Using a GoPro camera in tandem with each sensor, we assessed their capability to identify passing vehicles. This setup provided insights into the sensors’ performance under controlled yet realistic conditions.

3.2.1 Laser Sensor

Figure 6 presents the results from the stationary bike test using the laser sensor. Despite its high reliability in distance measurement, the sensor's frequency proved inadequate for accurately recording the distances of passing vehicles, even in moderate traffic. Although the product documentation advertised a frequency of 20Hz, real-world tests showed it to be inconsistent and often much lower.

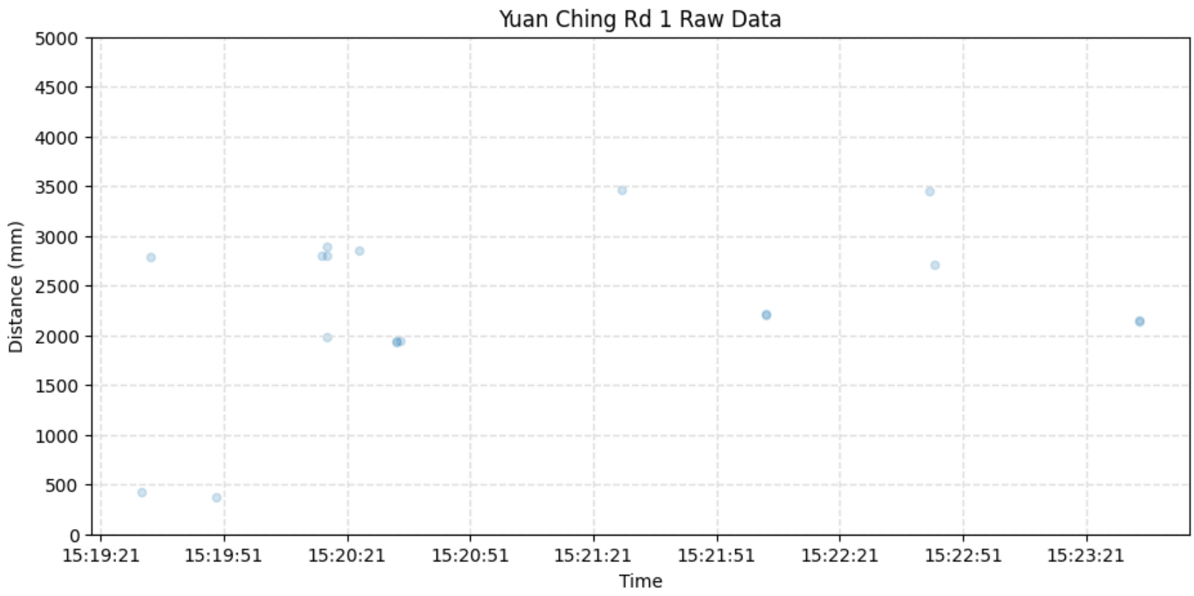

Fig. 6. Results from the laser sensor's stationary test.

3.2.2 LIDAR Sensor

The LIDAR sensor, with its impressive frequency reaching up to 200 Hz, was adept at detecting passing vehicles, as evidenced by the clusters of dark points in Figure 7. Having validated the LIDAR sensor's proficiency, we progressed to the mobile bike assessment.

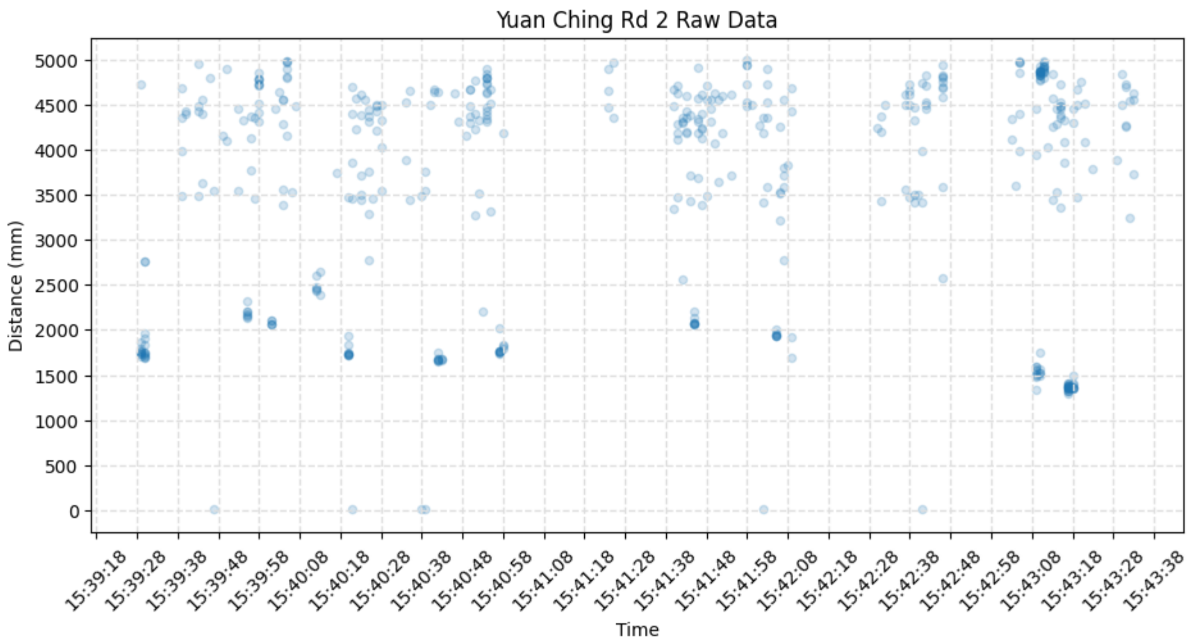

Fig. 7. Results from the LIDAR sensor's stationary test.

Next, we cross-referenced the video footage from the GoPro with the data collected. Each red circle in Figure 8 highlights the points representing a vehicle pass. Out of 12 vehicles, the sensor only failed to detect a single car at 15:42:08, resulting in an approximate success rate of 92% based on this limited dataset. This confirms that the dark point clusters generated by the sensor indeed represent the passing of vehicles. With this verification, we advance to the final evaluation of the complete setup.

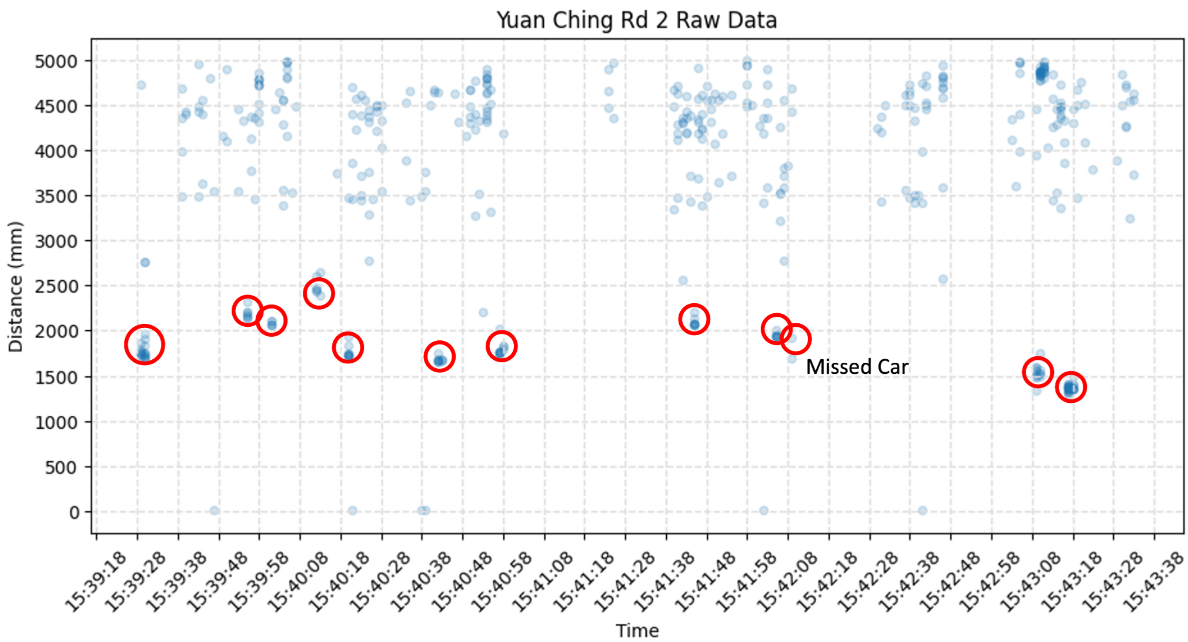

Fig. 8. Results from the LIDAR sensor's stationary test annotated.

4. Mobile Bike Test

To mimic the real-world scenario of a cyclist on the move, our sensor was mounted on a bicycle and cycled along a 5km route alongside moderate traffic in Singapore's Jurong West area as shown in Figure 9. This phase aimed to assess the challenges and practicality of each sensor during typical cycling activities.

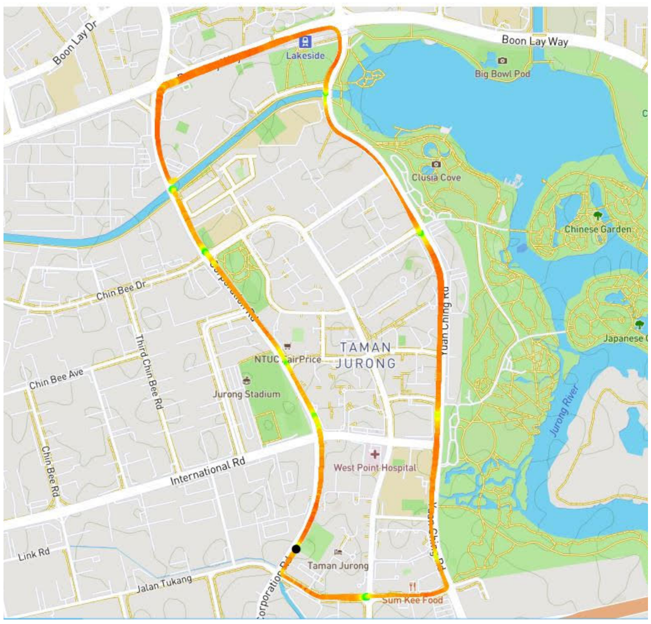

Fig. 9. Route cycled.

4.1 Setup

Our configuration integrated three primary components: the LIDAR sensor, a Raspberry Pi with its power supply, and the OAK-1 Lite camera by Luxonis. The principle behind this setup was to leverage the object detection capability of the OAK camera to identify an approaching car in proximity to the cyclist. Upon detection, the LIDAR sensor would activate to record distances. This approach not only streamlined the data collection process but also significantly reduced the occurrence of false positives and irrelevant data. By focusing measurements exclusively during confirmed vehicle presence, we can enhance data accuracy. Unlike other systems, our refined data processing eliminates the need for tedious manual cross-referencing with video footage or reliance on manual interventions like button-presses to ascertain data quality.

In our initial tests, we attached a GoPro to the bike to manually cross-check and validate the collected data. However, the GoPro was not part of the final configuration.

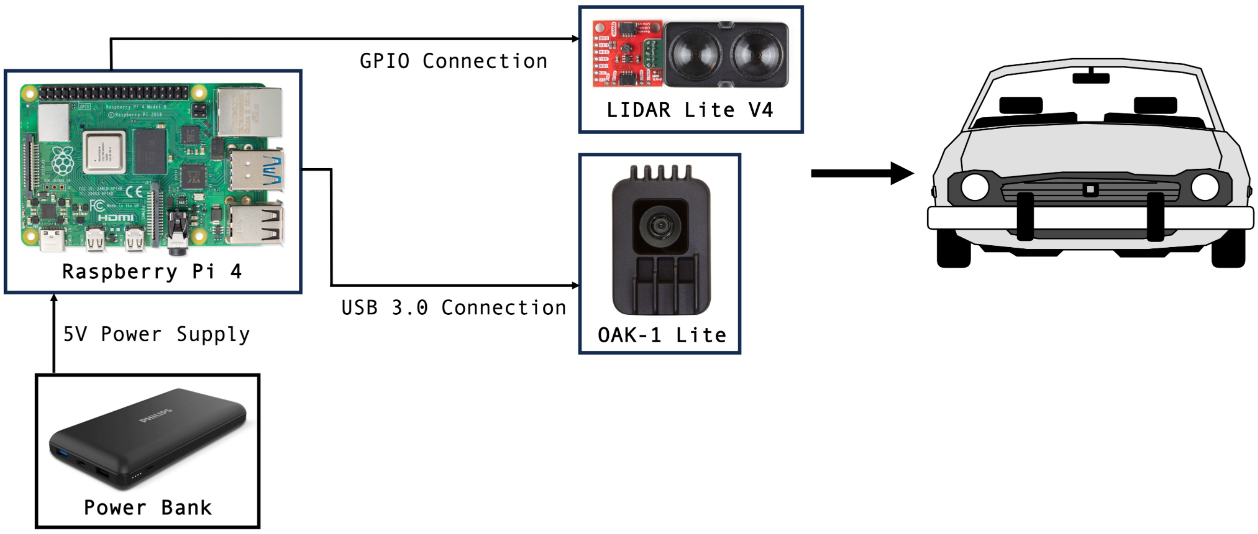

Fig. 10. Schematic of the setup.

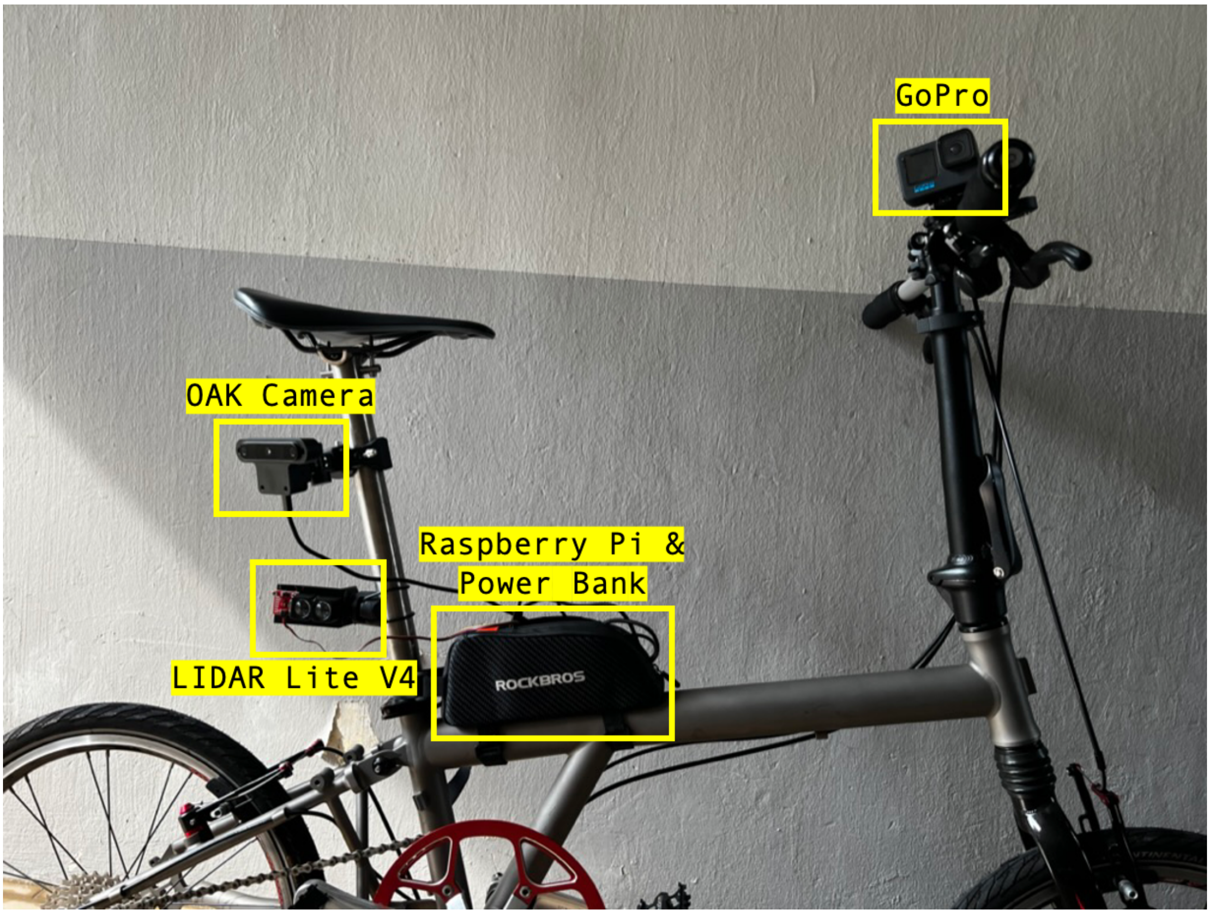

Fig. 11. Raspberry Pi, LIDAR sensor, and OAK camera mounted on the bike with a GoPro.

4.2. Preliminary Results

At first glance, the data seems riddled with noise. However, a detailed look reveals that most of the noise originates from readings above 3 meters, which are not important to our experiment as we are mainly concerned with close vehicle passes. Below this threshold, the data is notably cleaner, with pronounced dark clusters signaling vehicle passes. Interestingly, the broad gaps seen around 16:07:41 signify periods when the AI camera detected no vehicles, which contributed to reducing the overall noise in the dataset. To further clarify our findings, we cleaned our data by first removing all data points above the 3m mark. We then accentuate clusters, which are simply a continuous set of non-null data points. We calculated the average of these points and replaced the entire cluster with this average. Figures 12 and 13 display the data before and after this cleaning process.

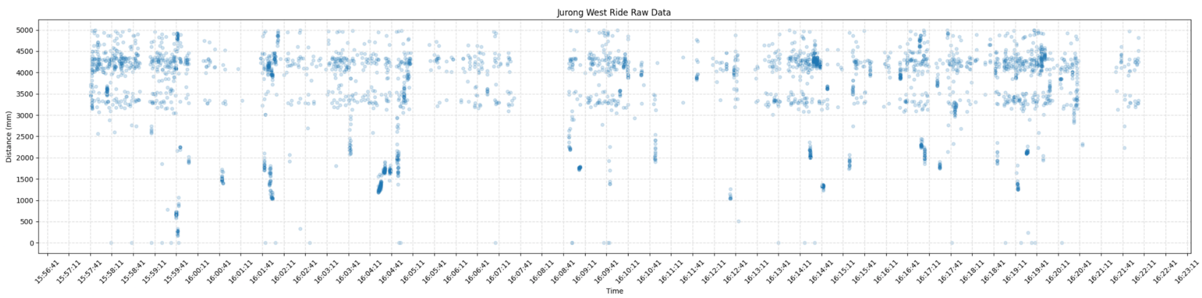

Fig. 12. Raw LIDAR data in conjunction with the OAK Camera.

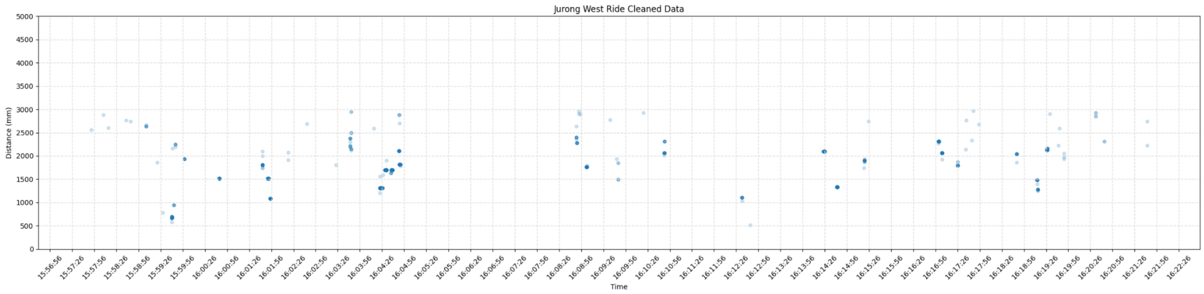

Fig. 13. Refined data from the LIDAR and OAK Camera.

To verify that these dark clusters truly represented vehicles, we cross-referenced our findings with GoPro footage, marking all vehicle passings in red. Overall, the sensor adeptly identified vehicles passing the cyclist. Of the 21 vehicles that overtook the cyclist in the same lane, our setup correctly identified 7 passed at a proximity of 1.5m or closer. Points not highlighted in red either indicate false positives or noise. The subsequent clustering algorithm will identify false positives, while isolated faint points represent noise.

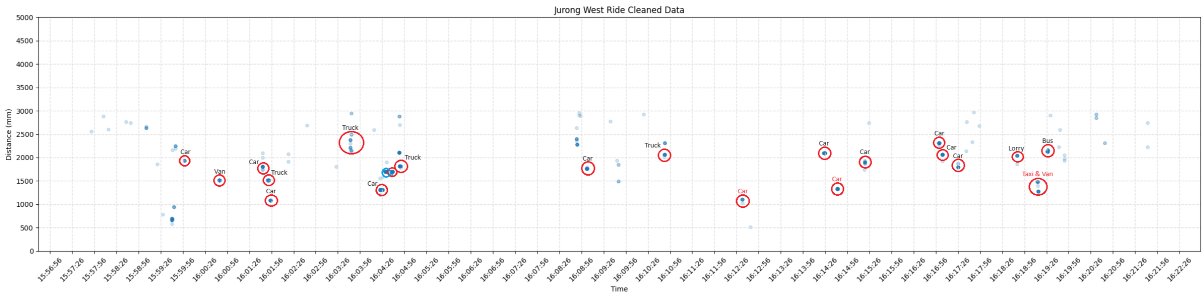

Fig. 14. Data collected with LIDAR and OAK Camera annotated using GoPro footage.

4.3. Automated Data Analysis

To enhance efficiency in the data collection process, we aim to replace the time-consuming manual identification of clusters through cross-referencing with the GoPro. Instead, an algorithmic approach that automatically recognizes clusters, representing vehicle passes, will be implemented.

4.3.1 Clustering Algorithm Selection

The sensor emits measurement signals at a frequency of approximately 20 Hz. Instead of producing one or two random data points, it should record a cluster of points that represent the distance of the overtaking vehicle during its pass. Hence, we require a cluster analysis to automatically identify vehicle passes.

Cluster analysis, also known as clustering, is a statistical technique that groups similar items or data points together based on their characteristics or the relationships between them. The aim is to maximize the similarity of items within a cluster and maximize the dissimilarity between different clusters. A clustering algorithm is a method that executes the clustering process. It classifies datasets into subsets (clusters) based on their similarities and differences. Table 6 shows a comparison between a few of the more popular clustering algorithms.

Table 6

General Comparison Between Different Types of Clustering Algorithms

	Working Principle	Number of Clusters	Sensitivity to Outliers	Use Cases
K-Means	Partitioning	Needs to be specified	High	Large datasets; when the shape of clusters is approximately spherical.
DBSCAN	Density-Based	Determined automatically	Low	When cluster shape is irregular and noise/outliers are present.
Hierarchical	Agglomerative or divisive	Visualized using dendrogram, cut at desired level	Moderate	Small datasets; when tree-like structure or hierarchy is required.
Agglomerative	Groups data into objects into a tree of clusters.	Needs to be specified	Moderate	When a hierarchical approach is desired.
Gaussian Mixture Model (GMM)	Uses probability distributions	Needs to be specified	Moderate	When clusters are elliptical or when probabilistic cluster assignments are desired.
Mean Shift	Mode seeking	Determined automatically	Moderate	Image segmentation, computer vision.

For the specific task of identifying close vehicle passes, DBSCAN (Density-Based Spatial Clustering of Applications with Noise) emerges as a preferred choice among clustering algorithms. Unlike K-Means or Gaussian Mixture Models, DBSCAN does not require a pre-defined number of clusters, making it adept at discovering clusters of varied shapes and sizes. Moreover, DBSCAN's inherent ability to segregate noise or outliers ensures that sporadic, unrelated data points (like random objects or anomalies) do not form erroneous clusters, a challenge that can affect some other algorithms. This noise-handling capability makes DBSCAN particularly suited for real-world data where outliers are common. In essence, for a dynamic setting like traffic with unpredictable passing patterns and potential anomalies, DBSCAN offers the robustness and adaptability necessary to discern meaningful clusters effectively.

4.3.2 DBSCAN

DBSCAN (Density-Based Spatial Clustering of Applications with Noise) is an algorithm adept at clustering and filtering noise or outlier data. Given a set of points in some space, it groups together points that are closely packed together (points with many nearby neighbors), marking as outliers points that lie alone in low-density regions.

We chose DBSCAN because it is particularly suited for problems where the number of clusters is not known, primarily because it does not require the number to be specified upfront. It naturally discovers clusters based on data density. Points in dense regions are grouped together, and sparse regions are treated as noise or boundaries between clusters. This is unlike algorithms like K-Means, where the 'K' needs to be pre-specified.

Let D be the data set of all points, Q be the query point, and $N(Q)$ represent the neighborhood of Q, which includes all points within distance ε of Q.As illustrated in Figure 15 by the orange point, a point Q is a *core point* if at least $minPts$ points are within distance ε of it.

Q is a *core point* if $|N(Q)| \geq minPts$

A point P is *directly reachable* from Q if point P is within distance ε from core point Q, shown by the blue points to the orange point.

P is *directly reachable* from Q if $P \in N(Q)$ and $|N(Q)| \geq minPts$

As illustrated by the green points, point P is *reachable* from Q if there exists a sequence of points:

$p_1, p_1, \ldots, p_n$ with $p_1 = Q$ and $p_n = P$ where p_{i+1} is directly reachable from p_i

Formally, a cluster in DBSCAN is a non-empty subset $C \subseteq D$ satisfying:

1. For any two points P and Q in C, if Q is reachable from P, then P and Q are part of the same cluster.
2. For any point Q in C if there is a point P in C such that Q is reachable from P, and P is a core point.

All other not reachable points are considered *outliers* or noise as indicated by the gray points and can be represented as:

$D \setminus \bigcup_{all\ clusters\ C} C$

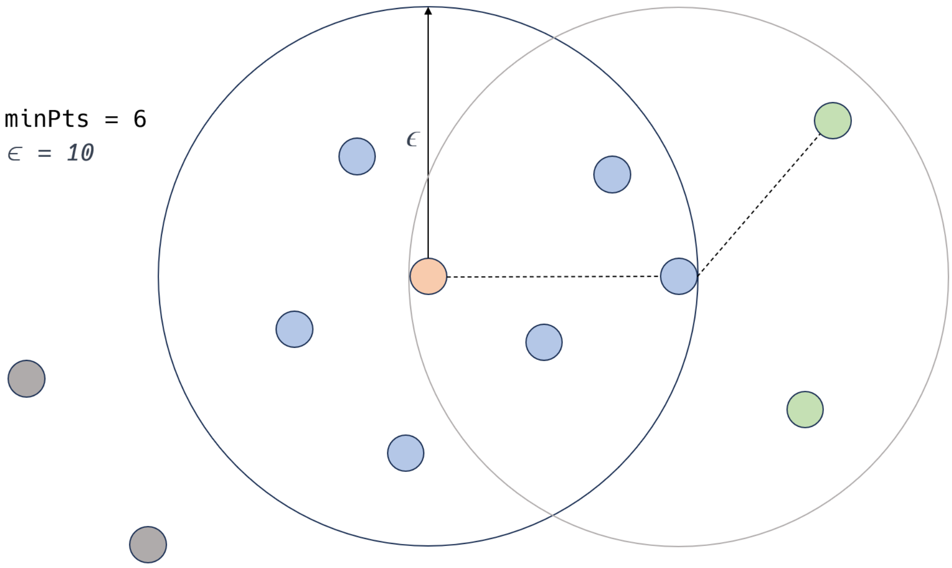

Fig. 15. DBSCAN illustration.

Therefore, the DBSCAN algorithm can be understood as a region query, where $N\epsilon(p)$ is the ε-neighborhood of the point Q in dataset D:

$$N_{\epsilon}(Q) = \{P \in D \mid dist(Q, P) \leq \epsilon\}$$

In our experiment, we calibrated ε to 0.02 and $minPts$ to 6. The results, as shown in Figure 16, depict the clusters identified by DBSCAN circled in blue which represent vehicle passes. There were four false positives detected by the algorithm, as marked with green squares, and the remaining points being noise. However, when distinguishing close vehicle passes ranging from 1m to 1.5m, DBSCAN demonstrated 100% accuracy. Clusters indicating passes under 1m are assumed to be anomalies, given the low likelihood of such close overtakes. Similarly, passes over 2m likely belong to vehicles in different lanes, and these can also be filtered. Therefore, with our preliminary results, we show that it is possible to create an automated framework that easily collects and analyses close vehicle passes with no reliance on manual techniques.

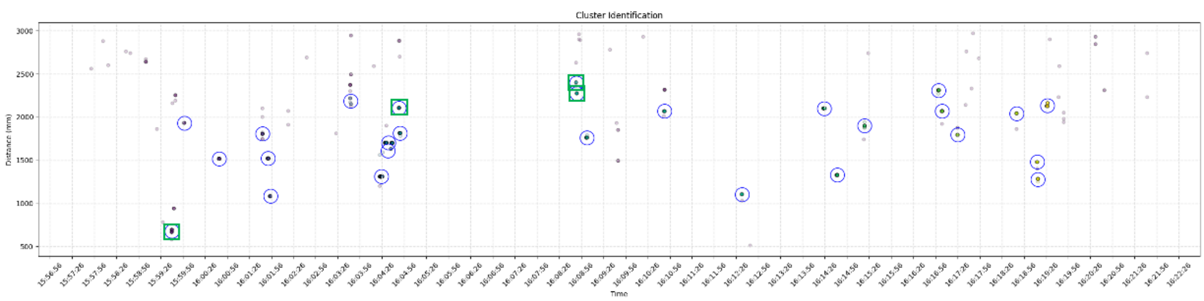

Fig. 16. Clusters identified using DBSCAN.

Using DBSCAN, we isolated points between 1m to 2m and averaged each cluster to represent a vehicle pass with a single point on a scatter plot. We then extracted relevant screenshots from the GoPro video and integrated them into an interactive plot. Users can click on a point to view the corresponding overtaking vehicle screenshot and its passing distance. In Figure 17, the clicked point is highlighted with a black circle, showcasing an overtaking car at that specific distance.

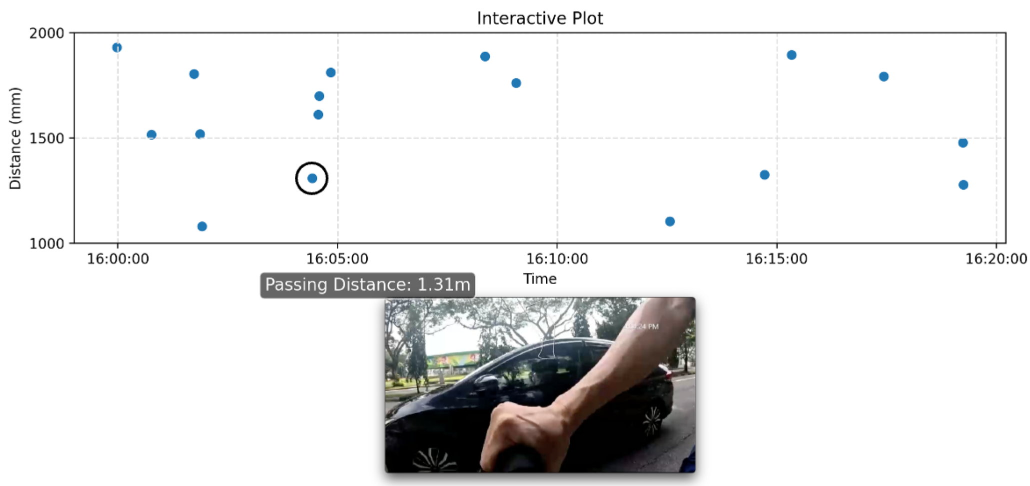

Fig. 17. Interactive plot depicting a vehicle overtaking at 1.31m.

5. Speed Considerations

Our current system lacks the capability to monitor the speed of passing vehicles. Considering that some countries adjust passing distance rules based on vehicle speed, this feature is significant and would offer deeper insights into cyclist and vehicle safety interactions.

To do this, the AI camera would use an object detection network such as YOLO and an object tracker to track the vehicles being detected, both of which have already been implemented in our setup. Once the vehicle is identified, its position is tracked across multiple frames. The change in position gives us the displacement of the vehicle.

For accurate speed estimation, the real-world distance the vehicle has traveled between frames needs to be determined. This can be achieved by first calibrating by using known reference objects or markings in the camera's view to establish a sense of scale. Next, we can use our distance sensor for depth estimation of the vehicle. To calculate the relative speed of the vehicle to the cyclist, we find the displacement of the vehicle and time difference between frames, and the speed can be calculated using:

$$speed = \frac{distance}{time}$$

6. Limitations and Future Work

The primary objective of this project was to explore the potential of new technologies like AI and machine learning to streamline and automate the process of collecting vehicle passing distances. While we have made progress, the current setup is not entirely complete. The combination of microcontrollers and sensors employed might not be the most efficient or cost-effective, suggesting that there could be alternatives better aligned with our goals and potentially more economical. Additionally, numerous clustering methodologies could enhance our results by minimizing false positives. A comprehensive evaluation across diverse datasets is crucial to affirm the universal applicability and reliability of our chosen techniques.

Another small improvement would be to fully automate the process of creating the interactive graph. By utilizing the AI camera to take a picture during each vehicle pass, we can directly associate each cluster with its corresponding image. This automation will allow for a more convenient and instant identification of close pass incidents.

Looking forward, the project's evolution will encompass the assessment of a wider array of sensors, accompanied by extensive on-road data collection. This amassed data will help to test various clustering techniques, adjusting parameters to discern the optimal method. Upon establishing this foundation, our vision is to consolidate the hardware and software into a unified, market-ready product kit.

6. Conclusion

Our research uses the latest technology to advance the boundaries of transportation safety. By integrating AI and machine learning with state-of-the-art sensors, we have unveiled a more streamlined, precise, and efficient methodology, hoping to offer a more efficient and easier alternative to traditional manual processes. With the foundation laid by our study, subsequent research can delve deeper into optimizing data collection techniques, thereby broadening the applicability and reliability of our findings.

Moreover, the existence of this research paves the way for a host of applications. Planners and policymakers can now benefit from data that is more easily collected, aiding in crafting more effective transportation safety measures. Researchers can further build on this foundation by testing a broader range of sensors and algorithms, ensuring the continuous evolution and enhancement of our initial efforts. Ultimately, we hope that our research is able to work towards the goal of fostering safer roads and a more bicycle-friendly urban environment.

Acknowledgements

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