An Automatic Procedure for Vehicle Tracking with a Roadside LiDAR Sensor

By Jianqing Wu

Connected-vehicle technologies, applications, and potential benefits have been studied in the United States since 2003 when the U.S. Department of Transportation (USDOT) initiated the Vehicle Infrastructure Integration (VII) program. With the real-time communication of vehicle-to-vehicle and vehicle-to-infrastructure, connected vehicles provide extended distance for drivers to “see” around corners or “through” other vehicles, so safety threats and traffic changes can be perceived earlier. Many potential benefits of connected vehicles, in the areas of highway safety, traffic mobility, and vehicle emissions, have been tested in pilot deployments in the United States. The full benefits of connected-vehicle systems need all vehicles to be equipped with connected-vehicle devices and broadcast their movement status in real time. However, the number of connected vehicles are still limited compared to the total number of vehicles on road. It was estimated that the mixed traffic with connected vehicles and unconnected vehicles will last for the next decade. Benefit from the fast development of intelligent transportation system (ITS) technologies, it’s possible to obtain real-time traffic data using loop detectors, video detectors, Bluetooth sensors, or radar sensors. But the data collected by those sensors do not meet the requirement of the connected-vehicle network.

Note: The paper was shortened from its original version for publication purposes.
The new light detection and ranging (LiDAR) sensors can detect the 360-degree surrounding objects with high accuracy and high frequency. During each scan, a LiDAR sensor collects a cloud of points with x, y and z coordinates of surrounding objects. LiDAR sensors work in days and nights without the influence of light condition. By setting up the LiDAR sensor along the roadside, high-resolution traffic data of the whole road network can be obtained. The high-resolution traffic data from the roadside LiDAR sensors can be coded into safety messages and broadcasted through the roadside DSRC devices to connected vehicles, pedestrians, and bicyclists. Any vehicles, pedestrians, and bicyclists with connected-vehicle devices will immediately benefit from the roadside LiDAR data.

Since roadside deployment serving connected-vehicle is a new application of the LiDAR, there are no existing algorithms that can process the LiDAR data directly. The purpose of this paper is to provide a procedure and related methods for LiDAR data processing. The procedure includes three major parts: background filtering, lane identification, and vehicle speed tracking. The vehicle can be continuously tracked with the proposed method.

### Roadside LiDAR Sensor

This research applied the Velodyne VLP-16, a cost-efficient 360-degree LiDAR sensor for analysis. The sensor has a detection radius of 100 meters and is designed for various applications, such as autonomous vehicles, robotics, and 3D mapping. It has 16 laser beams, collects data at the speed of 300,000 points/second, and covers a 360-degree horizontal field of view and a 30-degree vertical field of view with ±15 degrees up and down. The LiDAR sensor can be temporarily installed on a tripod for pilot study or permanently installed on roadside structures for long-term data collection.

The points cloud collected by roadside LiDAR sensor contains all objects in the scan range. Figure 1 shows the points cloud collected by VLP-16 LiDAR sensor temporarily installed at one intersection. In this frame, there are more than 18,000 points which form the shape of different objects.

#### Background Filtering and Lane Identification

##### Background Filtering

The background points include buildings, trees, ground points, et al. Without excluding background points, it is difficult to cluster and identify the vehicle points correctly. An automatic 3D-density-statistics-background-filtering (3D-DSF) algorithm was developed by the authors. The idea of the 3D-DSF was briefly summarized as follows. The algorithm firstly collects raw data in a period as initial input. The raw data are then aggregated into one 3D space based on their coordinates. The 3D space is then divided into multiple cubes for density statistics. Each cube can be identified as a background space or not. The point density in each cube can be calculated. Compared to the group of background points and ground points, the number of moving vehicle points is fewer. Some cubes can be identified as background space by giving an appropriate threshold. The threshold should be different

![Figure 1. Roadside LiDAR data.](image-url)
with different sites and varies with the number of objects in the aggregated frames. A detailed automatic threshold learning method was documented by the author in a previous study. The location of the background can be then stored in a profile (3D matrix). For real-time data processing, the points in each frame are firstly transferred into a 3D matrix and then compared with the location of background profile. Any point found in the location of background profile is then excluded from the database. Figure 2 shows an example of background filtering. The red points in Figure 2 are identified as background and excluded from the raw LiDAR sensor. The green points are identified as non-background (vehicle). The further before and after evaluation shows that the algorithm can exclude more than 97 percent of background points, and keep about 98 percent of vehicle points at the same time.

**Lane Identification**

Lane location is helpful to get lane-based traffic information. A lane identification algorithm- multi rectified density-based spatial clustering of applications with noise (MCDBSCAN) was developed by the author for lane identification. The idea of the MCDBSCAN is that after background filtering, the density of vehicle points should be much higher than other objects if multi frames (such as 1500 frames) are aggregated together. Similar with 3D-DSF, the whole space (here is 2D space) can be divided into small squares. Then by searching the squares with high vehicle points density, the squares representing road areas can be identified. The road boundary can be further extracted by searching the boundary of those squares representing road areas. The lane locations can be detected from road boundary with the width of the lanes.

**Vehicle Tracking Methodology**

After background filtering and lane identification, there are only vehicle points left on the road. To track the vehicles’ speed and location, points belonging to one vehicle need to be clustered into one group. Then the group can represent the vehicle and be continuously tracked. The vehicle tracking includes two parts: vehicle clustering and vehicle continuous tracking. The number of vehicles in one frame can be identified through vehicle clustering and the speed of each vehicle can be calculated through continuous tracking step.

**Vehicle Clustering**

Density-based clustering is very suitable for vehicle clustering in LiDAR data as the point density of vehicles is much higher compared with other area in the space. The density-based spatial clustering of applications with noise, also known as DBSCAN, is very effective to cluster density related points in the space.

Another advantage of DBSCAN is this algorithm does not need to know how many vehicles are on road in one frame. DBSCAN can learn the number of clusters automatically. The DBSCAN algorithm requires 2 parameters – epsilon (ε), which specifies how close points should be to each other to be considered a part of a cluster; and minimum number of points (MinPts), which specifies how many neighbors a point should have to be included into a cluster. For the same vehicle, the number of points varies with its distance to the LiDAR sensor. The number of points increases when the distance between the vehicle and LiDAR sensor decreases. If ε is too big, it may cluster two vehicles with small headway into one vehicle. If ε is too small, it may cluster one vehicle into several vehicles. And for MinPts, if the value is too big, vehicle with few points may be considered as noise. If MinPts is too small, the noise left by the background filtering may be clustered into the vehicle. The recommended value for ε is 1.2m and the recommended value for MinPts is 10 based on using the regression method introduced by Wu, et al. The testing results showed that the location of vehicles can be accurately matched to the corresponding lane.

**Vehicle Continuous Tracking**

To continuously track the speed and location of vehicle, it is necessary to select a representative point (tracking point) for the clustered group. A lot of previous studies used average location of all points (average point) in one group for vehicle tracking. But using average point may cause large errors as the location and number of points for one group varies with the distance from the LiDAR sensor, as shown in Figure 6. This algorithm selects

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**Figure 2. Background filtering result.**
the point nearest to the LiDAR in the vehicle as tracking point to reducing the error caused by the variance of average point. More specific, when vehicle is approaching the LiDAR, the nearest point is the front corner point. When vehicle is leaving the LiDAR, the nearest point is the back corner point. The Global Nearest Neighbor (GNN) was applied to track the same vehicles in different frames. The algorithm tracks the front key point when the vehicle approaching the sensor and tracks the back corner key point when the vehicle leaving the sensor. An analysis was performed to justify that the vehicle travel distance between adjacent frames (at 10 Hz) is much shorter than the distance between continuous vehicles in a road lane, so the GNN method works accurately in this process. Figure 3 presents the comparison of frame-to-frame travel distance and distances between different vehicles in the same lane. The curves of 1-second headway, 2-second headway, and 3-second headway describe the closest vehicle distance in one lane with different headways and different travel speeds. The curve of frame-to-frame distance at 10 Hz presents the travel distance of the same vehicle between adjacent frames (recorded at 10 Hz) at different travel speeds. The comparison shows that the vehicle travel distance between adjacent frames is much shorter than the distance between vehicles in the same lane. The customarily-suggested headway is 3 seconds for traffic safety. Although the chart is the comparison of the distance of vehicles in the same lane, similar traffic headways are needed when a vehicle changes lanes. Therefore, the GNN method can be used to track same vehicles efficiently in different frames.

**Case Study**

Two field tests were conducted to evaluate the accuracy of the vehicle tracking algorithm. The first test site is located at the T intersection of North Virginia Street at 10th Street in Reno, NV, USA. North Virginia Street is a two-way arterial road serving the major north-south urban traffic of Reno. This field test is used to evaluate the accuracy of identifying number of vehicles in one frame. The LiDAR is mounted on a tripod for short-term data collection. A 360 degree camera is installed near the LiDAR sensor to record the vehicle volume. Figure 4 shows the overview of the field test. The continuous frames of LiDAR data were made into a video and was uploaded onto YouTube, which can be reviewed through the link: https://youtu.be/3Y5zWVQKuhA.

The number of vehicles in each frame was extracted using the vehicle tracking method. Two students were employed to extract the number of vehicles by reviewing the videos to evaluating the accuracy. Table 1 shows an example of the evaluation results.

<table>
<thead>
<tr>
<th>Cumulative number of checking frames</th>
<th>10</th>
<th>20</th>
<th>30</th>
<th>40</th>
<th>50</th>
<th>60</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cumulative number of vehicles from the algorithm (NVA)</td>
<td>29</td>
<td>53</td>
<td>84</td>
<td>115</td>
<td>149</td>
<td>170</td>
</tr>
<tr>
<td>Cumulative number of vehicles by reviewing the LiDAR video and 360° video (NVV)</td>
<td>30</td>
<td>56</td>
<td>87</td>
<td>119</td>
<td>153</td>
<td>175</td>
</tr>
<tr>
<td>Cumulative Difference (NVV-NVA)</td>
<td>1</td>
<td>3</td>
<td>4</td>
<td>4</td>
<td>5</td>
<td></td>
</tr>
</tbody>
</table>

As shown in Table 1, not all vehicles can be detected by the algorithm in all frames. A further examination was conducted to identify the reason of vehicle missing in the results. By manually checking the video, it was found that the reason is vehicle occlusion issue, which means some vehicles were blocked by others. The vehicle occlusion can be eliminated by setting up multiple LiDAR sensors around the road with different directions.

The second site was selected in one parking plot in Northern area of University of Nevada, Reno to examine the accuracy of speed tracking. An onboard data logger with GPS antenna was installed on the testing vehicle to collect the speed through the On-board diagnostics (OBD) system and GPS location. The logger can collect the location and speed every 1 second. The LiDAR sensor with GPS antenna is installed along the roadside to collect the speed. The LiDAR sensor collected the location and speed every 0.1 second. Based on the GPS location of LiDAR, all of the points of LiDAR data can be matched to the corresponding location of the real world. The comparison of speed from OBD and tracking procedure is shown in Figure 5.

As shown in Figure 5, there are some variance in the speed obtained from tracking procedure. The speed variance is caused by the anomalous shape of vehicles scanned by LiDAR sensor. It is clearly shown that tracking the newest point can generate better speed estimation compared to tracking average point. Table 2 shows

![Figure 3. Comparison of frame-to-frame travel distance and distances between different vehicles in the same lane.](image-url)
the statistic results of the difference between speed from OBD and the proposed tracking procedure in Figure 5.

Table 2 Evaluation of Vehicle Tracking Method

<table>
<thead>
<tr>
<th>Speed from OBD (mph)</th>
<th>Tracked Speed (mph)</th>
<th>Speed Difference (mph) = Tracked Speed - Speed from OBD</th>
</tr>
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<tbody>
<tr>
<td>79</td>
<td>8.405525744</td>
<td>0.505525744</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0.3</td>
<td>0.594891824</td>
<td>0.294891824</td>
</tr>
<tr>
<td>1.17</td>
<td>0.259216607</td>
<td>-0.910783393</td>
</tr>
<tr>
<td>5.4346</td>
<td>6.346181216</td>
<td>0.911581216</td>
</tr>
<tr>
<td>9</td>
<td>9.093832182</td>
<td>0.093832182</td>
</tr>
<tr>
<td>12</td>
<td>12.96395329</td>
<td>0.963953294</td>
</tr>
<tr>
<td>12</td>
<td>11.4831078</td>
<td>-0.516892204</td>
</tr>
<tr>
<td>14</td>
<td>13.90884553</td>
<td>-0.091154468</td>
</tr>
<tr>
<td>17</td>
<td>18.11875783</td>
<td>1.11875783</td>
</tr>
<tr>
<td>Abs (Min Speed Difference)</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Abs (Max Speed Difference)</td>
<td>1.11875783</td>
<td></td>
</tr>
<tr>
<td>Cumulative Speed Difference</td>
<td>2.369712</td>
<td></td>
</tr>
</tbody>
</table>

Note: Time interval in Table 2 is 0.1 seconds.
As is shown in Table 2, there are some differences between tracked speed and the speed obtained from OBD. In general, the speed given by tracking algorithm fluctuates around the OBD speed. The max speed difference happens at the location when the vehicle has higher speed. The statistic results show that 90 percent of speed difference is less than 1.0 mph. The current algorithm can detect the vehicle with a max distance of 29.06m from LiDAR sensor in this pilot study. Vehicles with a distance more than 29.06m did not have a clear shape, which limits the tracking range of current procedure.

**Conclusion and Discussion**

This paper presents a novel application of LiDAR as the roadside sensor, which provide a solution to collect the real-time information of non-connected vehicles under the mixed traffic situation. A systematic procedure is documented for vehicle tracking with roadside LiDAR sensor. The entire procedure includes three major parts: background filtering, lane identification, and vehicle tracking. Two case studies were conducted to evaluate the effectiveness of the procedure. The results of the first study indicate that most vehicle can be detected by the algorithm except for the vehicle occlusion situation. The second field test shows that this procedure can track vehicle speed with a small variance using nearest points compared with average points.

This paper did not identify vehicle type because of the difficulty of vehicle classification from roadside LiDAR data. This paper can be considered as a first step for the application of LiDAR sensor in connected vehicle technologies. More effort is still needed in further studies. This paper did not provide vehicle type identification method as the shape of vehicle is not clear when the vehicle is far away from the sensor. But it is possible to estimate the vehicle type based on regression methods as point distribution of different type of vehicles is different at the same location. Another project that is expected to be conducted is how to distinguish vehicles, bicycles, and pedestrians in the LiDAR sensor. The shapes of vehicles and pedestrians are very different in 3D space, indicating the division of vehicles and pedestrians may work better considering the z-axis (height) information. As the VLP-16 sensor only has 16 beams, which did not often provide the whole shape of scanned objects in most position, the bicycles and pedestrians may not have obvious different shapes in the LiDAR data. The classification of bicycles and pedestrians may mainly rely on speed instead of shape. As seen in the case study, the range of current vehicle tracking procedure is around 30m within the LiDAR sensor. The detection range may be expanded by applying new algorithms or deploying multiple sensors on the road. How to integrate multiple LiDAR sensor can be another research topic.

**References**


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