

# Roadside LiDAR Sensors for Data Privacy Conform VRU Detection

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## Abstract

Detailed and reliable data is crucial to ensure the efficient, reliable, and safe operation of future transportation networks. However, the more detailed the information about traffic participants is, the less data privacy regarding individual mobility patterns or identification of individuals is typically guaranteed. This work presents the use of roadside LiDAR sensors for the detection and tracking of vulnerable road users (VRU) and vehicles in a privacy-compliant way based on an exemplary hardware setup. The described data processing approach enables numerous use cases in the fields of, among others, traffic monitoring, control, and safety analysis.

**Keywords:** LiDAR, Light Detection and Ranging, VRU, Vulnerable Road Users, Data Collection

## Introduction

LiDAR (Light Detection and Ranging) technology uses laser beams to measure distances and create high-resolution 3D models of the sensor's environment, including both static and dynamic objects. LiDAR sensors always incorporate two main components: A transmitter that emits light pulses with typical wavelengths between 250 to 1600 nm and a receiver that collects the reflected light pulses, converts the optical signal into an electrical quantity, and calculates the elapsed time between light pulse emission and collection of reflected photons. From this elapsed time, the distance between the LiDAR transmitter and the target reflecting the light pulse can be calculated (Roritz et al., 2022). LiDAR sensors can be categorized according to the beam steering of the emitted light pulse: Mechanical LiDAR sensors utilize a rotating assembly to create wide (typically 360°) fields of view (FOV), whereas solid-state LiDAR sensors avoid the use of rotating mechanical components leading to lower signal-to-noise ratios, narrower FOV and lower acquisition costs (Yahyaei et al., 2022; Khader et al., 2020).

Application-wise, LiDAR sensors can be grouped into stationary systems, mobile systems, and airborne systems. While mobile LiDAR systems are installed on road vehicles, trains, or boats and collect data within the flow of traffic, airborne LiDAR systems are mounted on aircrafts and capture features of the ground and built environment. Contrary to mobile and airborne systems, stationary LiDAR's are typically mechanical sensors installed at a fix position in the infrastructure (e.g., on a traffic pole) and they monitor a wide FOV around the sensor (Chang et al., 2014). Recently, pilot tests have been conducted to gather knowledge about optimal sensor installation heights and limitations of the system. A minimum installation height of 2.0 – 2.5 m is recommended in several publications to minimize occlusion effects limiting the detection accuracy. Furthermore, the use of several sensors at one location has proven to minimize occlusions due to the fusion of the data gathered by the individual sensors (Xu et al., 2018; Zhang et al., 2019).

In urban traffic, particularly at intersections, complex situations arise as multiple road users compete for limited space and collisions with motorized vehicles pose a high risk of severe injuries for VRU such as pedestrians and cyclists (Denk et al., 2022). Stationary LiDAR systems, capable of detecting motorized vehicles as well as VRU, could enable new urban traffic control and safety applications (Álvarez-Ossorio et al., 2023). In this paper we illustrate the use of roadside LiDAR systems for urban traffic control and safety applications by presenting the data collection process as well as the subsequent data processing of an exemplary hardware setup installed at a university campus in Germany. The outcome of the raw data processing is an object list containing information about all road users, which is suitable for utilization in numerous urban traffic control and safety applications.

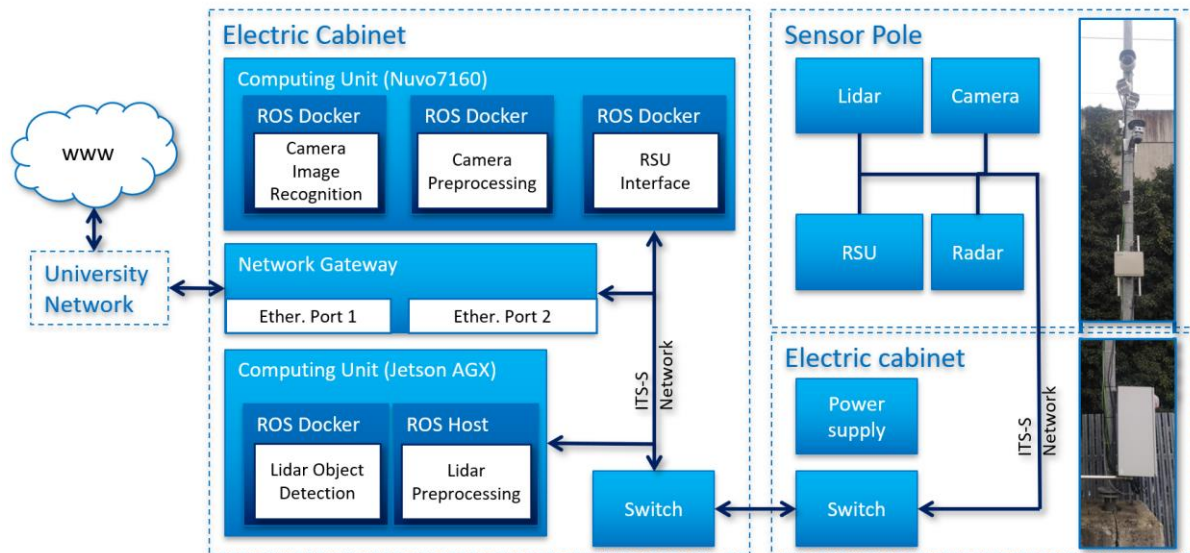
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## Methodology

The exemplary hardware setup shown in **Figure 1** was installed at the campus of the University of Applied Sciences Augsburg and consists of a sensor pole and an electric cabinet. The sensor pole holds the LiDAR sensor system used for this study as well as a roadside unit (RSU) for communication with connected vehicles and further stationary sensors. The used LiDAR system consists of two mechanical LiDAR devices: A mid-range 360° sensor (Ouster OS1-64) enables the detection of objects in a distance of up to 75 m to the sensor system, while a complementary blind spot sensor (RS-Bpearl) ensures the detection of objects closer to the sensor system.

**Figure 1.** Exemplary hardware setup, including network connections and computing units.



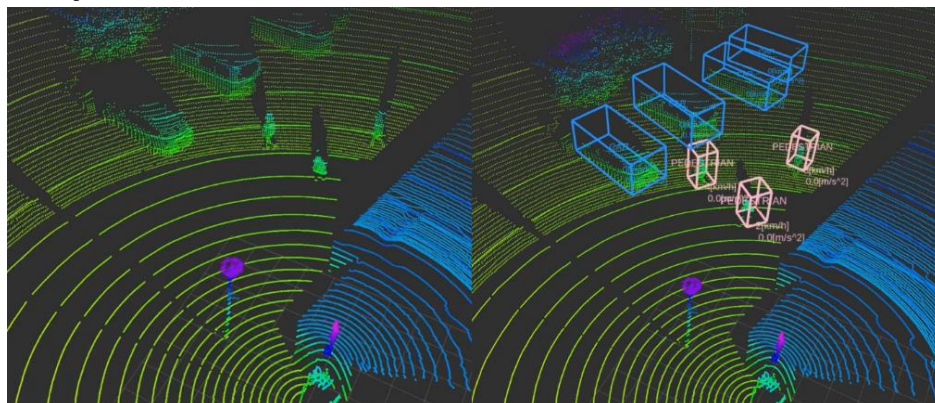
Source: Own elaborations

The LiDAR sensor system (as well as the RSU and further sensors) is bi-directionally connected to the local network through a Power-over-Ethernet (PoE) switch, ensuring the transmission of the collected raw data to the computing units. The computing unit allocated to the LiDAR sensor system is responsible for the pre-processing and object detection from the transmitted LiDAR raw data, resulting in an object list containing information about all road users. Additionally, an external network gateway enables remote access to the described system.

## Results

The raw data collected by the LiDAR sensors is a point cloud containing 3-dimensional coordinates and the intensity of reflection for each point sensed around the sensor. From this point cloud, a trained algorithm can detect different road users, classify them according to their type and track them over time. **Figure 2** shows a visualization of the LiDAR point cloud (left) as well as the subsequent object detection and classification (right) indicated by the bounding boxes around the objects.

**Figure 2.** LiDAR point cloud (left) with object detection and classification (right).



Source: Own elaborations

The visualization of the collected LiDAR point cloud shows the difference in the two individual LiDAR sensors: While the mid-range LiDAR provides a comparably dense point cloud after a certain distance to the sensor location, the blind-spot LiDAR senses the area closer to the sensor with a lower density. In addition, occlusions appear where objects reflect the emitted light pulses and prevent them from reaching surfaces behind the objects. Both the low density of the acquired point cloud and the presence of occlusion can lead to limited object detection and classification capabilities, which can be counteracted by the use of more than one sensor system as described earlier. The tracking of detected objects over several continuous measurements allows for the generation of object lists containing information about all road users. A schematic pseudo-object list corresponding to **Figure 2** is shown in **Table 1**. Every line of the object list contains the information of one object at a given Unix *timestamp*. When an object is detected for the first time it receives a unique numerical *id*, which is used in all future observations in which the system re-identifies that object. Furthermore, the type and dimensions of the bounding box are given for each object, as well as the position, heading angle, speed, and acceleration for each *timestamp*.

**Table 1.** Pseudo-object list corresponding to Figure 2

| Timestamp  | ID  | Classification | Position <sup>1</sup> x/y/z | Bounding Box Dimension x/y/z | Heading | Speed /Acceleration |
|------------|-----|----------------|-----------------------------|------------------------------|---------|---------------------|
| 1676019731 | 1   | Car            | 5.0/7.5/0.0                 | 2.7/5.5/1.7                  | 140°    | 0 / 0               |
| ...        | ... | ...            | ...                         | ...                          | ...     | ...                 |
| 1676019731 | 5   | Pedestrian     | 4.3/4.0/0.0                 | 0.4/0.4/1.7                  | 60°     | 1.2 / -0.08         |
| ...        | ... | ...            | ...                         | ...                          | ...     | ...                 |
| 1676019732 | 1   | Car            | 5.0/7.5/0.0                 | 2.7/5.5/1.7                  | 140°    | 0 / 0               |
| ...        | ... | ...            | ...                         | ...                          | ...     | ...                 |
| 1676019732 | 5   | Pedestrian     | 4.3/4.0/0.0                 | 0.4/0.4/1.7                  | 63°     | 1.1/ -0.02          |
| ...        | ... | ...            | ...                         | ...                          | ...     | ...                 |

(<sup>1</sup>) In a local or global coordinate system

Source: Own elaborations

## Conclusions

LiDAR sensors have numerous strengths -and some weaknesses- in comparison to alternative sensor technologies currently used in roadside monitoring applications such as inductive loops and video sensors. One of the clear advantages of LiDAR is its excellent capabilities for measuring distance, in theory with accuracies under a couple of centimeters for ranges over 150 meters, as opposed to several-meter accuracies obtained with video sensors (Berk, 2019). In practice, however, the LiDAR sensor's effective detection and tracking range is significantly smaller depending on the type of sensor, characteristics of the target object, environmental conditions, etc. (Zhang et al., 2020). Another relevant benefit of LiDAR technology is that it is based on active detection, rather than passive detection, and it therefore performs independently of the lighting conditions. Furthermore, LiDAR sensors do not record sensitive personal data (e.g., facial attributes, vehicle's plate number, etc.) and therefore overcome data privacy issues common with video recordings.

Among its main disadvantages, LiDAR sensors provide only a rough identification of the object contours due their limited angular resolution, nor detect the texture of the objects. Furthermore, the quality of the object detection is affected under severe weather conditions (e.g., fog, snow, and heavy rain), although to a much lesser degree than for video sensors. Besides, in most cases the negative weather impacts can be mitigated in the short and mid-range with additional signal processing (Van Brummelen et al., 2018). The high price of LiDAR sensors is a major obstacle hindering their popularization in roadside applications, but it has decreased significantly in the last decade and will continue to do so as it becomes more extended in the automotive industry. Furthermore, we argue that the life-cycle-cost rather than the acquisition cost of the sensors should be taken into account since the former might turn them competitive to conventional sensors (e.g., inductive loops). This is because LiDAR sensors are not affected by construction works and several lanes and approaches can

be monitored simultaneously with a single device (Sobie, 2016). The tracking of moving objects using only one LiDAR sensor still presents difficulties in contexts with frequent occlusions, particularly in areas with many pedestrians. However, this issue can be mitigated in the future by using sensors with higher resolution, implementing advanced tracking methods such as Kalman filters, and fusing the point cloud of several sensors located apart from each other (Margreiter et al., 2022).

As discussed in this work, LiDAR technology is an innovative and promising solution to perform roadside data collection of all traffic participants and it could provide valuable information to understand and model the complex interactions between different modes. This technology has gained maturity in the last decade and it is becoming more affordable. Besides, if future regulations ease the use of video sensors in public areas, it would be possible to fuse the data from video and LiDAR sensors. Thus, the former could capture the context, contribute to the classification and tracking of objects, and collect body pose information (valuable, for example, for short-term pedestrian movement prediction); while the latter could provide an accurate 3D map, speed measurements, etc.

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