Road Markings Segmentation from LIDAR Point Clouds using Reflectivity Information

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Abstract—Lane detection algorithms are crucial for the development of autonomous vehicles technologies. The more extended approach is to use cameras as sensors. However, LIDAR sensors can cope with weather and light conditions that cameras can not. In this paper, we introduce a method to extract road markings from the reflectivity data of a 64-layers LIDAR sensor. First, a plane segmentation method along with region grow clustering was used to extract the road plane. Then we applied an adaptive thresholding based on Otsu’s method and finally, we fitted line models to filter out the remaining outliers. The algorithm was tested on a test track at 60km/h and a highway at 100km/h. Results showed the algorithm was reliable and precise. There was a clear improvement when using reflectivity data in comparison to the use of the raw intensity data both of them provided by the LIDAR sensor.

I. INTRODUCTION

Nowadays, lane-detection algorithms are crucial for the implementation of Advanced Driving Assistant Systems (ADAS) with different levels of autonomy such as Lane Keeping Assistance (LKA), Lane Change Assistant (LCA), and Lane Departure Warning (LDW) among others. The development and deployment of vehicles with level 3 automation or higher (according to the automation levels represented in the Society of Automotive Engineers (SAE) J3016 standard [1], ranging from “no driving automation” (level 0) to “full driving automation” (level 5)) makes them even more important.

The estimation of the lane’s shape in structured roads very often relies on the white lines used as road markers and sometimes in the road curb itself. To their detection, most of the related works tend to process images taken by cameras located on the outside of the vehicle or installed under the windshield [2]–[4]. This image-processing approach exhibits great results under both, good lighting and weather conditions. However, it fails at nighttime, in bright sunlight, or under adverse weather conditions.

However, Light Detection And Ranging (LIDAR) sensors remain almost unaffected by poor lighting conditions [5] and provide an accurate and reliable way to measure the distances to objects around the vehicle. LIDAR prices have been dropping over the last few years resulting in a wider deployment and use in the autonomous vehicles field.

Since the lane-markings reflectivity is improved by reflective glass beads embedded in the surface of the paint, the intensity of the reflected laser beam is expected to be higher than the intensity of the beams reflected by the rest of the road (asphalt or concrete) [5]–[9]. However, the beam intensity is also affected by the distance to the target and the incidence angle against the surface. In recent years, LIDAR’s manufacturers like Velodyne Lidar and Ouster have begun to offer reflectivity information along with the intensity and range signals. Reflectivity data indicates information about the inherent reflective property of the target, being not affected by lighting conditions and range [10]. Therefore reflectivity is a powerful tool for road markings detection as can be seen in Figure 1.

In this paper, we review several road-marking detection algorithms (section II) primarily based on LIDAR intensity, range, or both. Later on, we propose our method to segment road-markings from LIDAR point clouds using the reflectivity information instead of the intensity channel. The whole procedure was implemented using the Point Cloud Library (PCL) [11] in C++ ensuring compatibility with Robot Operating System (ROS) among other common frameworks. The detailed description is in section III. The procedure was tested with two different datasets (section IV) and the results (sections V) demonstrate that the use of reflectivity information provides better results than intensity. Finally, the section VI concludes the present work outlining future research.

II. RELATED WORK

Vision-based works are not included in this section as they are outside of the scope of the study. Nevertheless, a full review can be found in [2].

Fig. 1. The same point cloud from the test track was colored based on the level of reflectivity (a) and level of intensity (b).
In [9] a 6-layers LIDAR sensor, with only three layers facing the ground, was used. A hybrid approach using range and intensity information was presented and the Otsu’s method [12] was used to distinguish between the road surface and lane marker signals [12]. A detailed analysis regarding the material of the road (asphalt vs concrete), the type of road markings (plain vs raised), and different weather conditions (rain, sun, and night) were presented as results. However, the study did not present quantitative results.

In [5] the authors presented a method for offline annotation of lane-markings. The lane-marking candidate points were detected as local maxima with an intensity value greater than a dynamic threshold. Odometry data was used to keep track of successive scans and the final candidates were then classified between solid or dashed lane-markings.

Both studies [10] and [13] achieved lane-markings detection using reflectivity information and tracking based on Extended Kalman filter. In [10], authors initially stacked consecutive one-dimensional LIDAR scans to generate a reflectivity map or image, which was processed using common image processing techniques (binarization, Canny filtering, fixed thresholding). Afterword, they generated the underlying lane model by approximating the filtered points using the Hough transform. In [13], authors used a Finite Impulse Response (FIR) bandpass filter on a 64-layer LIDAR sensor to remove noise. Then a fixed threshold was applied to obtain candidate line points. Finally, the authors fitted these points to clothoid curves to obtain the road markings.

In [14], the authors detected the road-marking points using a fixed threshold over the intensity channel of a 32-layers LIDAR sensor. First, the authors detected the road lines by searching for a set of parallel lines integrated into a digital map using a GNSS/INS system. They then used an expectation-maximization method to detect parallel lines. The same LIDAR was used in [15], where a modified version of Otsu’s method was applied to each scanned line. Then, a localization method based on the extracted road markings was presented. Finally, the resulting algorithm was improved in [15] and validated with a real test.

In [7] and [16], the intensity scans from an RS-LiDAR-16 were processed with a multi-threshold variation of Otsu’s method to determine road-markings candidate points. These candidates were then filtered with a Random sample consensus (RANSAC) line model.

In [8], the authors proposed a method based on map localization. The method relied on road lane markings detection. Under the assumptions of flatness and smoothness of highway road surfaces, a ring analysis was performed to determine the points over the road surface. Then, an intensity-based thresholding was applied to extract the road marking points. Finally, these detected lane markings were matched to an HD map using a Particle Filter (PF).

In [17] the authors used LIDAR scans to determine virtual lanes not related to the real lane-markings. First, a height-based filter eliminated the points of the road surface. Then, an unsupervised segmentation algorithm was run to cluster the points. Clusters with similar lateral positions were merged and two independent circular models were fitted to the clusters forming the so-called virtual lanes. A similar approach for unstructured roads was presented in [18].

The authors of [19] used a roadside LIDAR for lane detection. The approach consisted of identifying the ground plane, extracting the lane marking points based on the difference in laser intensity, and dividing the ground within the range of LIDAR scanning into different stripes to extract the lane markings.

III. IMPLEMENTATION

Our developed procedure comprises two main blocks with several sub-processes. The complete procedure is depicted in Figure 2 and the detailed explanation is depicted in the sections below.

Consider a LIDAR sensor with $N_L$ layers and $N_P$ points per layer. A single scan of the LIDAR sensor produces a pointcloud $\mathbf{P}_A$ defined as a $N_L \times N_P$ set of points $\mathbf{p}_{ij} \in \mathbb{R}^6$:

$$\mathbf{p}_{ij} = [x_{ij} \ y_{ij} \ z_{ij} \ r_{ij} \ I_{ij} \ R_{ij}]$$

(1)

For each point $\mathbf{p}_{ij} \in \mathbf{P}_A$, the following quantities are defined:

- $x_{ij}, y_{ij}, z_{ij}$ are the 3D spatial coordinates of the point from the LIDAR reference frame.
- $r_{ij}$ is the distance (range) from the LIDAR reference frame to the point.
- $I_{ij}$ and $R_{ij}$ are the intensity and reflectivity levels respectively.
- $i$: is the $i$-th layer in which the point is located, indicated by an integer between 1 and $N_L$.
- $j$: is the $j$-th point index within the layer indicated by an integer between 1 and $N_P$.

A. Pre-filtering

Point clouds obtained from multi-layer 3D-LIDAR sensors contain massive amounts of data. Thus, it is important to reduce the size in order to improve the processing speed in
further steps. Getting rid of non-relevant information is the best way to achieve this reduction. Therefore, we implemented a pre-filtering method that relied on the following two sources of spatial information for each point in the point cloud:

- **Layers reduction**: We first filtered out the LIDAR layers that were scanning above the horizon, as they acquired data from objects in the environment that are utterly irrelevant for the algorithm (buildings, trees, traffic signs, etc). In our implementation, we used only the 30 lower layers of our 64-layers LIDAR.

- **Height-based filter**: Similarly, we performed a filtering over the $z$-axis (perpendicular to the floor), by keeping the points between a lower ($z_L$) and upper threshold ($z_U$).

Consider $P^A$ as the original pointcloud, then, the pre-filtered pointcloud $P^B \subset P^A$ is a set obtained by the following rule:

$$P^B = \{ \mathbf{p}_{ij} \in P^A : Z_L \leq z_{ij} \leq Z_U, 0 \leq j < N_P \} \quad (2)$$

**B. Road plane segmentation**

Once the points are limited to the vicinity of the road plane, we used RANSAC as an iterative method to find the plane model $(a, b, c, d)$ which best fits the point cloud $P^B$. We then filtered the points that did not fit into the plane model within a threshold ($TH_{plane}$) obtaining a new pointcloud $P^C$ defined as:

$$P^C = \{ \mathbf{p}_{ij} \in P^B : |ax_{ij} + by_{ij} + cz_{ij} + d| \leq TH_{plane} \} \quad (3)$$

An example of the results after executing the pre-filtering along with the plane segmentation can be seen in Figure 3a.

**C. Region growing clustering**

A region-growing clustering was implemented in order to filter out points that did not belong to the road but the curb, the sidewalk, or other low-height structures. For each point, we analyzed the vicinity to find the $K_{RGC}$ nearest neighbors and then estimated the normal to the neighbors’ surface evaluated in the original point. Then, the clustering algorithm selected a point in the cloud and started growing a region iteratively based on two thresholds. When the angle between two points’ normals was less than $TH_{angle}$ and the difference between their curvatures was less than $TH_{curvex}$, they were considered to be in the same region. An example of the resulting point cloud after the execution of the clustering is depicted in Figure 3b.

**D. Adaptive thresholding**

Since the LIDAR layers $(i)$ could differ in calibration, the reflectance of the same object could produce different values in two different layers. Thus, a different threshold was calculated for each one of the layers $(i)$. First, a reflectivity histogram $(h_i(k))$ of size $N_{bins}$ was built considering the $N_{P_i}$ points inside each one of the layers $(i)$.

At this point, a threshold was applied across the reflectivity channel to split the remaining data points between two possible classes: road ($C_R$) and road markings ($C_M$). As seen in the literature, Otsu’s method [12] is widely used to find the threshold that maximizes the inter-class variance ($\sigma^2_R(t)$) (or in other words minimizes the intra-class variance) [7], [9], [15], [16].

$$\sigma^2_R(t) = \omega_R(t)\omega_M(t)(\mu_R(t) - \mu_M(t))^2 \quad (5)$$

Where $\omega_R(t)$ and $\omega_M(t)$ are the probabilities of two classes separated by a threshold $t$ and $\mu_R(t)$ and $\mu_M(t)$ are the respective averages. All of them were calculated as follows:

$$\omega_R(t) = \sum_{k=0}^{t-1} h_i(k) \quad (6)$$

$$\omega_M(t) = \sum_{k=t}^{N_{bins}} h_i(k)$$

$$\mu_R(t) = \frac{\sum_{k=0}^{t-1} k \times h_i(k)}{\omega_R(t)}$$

$$\mu_M(t) = \frac{\sum_{k=t}^{N_{bins}} k \times h_i(k)}{\omega_M(t)}$$

In order to speed up the processing time and reduce the number of points with low reflectivity values, we proposed an initial
threshold similar to the one presented in [7] and [16]. We calculated the mean value of reflectivity ($\bar{R}_i$) along with the variance ($\text{VAR}(R_i)$) across all the points ($j$) in layer ($i$):

$$\bar{R}_i = \frac{\sum_{j=1}^{N_{Pi}} R_{ij}}{N_{Pi}}$$

$$\text{VAR}(R_i) = \frac{\sum_{j=1}^{N_{Pi}} R_{ij}^2}{N_{Pi}} - \bar{R}_i^2$$

Then, the computation of the adaptive threshold was executed as follows:

- A layer $i$ was selected and the histogram $h_i(k)$ is calculated.
- Set up an initial value for $\omega_{R,M}(0)$ and $\mu_{R,M}(0)$.
- An iterative process was executed across all the possible values of $t$ starting with $t = \bar{R}_i + \text{VAR}(R_i)$ as the initial value instead of 0.
- $\sigma^2_b(t)$ was calculated.
- The maximum value of $t$ was chosen as the final threshold.
- All the points with a reflectivity value equal or greater than the threshold were marked as road markings candidates.

Figure 3c shows that most of the points that were not related to the road markings were removed from the original point cloud. However, there were still outliers to be treated with the next step.

E. Line fitting

We applied RANSAC as an iterative method to find the line models which fit the road markings candidates resulting from the previous step. Once a line model was found, the supporting points were removed from the cloud and another line model was sought. The algorithm stopped when a maximum number of lines were found ($N_l$) or when the last line model found was supported by a small number of real points ($\leq N_p$). In Figure 3d, the lines and their supporting points detected as road-markings are depicted in red. The lines and points that were rejected by the algorithm due to too few supporting points are depicted in light blue.

IV. Experiments

A. Setup

To acquire the pertinent data to test the proposed approach we relied on the JKU-ITS research vehicle (See Figure 4). It consisted of a 2020 hybrid RAV4 from Toyota geared with an OS2-64 LIDAR as well as an IMU, GPS, and a monocular camera [20]. The acquisition system was based on ROS running in a laptop connected to the sensors. The vehicle was used to record two different datasets on which the algorithm was tested afterwards. The final values set for the different variables described in section III are depicted in Table I.

From each dataset, we randomly selected 200 frames and then ran them through the algorithm offline. The metrics we chose to evaluate the result were precision, recall, and F1-score which are widely used in the literature [7], [16], [21].

To this end, we first defined:

- True Positives ($TP$): points marked as road-markings that supported a line that was in fact a lane-marking on the road.
- False Positive ($FP$) = points marked as road-markings that supported a line that was not a lane-marking.
- False Negatives ($FN$) = Points filtered out but that supported a line that was in fact a lane-marking on the road.

Then, we calculated the metrics according to [21]:

\[
\text{Precision} = \frac{TP}{TP + FP} \tag{8}
\]

\[
\text{Recall} = \frac{TP}{TP + FN} \tag{9}
\]

\[
\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{10}
\]

In order to assess the differences between reflectivity and intensity data from the LIDAR, we also ran the intensity data through our algorithm just by changing the data used to build the histogram described in section III-D.

B. Test track dataset

This dataset was recorded in the Digitrans test track [22] located at St. Valentin, Austria, and the technical details are described below:

- 1100m total longitude (940m straight). 8m wide two-lanes track.

\[
\begin{array}{ll}
\text{Variable} & \text{Value} \\
Z_l & 1.44m \\
Z_u & 2.44m \\
TH_{\text{plane}} & 0.30m \\
K_{\text{RGC}} & 30 \\
TH_{\text{angle}} & 2^\circ \\
TH_{\text{curve}} & 1 \\
N_{\text{bins}} & 256 \\
N_L & 10 \text{ lines} \\
N_P & 10 \text{ points} \\
TH_{\text{lines}} & 0.15m
\end{array}
\]

Fig. 4. The JKU-ITS research vehicle [20] was used to collect the data.
Fig. 5. (a) and (b) depict the point clouds (dark gray) recorded when traversing the 6-lane segment of the test track. Red points are the detected road markings and blue lines indicate the line models. (c) and (d) shows the onboard camera images at the same time that (a) and (b) were recorded. In (c) the sun was in front of the vehicle making lane determination difficult with an image-only approach.

- There is a middle segment of 450m with 6-lanes and 20m wide.
- Left curve minimum radius 45m.
- Right curve (Roundabout) minimum radius 48m.
- Different types of markings: flat thin-layer and structured road markings, white and orange (Delivered and applied by SWARCO Road Marking Systems [23]).
- Main material: asphalt. There are other side roads made out of concrete.

To validate our proposed algorithm we acquired data on lightning conditions that interfere with the camera of the car. We made sure to drive through the test track during sunset hours to obtain conditions where the sun faced directly to the front of the car when driving one way.

C. Highway dataset

This dataset was acquired in two different locations. The first one was a segment of the A7 highway around Linz in Austria during regular traffic conditions and typical daylight. The second location was a segment of the A3 highway near Bonn in Germany during regular traffic under low light level (cloudy evening). Unlike the first dataset, in this one there were occlusions caused by other vehicles on the road as well as road-markings in bad conditions. On the other hand, this dataset had no pronounced curvatures, which was advantageous for the representation of straight segments used in the developed algorithm.

V. RESULTS

The detailed results from both datasets are depicted in Table II. The best results were obtained on the test track where road markings are kept in good condition. In the highway dataset, there is a slight reduction in the F1 score due to two reasons. First, the road markings conditions were not the same as in the test track. Second, the vehicle was driven at high speed. This made the detection of the points over the dashed center-line difficult. At high speed, the points supporting the dashed center-lines are too sparse and the algorithm filtered them out (as can be seen in Figure 6). As can be seen in Figure 5, our algorithm was not restricted to identifying the lane-lines where the vehicle was traversing but almost all the supporting points of the available lane-lines on the road.

It is also reliable under different lighting conditions, with no detectable differences along the three lighting levels that were tested: high light level when the vehicle was driven with the sun in front; normal lighting level (daylight); and low level of light (cloudy evening). The results depicted in Table II and Table III show a slight advantage when using reflectivity data instead of intensity data when both channels are run through the exact same algorithm thus confirming the hypothesis proposed in this work.

VI. CONCLUSION AND FUTURE WORK

In this paper, we introduced a method to detect road-marking points from LIDAR data. In contrast to currently available methods, our procedure was not limited to the current lane the vehicle is traversing and was able to extract the road markings from all the lanes of the road which is an important feature for lane changing algorithms. The results showed an improvement just by using the reflectivity data
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Currently, we are working to add a tracking system to preserve the road-marking information over time and reduce the detected false negatives. In the near future, we plan to substitute the line models described in section III-E with semicircular arcs to improve the detection in curves. We also plan to test the procedure in other environmental conditions like haze, light snow, and nighttime.

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