Future Technology
Open Access Journal
ISSN 2832-0379

May 2026| Volume 05 | Issue 02 | Pages 336-346

Journal homepage: https://fupubco.com/futech

https://doi.org/10.55670/fpll.futech.5.2.30

Future Publishing LLC

Article

An affordable mobile LiDAR approach for efficient three-dimensional analysis of urban traffic

Sassi Naoufal[1], Akourri Omar[1], Benbba Brahim[2]*

[1]Laboratory of Materials Engineering, Systems and Energy (MaSEEL)-UAE/U04FST, Abdelmalek Essaadi University, Tangier, Morocco
[2]Marketing, Logistics and Management Laboratory (MLM Lab), ENCG Tangier, Abdelmalek Essaadi University, Morocco

ARTICLE INFO

Article history:
Received 01 November 2025
Received in revised form
22 February 2026
Accepted 02 April 2026

Keywords:
Urban traffic management, Mobile lidar, 3D point clouds, Artificial intelligence, Vehicle detection, Smart cities

*Corresponding author
Email address:
b.benbba@uae.ac.ma

DOI: 10.55670/fpll.futech.5.2.30

ABSTRACT

Urban mobility management is an issue that smart cities cannot ignore, and it requires reliable, sustained, and precise dynamic monitoring of traffic flows. This paper introduces a cost-effective mobile LiDAR-based methodology for three-dimensional urban traffic analysis, providing the high-resolution spatial data necessary for future AI-driven mobility decoding. We use real-world data acquisition rather than conventional studies that rely on traffic simulation tools, such as VISSIM or AIMSUN, to model traffic dynamics, including vehicle volumes, vehicle shapes, inter-vehicle distances, and automatic vehicle counting. The LiDAR system was a mobile system that used a terrestrial laser scanner (TLS) to capture high-density 3D point clouds at various urban intersections with no heavy infrastructure. The suggested methodology encompasses the whole processing chain, i.e., data collection, preprocessing, object segmentation, vehicle localization, volume estimation, and infrastructure element localization. The experiment at two intersections in the city of Tangier (Morocco) demonstrates that the obtained real-world LiDAR data is comprehensive, visually accurate, and suitable for training artificial intelligence models for traffic analysis and management. The proposed workflow provides a foundation of geometric data that could be used for future AI-based traffic analysis, following further annotation and model development.

1. Introduction

Urban mobility management is a major challenge for smart cities and systems that are able to accurately, robustly, and continuously monitor traffic flows. In this context, LiDAR technology is a promising approach because it can record dense three-dimensional information with low sensitivity to lighting variations and certain environmental conditions [1,2]. This capability aids reliable geometric modeling of urban scenes and enables the extraction of traffic-related spatial features that are not readily obtainable from conventional two-dimensional imaging systems. Compared with traditional video surveillance, LiDAR can provide direct three-dimensional measurements, including object geometry, volume characteristics, and inter-vehicle distances. Unlike 2D cameras, which require additional calibration and depth estimation procedures, LiDAR can be used directly to capture the spatial structure of the traffic scene. This makes it especially suitable for the analysis of urban traffic, where accurate geometric information is essential for understanding the distribution of vehicles and their interactions with roadways. A large part of the existing literature on traffic analysis relies on simulation tools such as VISSIM or AIMSUN to study intersection operations and predict traffic behavior. Although these tools are useful, they are based on predefined scenarios and might not fully capture the complexity of real urban traffic conditions. In contrast, the current research is devoted to the real-world acquisition of LiDAR systems and to directly observing traffic-related variables such as the number of vehicles, their shapes and (approximately) volumes, and the spacing between vehicles. The resulting point clouds also give realistic three-dimensional representations of the surveyed urban environment [3]. The central question of this research is whether an affordable mobile LiDAR system can deliver adequate spatial accuracy for practical three-dimensional urban traffic analysis. Mobile laser scanning has emerged as an efficient method for acquiring dense three-dimensional data of cities and enabling large-scale modeling of cities [4]. The flows are suggested from data acquisition, preprocessing, object segmentation, vehicle localization, volumetric estimation, and inter-vehicle distance measurement. The novelty of this study is to demonstrate that an affordable handheld mobile SLAM-LiDAR system can provide practical 3D urban traffic analysis using a unified, low-cost workflow. Unlike costly fixed or vehicle-based systems, the proposed works integrate mobile acquisition, point cloud preprocessing, DBSCAN-based vehicle segmentation, and geometric analysis within a unified, operationally effective framework. In addition, the work offers a real-world example from two urban intersections in Tangier, Morocco, which is underrepresented in the literature on LiDAR-based traffic studies. The combination of advanced AI for interpreting mobility is not within the direct scope of the current work. Rather, this study is a groundwork data acquisition and preprocessing stage that may facilitate future data-driven and AI-assisted traffic analysis models.

2. Methodology

The present work is based on an integrated methodological framework that leverages terrestrial laser scanner (TLS) point clouds to enhance urban traffic monitoring and spatial analysis. Traditional traffic management has relied on magnetic loops, inductive sensors, and video surveillance [5]. Magnetic loops and inductive sensors are limited to fixed locations and provide only partial traffic information without geometric continuity. Video systems cover wider areas but are affected by occlusions, lighting changes, shadows, and weather, and they generally cannot provide accurate three-dimensional measurements of vehicle shape, spacing, or volume. Consequently, conventional systems often lack spatial coverage, geometric precision, and environmental robustness. Recent studies have highlighted the need for high-resolution 3D sensing in complex urban settings [5-7]. LiDAR addresses these limitations by producing dense, centimeter-level 3D point clouds and reliable urban models [6]. For positioning and orientation, the device relies on SLAM (Simultaneous Localization and Mapping) technology, which remains stable in urban canyons where GNSS signals are often blocked. Like similar pulsed 3D LiDAR sensors, it measures distance using the time of flight (ToF) of emitted laser pulses reflected from surfaces. The SLAM-based LiGrip O1 follows the same principle as modern mobile mapping systems, enabling stable and accurate capture over medium-to-long distances in urban and outdoor environments. The use of point cloud data as a resource is useful in several applications, such as:

- Traffic signal cycle optimization,
- Dynamic traffic flow management,
- Improvement of intersection safety,
- Intellectual production of forecasting and predictive instruments,
- Introduction of sustainable mobility in smart city systems [7].

3D point clouds provide an effective representation of urban environments, where buildings, vehicles, and trees often create occlusions. Their dense array of points and multi-view capture capabilities aid in full-scene geometry construction, examination of partially obscured regions, and accurate determination of distance and volumes, notwithstanding obstructions. Such an abundance of information facilitates the use of applications such as 3D mapping, urban planning, and traffic simulation. The general objective of this study is to examine the use of LiDAR point clouds for spatial analysis and partial automation of urban traffic monitoring. The specific objectives are:

- to scan an urban intersection and produce a representative high-resolution point-cloud dataset;
- to automatically extract vehicle counts and measure inter-vehicle distances and vehicle volumes for traffic density and safety assessment;
- to identify and characterize infrastructures such as lanes, intersections, and parking areas through spatial analysis;
- to monitor flows and mobility dynamics in sensitive areas while ensuring data confidentiality.

In the real world, such information would be treated only by the competent authorities and kept secret. To address this concern, only company-owned vehicles were used, and their license plate numbers are documented. During the experiment, traffic within the study area was diverted as much as possible to minimize external complexity and ensure stable volumetric measurement conditions. These vehicles were recreated from the 3D point cloud, demonstrating that point clouds can capture fine details such as written signs. The integration of advanced artificial intelligence strategies, including machine learning algorithms for behavioral decoding [1,2], is considered a future extension of this methodological framework and is not fully implemented in the present study. An overall workflow is provided to illustrate the methodological pipeline from data acquisition to spatial analysis, while indicating possible routes for future AI-based extensions (Figure 1).

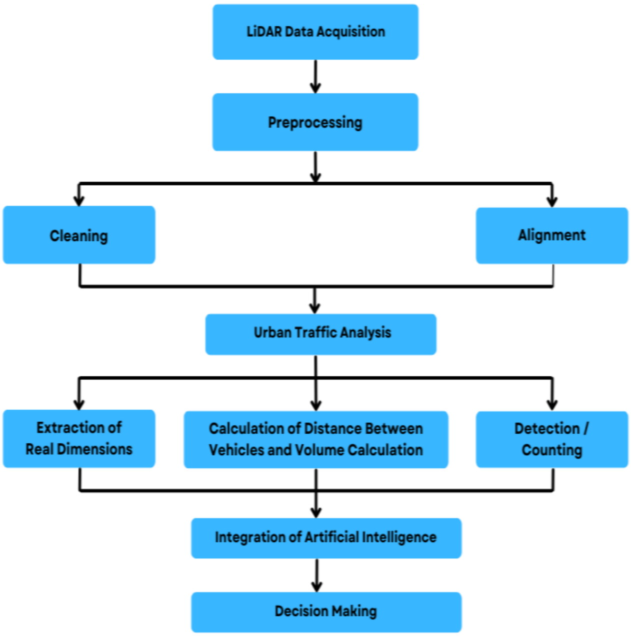


Figure 1. Workflow of the methodology

The method begins with a field mission to acquire 3D point-cloud data using a mobile LiDAR scanner. Preprocessing was performed in LiDAR360MLS, including filtering, noise removal, strip alignment, normalization, subsampling, and color extraction. Overlapping strips were aligned using the Boresight/Strip Alignment module, while outliers were removed through a statistical filter based on neighbor distance, threshold, and isolated-point detection.

Terrain effects were corrected by normalization, and point density was reduced according to analysis needs using subsampling methods. Visualization was improved through PCV and image color extraction. Data quality was evaluated by using point density, outlier removal rate, and RMS deviation metrics. After data processing and structuring, the analysis will focus on identifying traffic objects (vehicles, pedestrians, urban equipment) and automatically counting vehicles. We explain that, in the present work, Automated Detection is defined as the algorithmic classification of vehicles in the raw point cloud using the DBSCAN clustering algorithm, whereas Localization is the positioning of the clusters within the SLAM-generated coordinate frame. Finally, a literature benchmarking using an artificial intelligence approach was conducted to assess the applicability of the proposed methodology, identify its weaknesses, and outline the way forward [8]. The uniqueness of the proposed research lies in the application of a low-cost handheld mobile SLAM-LiDAR system to practical 3D traffic analysis in an urban environment. The suggested approach combines low-cost data collection, the DBSCAN vehicle segmentation algorithm, and geometric measurements at real intersections in the city, offering a more accessible and less expensive alternative to the more costly traditional methods of monitoring traffic.

2.1 Experimental implementation of the methodology

The data collection used a hybrid scheme combining static and mobile approaches. The initial capture of each location consisted of short, static scans, followed by mobile SLAM scans along road edges and approaches. At 1-1.2 m/s, mobile acquisition took approximately 60 minutes per site, capturing spatial snapshots rather than tracking.

Data collection was done with the LiGrip O1 Lite system developed by GreenValley International. This handheld, portable LiDAR scanner has a range of 70 m, a relative accuracy of 1-2 cm, and a compact size of 1 kg, making it appropriate for dense urban settings where vehicle-mounted LiDAR scanners are impractical [9]. Its high-resolution display is 200,000 points/s, which is an average density of approximately 2,500-4,500 points/m^2 in the area of study. The handheld SLAM-based system, with an estimated cost of 10,000-25,000, is much cheaper than vehicle-mounted Mobile Mapping Systems, which could cost more than 200,000, and is therefore available to municipal traffic management [10]. The device has several sophisticated mapping modes, such as:

- SLAM (Simultaneous Localization and Mapping),
- RTK-SLAM, integrating real-time GNSS corrections,
- PPK-SLAM, enabling precise post-processing of trajectories [11].

The LiGrip O1 Lite offers operational flexibility for applications such as architectural modeling, precision topography, 3D facade reconstruction, and volumetric analysis of complex facilities. These capabilities are also relevant to dynamic urban traffic monitoring, where metric accuracy, rapid deployment, and signal reliability are essential [12]. Table 1 summarizes the main features of the LiGrip O1 Lite. As the specifications in Table 1 indicate, the chosen device offers an appropriate trade-off among measurement accuracy, portability, and deployment flexibility, making it highly suitable for scalable traffic monitoring solutions in the future smart city environment [6,7]. In this study, various specialized software tools were used to develop a full LiDAR data processing workflow, from point cloud acquisition through analysis and interpretation to support urban traffic management. The tools serve a purpose in the workflow, which includes data cleaning, visualization, sophisticated processing, and the derivation of quantitative indicators needed to evaluate traffic [13]. The consistent combination of these software programs assists in:

- Enhance the precision of the outcomes obtained,
- Reduce processing times,
- Increase the accuracy of analyses and measurements retrieved,
- Optimization of data application in practice [14].

Table 2 shows the primary software to be used and their functional roles in the proposed methodology.

Table 1. Specifications of the LiGrip O1 mobile laser scanner

Specifications	Details
Weight and Compactness	1.0 kg - lightweight and easy to handle
Measurement Accuracy	±2 cm (relative), ≤5 cm
LiDAR Range	Up to 70 m at 80% reflectivity
Colorized Point Cloud	Real-time LAS output with RGB colors
Mapping Methods	SLAM, RTK-SLAM, PPK-SLAM

Table 2. Main software used

Software	Primary Use
LiDAR360 MLS	Processing and structuring point clouds from the laser scanner
Autodesk ReCap	Cleaning, aligning, and preparing LiDAR data
CloudCompare	Metric calculations, 3D visualization, segmentation, and advanced analysis

All of these software tools coherently create a processing pipeline that is efficient enough to provide precise segmentation, visualization, and quantification of an urban traffic scene from mobile LiDAR data [6,13]. Furthermore, the trajectory alignment performed in LiDAR360MLS achieved a relative RMSE of ±1 cm and an absolute spatial accuracy of ±3 cm, ensuring the metric precision required for sub-decimeter volumetric calculations. Manual validation was conducted on representative subsets from both study sites. A total of 17 vehicles were visually verified against segmented LiDAR clusters, including 11 in Tanja al Balia and 6 at Ibn Battouta Roundabout. A detection was considered correct when a segmented cluster corresponded to a visually confirmed vehicle in the point cloud view and the field record. LiDAR-derived inter-vehicle distances were also compared with manually measured ground-truth values for selected vehicle pairs. This procedure was used to assess the reproducibility of vehicle counting and geometric measurement under the adopted workflow.

3. Experimentation

3.1 Study Areas

The experimental campaign was done in two representative traffic areas within Tangier, Morocco: Tanja al Balia and Ibn Battouta Roundabout. Tangier was chosen for its complex urban geometry, heterogeneous traffic structure, and position within the Moroccan movement. Traffic comprises passenger vehicles, motorcycles, buses, taxis, and heavy commercial vehicles, and generates varied, often congested flow conditions. This difficulty is supported by the economic and logistical activity of Tangier, especially that related to Tanger Med Port, commuting, and school-related traffic, and seasonal traffic. Consequently, spatial indicators such as vehicle distribution and road occupancy become particularly pertinent. The data were collected at the two sites using a hybrid mobile/static method, with a total survey time of approximately 120 minutes, and were gathered using LiDAR data. The width of the road was measured at 7.112m, and 17 vehicles were taken through. There were no official AADT values or speed measurements obtained using instruments. Ibn Battouta Roundabout (35.7035990, -5.9287110) was the first study site because of the high density of heterogeneous traffic and its complicated geometry, and the second roundabout was in the area of 35.73, -5.74 with an alternative layout to compare the two across the urban environments. The tests on LiDAR scanner functionality, point cloud quality, and the segmentation, classification, automatic detection, and vehicle-counting algorithms used in this study were conducted there. Figure 2 shows the mixed-traffic location in an economically active area of Tangier, whereas Figure 3 depicts the Ibn Battouta Roundabout, which has more vehicles and more complex routes. Figures 4 and Figure 5 show the geometric dimensions and layout of Experimental Zones 1 and 2, highlighting lane patterns, intersection geometry, and traffic organization relevant to this study.

Figure 2. Experimental Zone 1 in the economic activity area in Tangier (coordinates in WGS84 system: Lat: 35.739185134407165, Lon: -5.74962804689346)

Figure 3. Experimental Zone 2 at the Ibn Battuta Roundabout in Tangier (coordinates in WGS84 system: Lat: 35.70571217896335, Lon: -5.933754639075064)

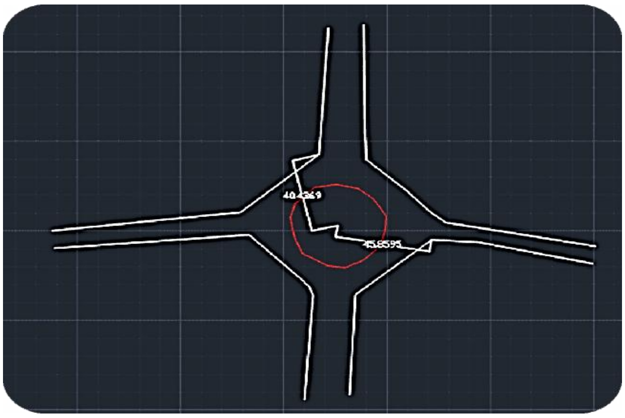


Figure 4. Experimentation zone 1

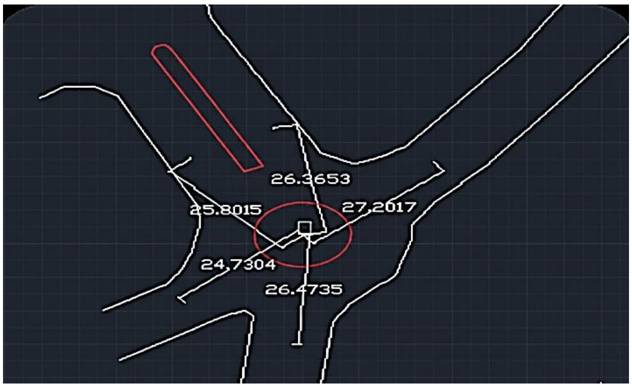


Figure 5. Experimentation zone 2

4. Experimental results

4.1 Scan results after preprocessing and cleaning

After acquisition, raw LiDAR data were processed in LiDAR360 MLS [13] for alignment, noise and outlier removal, and generation of colored LAS point clouds [6,7]. This workflow produced dense 3D data suitable for traffic analysis and panoramic visualization. Autodesk ReCap Pro [13] was then used for visualization, quality control, and validation. This step enabled:

- Checking the continuity and the density of the 3D model,
- Detection of possible geometrical inconsistencies,
- Establishing the accuracy of the reconstruction in comparison with the actual geometry of the intersection [6]

The core findings of this preprocessing step, along with their visualizations, are illustrated in Figure 6 and Figure 7.

Figure 6 depicts the final 3D point cloud of Zone 1, with a high spatial resolution of 200,000 points per second of acquisition. Figure 7 geometrically reconstructs the Ibn Battuta Roundabout and visualizes it to achieve metric continuity of volumetric analysis. Figures 6 and 7 show clean, well-organized point clouds that provide the spatial density and geometric continuity necessary for effective traffic analysis, object segmentation, and spatial measurement. This detail can benefit the development of advanced traffic systems that require fine-grained 3D perception capabilities for vehicle identification, distance calculation, and infrastructure-aware control [6,7].

Figure 6. Scan result after processing in Zone 2 (economic activity area)

Figure 7. Scan result after processing in Zone 1 (Ibn Battuta Roundabout)

4.2 Results of urban traffic analysis

Automated vehicle counting was performed using CloudCompare software [13], and the results were manually verified by field technicians. It uses the DBSCAN algorithm proposed by Ester et al. [15] to cluster 3D point clouds, treating dense clusters as objects and sparse points as noise. This is a density-based method that is well-suited to complex environments in remote sensing and on-land laser scanning [6]. Clustering parameters in the vehicle segmentation stage of DBSCAN were epsilon = 0.50 m and MinPts = 30. The epsilon value was selected to ensure spacing between nearby cars in crowded urban scenes, and MinPts helped eliminate isolated noise and very small non-vehicle groups. These settings have been used consistently for point clouds with densities of approximately 2,500-4,500 points/m^2. LiDAR detections versus manually checked ground-truth counts of representative scenes at each of the two study sites were used to estimate performance. As shown in Table 3, LiDAR detections fully matched the manual counts in the validation samples.

Table 3. Manual vs. LiDAR-based vehicle counts for validation at the two study sites

Study Location	Acquisition Mode	Manual Ground Truth (N)	LiDAR Detection (N)	Accuracy (%)
Zone 1: Tanja al Balia	Mobile/ Static	11	11	100%
Zone 2: Ibn Battouta Roundabout	Mobile/ Static	6	6	100%

The quality of clustering was evaluated using the Silhouette Coefficient (Si) to assess the strength of segmentation, as it measures the cohesion and separation of the clusters. When the values approach +1, it means that the vehicle clusters are well-outlined and clearly separated from environmental noise, such as road surfaces and vegetation. The parameters of DBSCAN in this work were chosen based on the density of point-clouds of scenes of urban environments, and epsilon and minPts were chosen empirically to guarantee proper segmentation of vehicles. The sensitivity tests, conducted with various parameter values, ensured good clustering across varying vehicle densities and urban forms. Clustering performance was verified through a manual check by on-site technicians. This ground-truth comparison was performed using the controlled sample of company vehicles, and we achieved a 100% detection rate in the study zone. The selected DBSCAN parameters were appropriate for the traffic density that was encountered in the city.

While a traditional Confusion Matrix is usually used for supervised classification tasks, one piece of evidence that our unsupervised segmentation is robust is that the algorithm's results in this case are consistent with the ground-truth observations. In the controlled tests at the Ibn Battouta roundabout, the zero False Discovery Rate confirms the reliability of the parameters (epsilon) and MinPts chosen for vehicle detection. This step is one of the main components in the methodology as it will be the basis of the further analytical operation, i.e.:

- Spatiotemporal monitoring of automobile movement,
- Determination of vehicles during their transit in the intersection,
- Traffic flows behavioral analysis [1,2].

The LiGrip 01 Lite can use a Simultaneous Localization and Mapping (SLAM) algorithm for positioning and is known to not require constant GNSS signals to remain stable. To track the object across the scene, the system employs a centroid-based tracking algorithm to track changes in the segmented clusters of vehicles between successive scan frames. In addition to vehicle counts, the algorithm can provide valuable mobility data, such as inter-vehicle interactions, to aid in traffic modeling, urban planning, and infrastructure evaluation [7]. DBSCAN is highly applicable to large LiDAR point clouds, as it reliably separates objects across different densities and minimizes noise-induced errors [6]. Figure 8 shows that it was able to single out specific groups of vehicles in the controlled version of the scene. Figure 8 demonstrates automated vehicle detection using the DBSCAN algorithm, resulting in a 100% detection rate within the controlled test zone.

The distance between vehicles was derived from the SLAM-optimized point cloud. The geometric accuracy of mobile laser scanning systems has been widely validated for reliable spatial measurement [16], and the results are consistent with the sensor's specified relative accuracy of ±2 cm. In this study, inter-vehicle distances were first measured manually in ReCap Pro as approximate bird's-eye estimates. They can also be computed directly from LiDAR point-cloud coordinates as Euclidean distances between vehicles, providing more precise and reproducible gap measurements while reducing manual estimation errors. To assess spatial reliability, LiDAR-based inter-vehicle distances were compared with manual reference measurements. Absolute errors were 0.020 m and 0.012 m, with a mean absolute error of 0.016 m, remaining within the LiGrip 01 Lite operational accuracy threshold. Table 4 directly compares the manual and LiDAR distance measurements. The measured inter-vehicle gaps of 2.820 m and 4.196 m indicate moderate short-range spacing within the roundabout approach, while the estimated vehicle bounding volume of 9.718 m^3 is consistent with a standard passenger car class. These measurements demonstrate that the workflow can recover geometrically meaningful traffic indicators from a handheld mobile LiDAR setup. Figure 9 shows relative spatial measurements derived from the SLAM-optimized point cloud. Figure 9 quantifies the inter-vehicle gap between two company vehicles, measured at precisely 2.820 m. Figure 10 shows a secondary spatial measurement between trailing vehicles, recorded at 4.196 m.

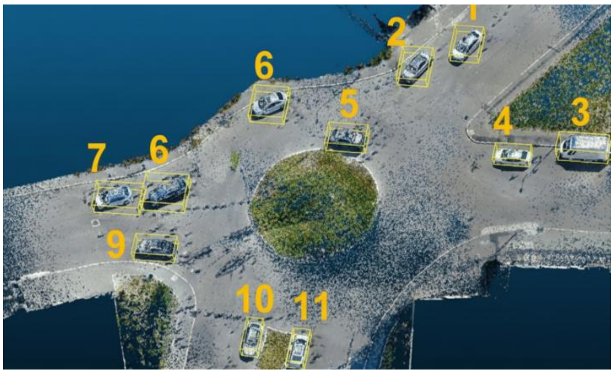


Figure 8. Result of automatic counting with DBSCAN

Figure 9. Calculation of the distance between vehicles

Figure 10. Calculation of the distance between vehicles

Table 4. LiDAR and manual inter-vehicle distance validation results with absolute errors

Reference Measurement	Manual Ground Truth (m)	LiDAR Output (m)	Absolute Error (m)	Reference Measurement
Inter-vehicle Gap A	2.80	2.820	0.020	Inter-vehicle Gap A
Inter-vehicle Gap B	4.21	4.198	0.012	Inter-vehicle Gap B
Mean Absolute Error (MAE)	--	--	0.016	Mean Absolute Error (MAE)
System Precision Bound	--	--	±0.02	System Precision Bound

The measurements of the inter-vehicle distance, as depicted in Figures 9 and 10, give first-hand information on the microscopic behavior of traffic. These fine details of space may be used to determine unsafe following distances and congestion patterns. Such measurements could be applied in the future to the connected and autonomous vehicle environment to evaluate the adherence to safety regulations and support cooperative driving policies via vehicle-to-infrastructure (V2I) communication [17,18]. The volumetric estimation shown in Figure 11 demonstrates that mobile LiDAR can capture not only vehicle presence but also their three-dimensional physical characteristics [19]. Vehicle volume assists in better traffic composition analysis to distinguish between smaller passenger cars and larger vehicles, and this feature applies to future traffic digital twins and geometry-based predictive modeling [20,21]. The actual vehicle volume can be calculated from the point cloud. After vehicle segmentation, an Axis-Aligned Bounding Box (AABB) was used to estimate the volume (V). Minimum and maximum coordinates were taken along the x, y, and z axes to determine length (L), width (W), and height (H), and volume was calculated as volume = L × W × H. To minimize sensor noise and sparse edge effects, an SOR filter was applied prior to measurement to better enclose the core vehicle geometry. To move beyond a static description, the measured road width (7.112 m), inter-vehicle distances (2.820 m and 4.196 m), and vehicle volume (9.718 m^3) were analyzed to assess lateral clearance, spatial headway, lane occupancy, and saturation flow at Ibn Battouta Roundabout. These measures, taken together, offer a systematic way to understand the arrangement of vehicles within the geometric parameters of the urban road network in Tangier. Descriptive statistics describe the state of the scanning and the extracted features of the traffic. LiGrip O1 Lite got approximately 200,000 points/s over a 70 m range, producing point clouds of roughly 3,500 points/m^2. Data collection lasted 120 minutes, during which 17 vehicles were segmented and analyzed (Table 5).

The clarity of vehicle license plates in the colorized LiDAR point clouds shown in Figure 12 and Figure 13 indicate the dataset's high spatial resolution. These details are presented only to demonstrate data richness and do not represent an automated license plate recognition process. It should be noted that this study does not implement automated license plate recognition; the observations only illustrate data richness and do not imply operational identification or privacy-sensitive processing.

Figure 11. The 3D bounding box used for volumetric estimation, resulting in a total volume of 9.718 m^3 based on dimensions of 5.457 m × 1.781 m × 1.0 m

Table 5. Descriptive statistics of LiDAR acquisition and extracted traffic parameters

Parameter	Metric / Value
Point acquisition rate	200,000 pts/s
Sensor range	70 m
Average point density	3,500 pts/m^2
Total acquisition time	120 min
Total segmented vehicles	17
Road width measured	7.112 m

Figure 12. License plate identification from LiDAR point cloud - car 1

Figures 13. The high-definition capture capability of the LiCam, providing clear visual identification of license plates from Car 2

5. Benchmarking existing databases and studies

5.1 Considered datasets

The present research is based on three datasets to compare and contrast the various solutions to the problem of traffic perception and management at intersections:

- **LUMPI (2022) (Steffen Busch1, 2020):** Multi-perspective dataset (LiDAR + cameras) centered on an urban intersection, which is based on detection, tracking, and cooperative perception [23,24].
- **Int2sec (2024) (Miao Tang1, 2024):** Multi-scene, multi-LiDAR benchmark that involves 10 intersections, which are used to detect and track 3D objects in the realm of intelligent intersections digital twins [25].
- **Our Data (2025):** In a city, close to an industrial zone, in Tangier (Morocco), a laser scanner was used to study the traffic in the local area and test the detection and tracking systems locally.

Data acquisition at each intersection used a hybrid approach, with 1 hour in static TLS mode and 1 hour in mobile mode. The mobile mode was specifically used to enhance the angle of view, significantly reducing the 'occlusion' effect caused by stationary roadside infrastructure. Table 6 presents a comparative analysis of the prominent features of the present LiDAR-based traffic data sets and the data set proposed in this research, including study area, purpose, time of day, and weather conditions. This comparison shows that although the proposed dataset has a smaller spatial scale, it focuses on real-world data acquisition using a relatively inexpensive mobile system, filling a gap in existing benchmarks, which are frequently large-scale or simulation-driven deployments. Table 7 compares the sensing settings and data features of the datasets under consideration, including sensor types, data formats, acquisition ranges, and measurement accuracy. As Table 4 illustrates, the sensing architecture of this study provides a simplified yet viable alternative to multi-LiDAR designs by demonstrating that high-value traffic analysis can be achieved using lightweight, low-cost mobile mapping systems.

5.2 Dataset visualization

Figures 14-16 are visual representations of the LUMPI dataset, the Int2Sec dataset, and the dataset proposed in this paper, respectively, which allow for a qualitative comparison of point cloud densities, scene complexity, and sensing configurations across various traffic perception strategies [24,25].

Table 6. Main characteristics of these datasets

Characteristic	LUMPI (2022)	Int2sec (2024)	Our Data (2025)
Purpose	Detection, tracking, and cooperative perception at an intersection	Multi-scene benchmark for 3D tracking and digital twins	Traffic management study with a laser scanner
Study area	1 intersection, Hanover, Germany	10 intersections, Wuhan, China (~49 km^2)	1 intersection, Tangier, Morocco
Environment	Dense crossroads: cars, buses, trucks, cyclists, pedestrians	Various intersection types and traffic conditions	4-lane intersection **Site 1:** the north-west approach: 9.1 m, while the north-east, south-west, and south-east approaches measure 6 m each. **Site 2:** Northern approach: 16m Southern approach: 23m Eastern approach: 15m Western approach: 13m
Weather/Time	Sunny, cloudy, foggy	Sunny, rainy, cloudy; day/night; morning, noon, afternoon, evening	Sunny (1 PM-3 PM)
Duration	145 min	11,076 LiDAR frames, 60.1 km annotated trajectories	2 h (static and mobile modes)
Number of scenes	1	10	1

Table 7. Sensor and data characteristics

Characteristic	LUMPI (2022)	Int2sec (2024)	Our Data (2025)
Sensors	5 LiDAR + 3 cameras + RIEGL VMX-250	2 LiDARs (80 beams) + GNSS + Jetson Orin Nano	Mobile laser scanner
Data type	Videos (MP4), LiDAR point clouds (PLY), 2D/3D annotations, orthophoto, road map	LiDAR point clouds (PCD/PLY), 3D annotations, trajectories, motion states, metadata	Colored point clouds (.las), images (.jpg/.bin)
Cameras	Raspberry Pi Cam v2, ATOM One, Xiaomi Yi Cam	None	LiCam integrated LiGrip O1 Lite (3840×2160 px)
LiDARs	Velodyne HDL-64E, VLP-16, Hesai Pandar64, PandarQT	Dual LiDAR 80, range ≤230 m, accuracy ≤3 cm, 10 Hz	LiGrip O1, range ≤70 m, accuracy ≤5 cm, 10 Hz, density 200,000 pts/s

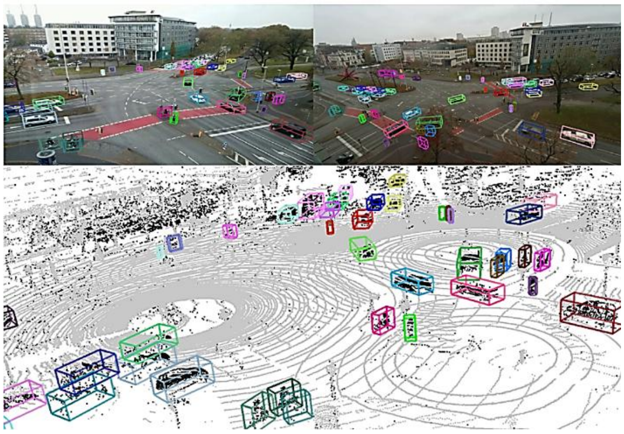


Figure 14. A reference scene from the LUMPI dataset, which comprises 145 minutes of multi-sensor data from Hanover

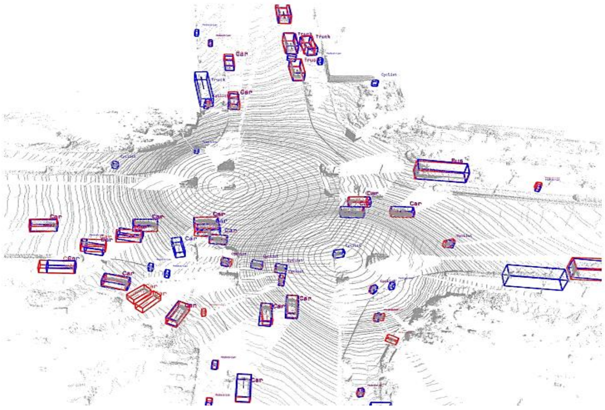


Figure 15. The Int2sec benchmark covering 10 intersections and containing 11,076 LiDAR frames

Figure 16. The local dataset acquired over a 2-hour duration with a relative measurement accuracy of ±2 cm

These visual comparisons highlight differences in acquisition scale, sensor configuration, and point-cloud density between benchmark datasets and this study, while showing that the proposed low-cost mobile LiDAR data still provides sufficient spatial resolution and visual fidelity for traffic analysis and future AI training [1,2,6].

5.3 Presentation of the studies

Study 1: Multi-sensor LiDAR fusion at an urban intersection in Sofia (Bulgaria)

The presented work investigates a multi-sensor LiDAR fusion system at a busy urban intersection in Lozenets, Sofia, to assess dense LiDAR coverage with machine learning for precise traffic perception and path analysis [18,20]. The system used six Ouster OS1-128 sensors (360° × 45° FOV, up to 200 m range, ±3 to ±10 cm accuracy, IP68/IP69K). A Random Forest classifier, including an enhanced RF-2 variant with geometric feature ratios, improved accuracy to 0.998-0.999. The study detected 516 traffic objects, reconstructed 10 full vehicle paths, and identified two trajectory violations. Figure 17 shows a sample of object detection outputs from a similar multi-sensor LiDAR study, which can be used to benchmark the capabilities and state of current traffic perception methods.

In contrast to the multi-sensor study, which relies on six synchronized LiDAR sensors, our approach relies on the 3D point cloud itself. Consequently, the framework can be used irrespective of the type of data obtained using a fixed scanner, a mobile scanner, or a multi-sensor system. This hardware agnosticism makes the approach more scalable and flexible and simplifies its transferability to other urban settings and acquisition settings.

Study 2: Simulated LiDAR-based traffic dataset for intelligent intersection analysis

The current paper presents a simulation-based approach for generating an annotated 3D LiDAR dataset to aid traffic management and perception functions at complex urban intersections. Its primary goal is to enable training and testing of deep learning models to detect 3D objects and segment individual object instances under controllable yet realistic traffic settings [21,25].

Workflow and simulation environment: The experiment was developed in a modeled four-way urban intersection (built in Blender 3.6) using the BLAINDER LiDAR-rendering module. Each scene included 15-35 vehicles, approximately 40 pedestrians, and road features (sidewalks and traffic lights). The deep learning models were PV-RCNN, which performs 3D object localization, and PointGroup architecture, which performs instance segmentation. Performance was reported as 80.66% mAP for detection, 85.91% PQ, and 96.43% SQ for segmentation. It was demonstrated that traffic participants were accurately localized and separated into fine-grained categories, confirming the usefulness of simulated LiDAR datasets for training models and benchmarking prior to real-world deployment.

Figure 18 illustrates the 3D object detection results, for an example simulated LiDAR dataset from Binshaflout et al., using deep learning techniques, which represent state-of-the-art AI traffic perception capabilities and serve as a benchmark for integrating with real-life mobile LiDAR data. As Figure 19 depicts, instance segmentation results for a simulated LiDAR scenario are shown, with each traffic member segmented at the point level using deep learning models. Although the simulated LiDAR datasets perform well in controlled environments, applying these findings to real-world settings is challenging due to the domain adaptation gap that arises under different conditions, such as noise, point density, occlusions, reflectance, and urban variability.

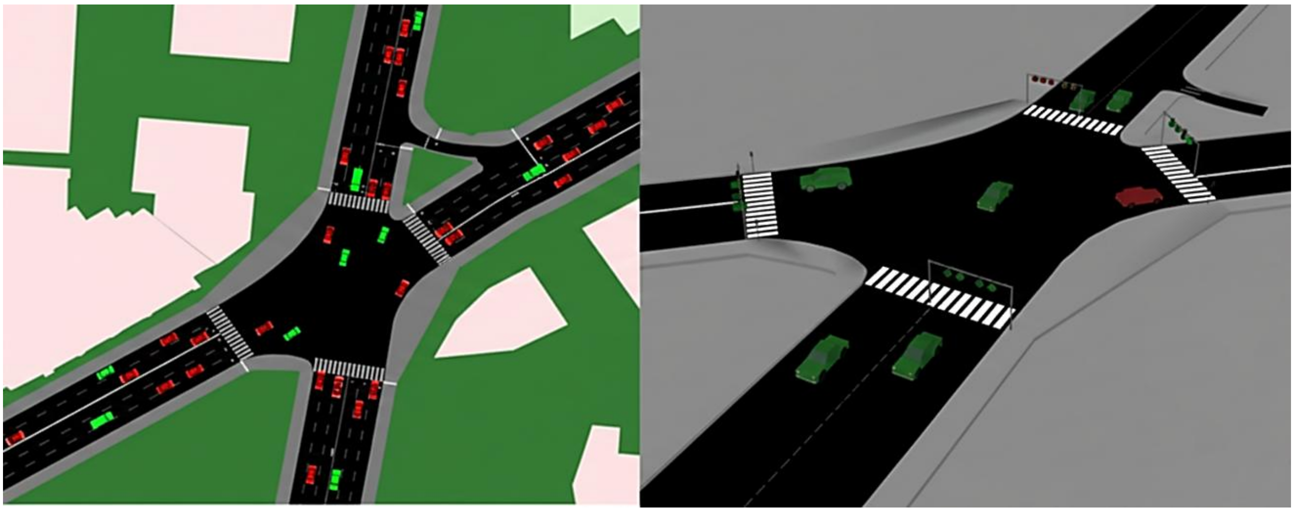


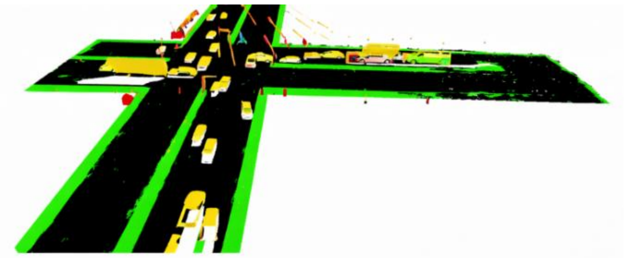
Figure 17. Detection result

Figure 18. Detection result (Binshaflout)

Simulation can thus be applied for low-cost pre-training and benchmarking, but real-world LiDAR data are needed for robustness and operational reliability. In this context, our mobile LiDAR dataset can complement synthetic data in a hybrid training strategy, with models pre-trained on simulated data and fine-tuned on real urban point clouds to improve generalization and reduce manual annotation.

5.4 Benchmark synthesis

Comparative analysis shows that multi-sensor datasets such as LUMPI and Int2Sec provide high precision and broad coverage but depend on permanent, synchronized LiDAR infrastructure, which limits affordability and flexibility, whereas simulation-based datasets support controlled pre-training but suffer from domain adaptation gaps in real urban conditions. In contrast, the mobile LiDAR dataset proposed here offers a real-world, cost-effective, and flexible single-scanner framework that supports point-cloud-based traffic analysis and can also complement synthetic data in hybrid training to improve generalization and reduce annotation effort.



(a) Semantic segmentation result

(b) Instance segmentation result

Figure 19. Segmentation result (Binshaflout)

6. Conclusion

This study shows that real mobile LiDAR acquisition can support practical and affordable three-dimensional urban traffic analysis. Based on field data from two intersections in Tangier, Morocco, the LiGrip O1 Lite produced dense colourised point clouds from which vehicle counts, inter-vehicle distances, volumetric estimates, and infrastructure layout were extracted. The results indicate that the workflow is suitable for vehicle segmentation and geometric traffic assessment in real urban settings. Comparison with datasets such as LUMPI and Int2Sec suggests that, despite its lower cost and simpler setup, the proposed system still provides sufficiently rich data for meaningful 3D traffic analysis. This work does not claim full automated recognition or operational AI deployment, but rather presents a real-world geometric dataset and a preprocessing framework that can support future data-driven and AI-assisted traffic studies. A further contribution is the provision of local data from Moroccan intersections, which remain underrepresented in LiDAR-based traffic research.

Ethical issue

The authors are aware of and comply with best practices in publication ethics, specifically regarding authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with research ethics policies. The authors adhere to publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement

The manuscript contains all the data. However, more data will be available upon request from the corresponding author.

Conflict of interest

The authors declare no potential conflict of interest.

References

[1] S. Busch, C. Koetsier, J. Axmann, and C. Brenner, “LUMPI: The Leibniz University Multi-Perspective Intersection Dataset,” in Proc. IEEE Intelligent Vehicles Symposium (IV), Aachen, Germany, Jun. 2022, pp. 1127-1134. doi: 10.1109/IV51971.2022.9827157

[2] M. Tang, D. Yu, P. Li, C. Song, P. Zhao, W. Xiao, and N. Chen, “A Multi-Scene Roadside LiDAR Benchmark towards Digital Twins of Road Intersections,” ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. 10, pp. 341-348, 2024. https://doi.org/10.5194/isprs-annals-X-4-2024-341-2024

[3] A. Jamshidnejad and M. J. Mahjoob, "Traffic simulation of an urban network system using agent-based modelling," 2011 IEEE Colloquium on Humanities, Science and Engineering, Penang, Malaysia, 2011, pp. 300-304, doi: 10.1109/CHUSER.2011.6163738.

[4] C. Wang, C. Wen, Y. Dai, S. Yu, and M. Liu, “Urban 3D modeling using mobile laser scanning: A review,” Virtual Reality & Intelligent Hardware, vol. 2, no. 3, pp. 175–212, 2020..

[5] R. Hoogendoorn and S. Hoogendoorn, “Traffic flow theory and modelling,” in Traffic Flow Theory, Elsevier, 2013, pp. 125-159.

[6] Vosselman, George, and Hans-Gerd Maas. Airborne and terrestrial laser scanning. Whittles publishing, 2010. https://doi.org/10.1080/17538947.2011.553487

[7] S. Gargoum and K. El-Basyouny, "Automated extraction of road features using LiDAR data: A review of LiDAR applications in transportation," 2017 4th International Conference on Transportation Information and Safety (ICTIS), Banff, AB, Canada, 2017, pp. 563-574, doi: 10.1109/ICTIS.2017.8047822.

[8] A. Nguyen and B. Le, "3D point cloud segmentation: A survey," 2013 6th IEEE Conference on Robotics, Automation and Mechatronics (RAM), Manila, Philippines, 2013, pp. 225-230, doi: 10.1109/RAM.2013.6758588.

[9] GreenValley International, GreenValley International - Official Website. [Online]. Available: https://www.greenvalleyintl.com/

[10] J. Zhang and S. Singh, “LOAM: LiDAR Odometry and Mapping in Real-Time,” in Proc. Robotics: Science and Systems (RSS), Berkeley, CA, USA, 2014.

[11] T. Qin, P. Li, and S. Shen, “VINS-Mono: A Robust and Versatile Monocular Visual-Inertial State Estimator,” IEEE Transactions on Robotics, vol. 34, no. 4, pp. 1004-1020, Aug. 2018. doi: 10.1109/TRO.2018.2853729.

[12] M. Rutzinger, B. Höfle, and N. Pfeifer, “Object-based point cloud analysis of full-waveform airborne laser scanning data,” ISPRS Journal of Photogrammetry and Remote Sensing, vol. 66, no. 6, pp. 760-769, 2011. https://doi.org/10.3390/s8084505

[13] CloudCompare Development Team, “CloudCompare—3D point cloud processing software,” Version 2.13, 2024. [Online]. Available: https://www.cloudcompare.org

[14] Autodesk Inc., “Autodesk ReCap Pro: Reality capture and point cloud processing,” 2023.

[15] M. Ester, H.-P. Kriegel, J. Sander, and X. Xu, “A Density-Based Algorithm for Discovering Clusters in Large Spatial Databases with Noise,” in Proc. KDD, 1996, pp. 226-231.

[16] Y. Lin, J. Hyyppä, H. Kaartinen, and A. Kukko, “Performance analysis of mobile laser scanning systems in target representation,” Remote Sensing, vol. 5, no. 7, pp. 3140–3155, 2013.

[17] O. Kilani, M. Gouda, J. Weiß, and K. El-Basyouny, “Safety assessment of urban intersection sight distance using mobile LiDAR data,” Sustainability, vol. 13, no. 16, Art. no. 9259, 2021. https://doi.org/10.3390/su13169259

[18] R. Rajamani, Vehicle Dynamics and Control, 2nd ed. New York, NY, USA: Springer, 2012. https://doi.org/10.1007/978-1-4614-1433-9

[19] A. Kukko, H. Kaartinen, J. Hyyppä, and Y. Chen, “Multiplatform mobile laser scanning: Usability and performance,” Sensors, vol. 12, no. 9, pp. 11712-11733, 2012. https://doi.org/10.3390/s120911712

[20] J. Liu, X. Mao, Y. Fang, D. Zhu and M. Q. . -H. Meng, "A Survey on Deep-Learning Approaches for Vehicle Trajectory Prediction in Autonomous Driving," 2021 IEEE International Conference on Robotics and Biomimetics (ROBIO), Sanya, China, 2021, pp. 978-985, doi: 10.1109/ROBIO54168.2021.9739407.

[21] F. Tao, Q. Qi, A. Liu, and A. Kusiak, “Digital twins and cyber-physical systems toward smart cities,” IEEE Transactions on Industrial Informatics, vol. 15, no. 4, pp. 2405-2416, 2019. https://doi.org/10.1016/j.eng.2019.01.014

[22] H. Ma, Z. Pei, Z. Wei, and R. Zhong, “Automatic extraction of road markings from mobile laser scanning data,” Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci., vol. 42, pp. 825-830, 2017. https://doi.org/10.5194/isprs-archives-XLII-2-W7-825-2017

[23] Cavoukian, A. (2009). Privacy by design: The 7 foundational principles. Information and privacy commissioner of Ontario, Canada, 5(2009), 12.

[24] T. T. Vu, F. Yamazaki, and M. Matsuoka, “Multi-scale solution for building extraction from LiDAR and image data,” Int. J. Appl. Earth Observ. Geoinf., vol. 11, no. 4, pp. 281-289, 2009. https://doi.org/10.1016/j.jag.2009.03.005

[25] E. Binshaflout, C. Zaghouani, N. Guefrachi, C. Antoniadis, H. Ghazzai, A. Alsharoa, and G. Setti, “Annotated 3D Point Cloud Dataset for Traffic Management in Simulated Urban Intersections,” in Proc. IEEE ISCAS, London, UK, May 2025, pp. 1-5. doi: 10.1109/ISCAS56072.2025.11044184.