

Road Profile Analysis Based on Elevation Map with LiDAR for Autonomous Driving

Kosuke Suzuki¹⁾ Ryo Yanase²⁾ Keisuke Yoneda²⁾ Naoki Suganuma²⁾

1) Kanazawa University, Kakumamachi, Kanazawa, Ishikawa, 920-1192, Japan (E-mail: k_suzuki@stu.kanazawa-u.ac.jp)

2) Kanazawa University, Kakumamachi, Kanazawa, Ishikawa, 920-1192, Japan

KEY WORDS: Safety, Intelligent vehicle, Road environment recognition, Elevation map, LiDAR [C1]

Today, the development of autonomous driving technology is being actively pursued internationally. In the driving environment of autonomous vehicles, there may be obstacles such as falling objects and unevenness due to the topography, aging, and road structure. In order to realize safe and comfortable driving, autonomous vehicles must be able to recognize these factors in real time and decelerate, stop, or avoid them appropriately. As a method of recognizing the surrounding environment using LiDAR (Light Detection and Ranging), obstacles are detected based on a single frame of 3D point clouds, and an obstacle map is created to show the relative positions of the obstacles. However, this method can't continuously detect obstacles as small as a curb because the density of the point cloud becomes sparse in the far distance. Such undetection has a significant negative impact on driving safety and comfort. Therefore, in this study, DEM (Digital Elevation Map) by LiDAR is used to detect short obstacles and unevenness. A DEM is a map that represents the topography around a vehicle by recording height information, and can be generated densely by accumulating 3D point clouds in time series. This research proposes a method for creating a map that expresses the degree of unevenness as a driving risk value (hereinafter called driving risk map) in order to enable autonomous vehicles to operate their speed in response to road surface unevenness.

The following procedure is used to create a driving risk map. First, a DEM is created for one frame from the 3D point clouds. To prevent influence from moving objects, the corresponding point clouds is rejected based on the coordinate information of the moving object. Then, the DEM is mapped to the DEM accumulated up to the previous frame, and the DEM is updated using statistical methods such as minimum variance estimation. By repeating the above operations, a high-density DEM can be obtained. However, this DEM contains steady road gradients and noise, making it difficult to distinguish between the unevenness to be detected. Therefore, the absolute coordinate system DEM is leveled with respect to the vehicle's attitude, and only edges caused by the gradient of unevenness are extracted by filtering such as noise removal and first-order differentiation. The degree of unevenness is then normalized by a certain criterion to obtain a driving risk value that indicates the need to slow down or stop at each location. This mapping of driving risk values is called a driving risk map.

Next, the results of the driving risk map generation are evaluated. Fig. 2 shows the results of outputting the driving risk map in an environment with curbs and speed bumps as shown in Fig. 1. The degree of unevenness corresponds to the shade of color, indicating that curbs and speed bumps can be detected separately. Furthermore, the detectable distance of continuous curbs is compared with the conventional method based on clustering of points in a single frame to confirm the usefulness of obstacle detection using a driving risk map. The evaluation method is to specify a rectangular frame within which a curb on the left side of the vehicle exists (8m long and 0.5m wide), and to verify the relationship between the obstacle occupancy rate within the frame and the distance from the vehicle to the center of the curb. As shown in Fig. 3, the proposed method showed that the occupancy rate exceeded 0.54 at a distance of 25.4m, while the conventional method using clustering recorded the highest value of 0.54 at a distance of 16.7m. In addition, The driving risk map for each distance from the obstacle was confirmed. The distance at which it becomes possible to detect an 8-m-long curb to the extent that a 2-m-wide car cannot pass over it was 20.6m for the conventional method and 35.2m for the proposed method.

The proposed method enables robust detection of small obstacles such as curbs from farther away. However, obstacles with a height of a few centimeters, such as speed bumps, are difficult to distinguish from false positives that appear on the road, so it is necessary to consider fusion methods with other sensor information, such as camera images, to distinguish them.

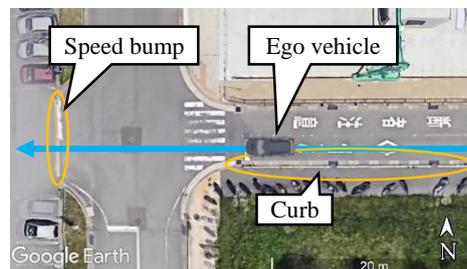


Fig.1 Experimental environment

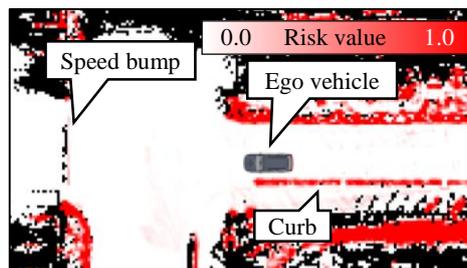


Fig.2 Driving risk map

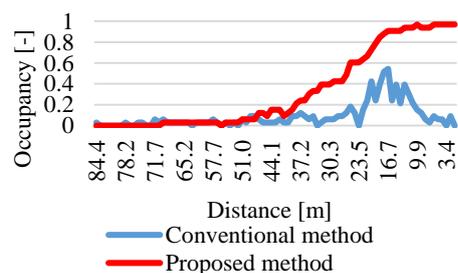


Fig.3 Occupancy of the curb