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Road Traffic Marking Extraction Algorithm Based on Fusion of Single Frame Image and Sparse Point Cloud

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ABSTRACT: A localization method of traffic signage in LiDAR data is proposed for the panoramic images, and point cloud data acquired by vehicle-mounted mobile laser scanning equipment. The method can make full use of the detection results of deep learning in road images to accurately locate the range of traffic signage in the point cloud data. Then, it further combines the depth image to determine the extraction range and obtain the point cloud region where the traffic sign is located. After, the acquired point cloud region is subjected to a CSF filtering algorithm to remove the ground. The clusters are clustered using the region growing method, and the clustered target clusters are filtered using intensity filtering and RANSAC plane fitting to narrow the target range. For the remaining coarse class clusters, traffic signage is extracted using dimensional features based on the PCA method, while noise points with abnormal dimensionality are removed. In comparison with other commonly used point cloud segmentation extraction methods, it has a better extraction effect.

KEYWORDS: lidar point cloud; object detection; panoramic image; convolutional neural network; projection transformation

I.INTRODUCTION

Traffic sign detection is an important part of driverless and assisted driving. Vehicles need to detect traffic signs on the road ahead in order to obtain road information. Automatic detection and accurate identification of road signs from complex scenes is an important guarantee for driving safety, which is of great significance in the field of intelligent driving. Conventional road sign detection involves finding traffic signs in road images obtained from image acquisition systems, which is a typical image recognition problem, usually based on the color [1,2,3], shape [4,5,6], and multi-feature fusion method. The detected area also needs to be recognized by certain algorithms. At present, the mainstream methods of traffic sign recognition include template matching and machine learning, among others.

Image template matching refers to the process of matching the corresponding relationship between the image to be identified and the template image by translation search. Image template calculating the similarity between the image to be detected and the template, which is widely used in the field of computer vision. Wang Y [7] incorporates OCR techniques to template matching, but the recognition effect is greatly affected by occlusion and angle. Qian R [8] proposed a representation based on new geometric shape features, namely the real-time traffic sign detection system based on template matching of multilevel chain code histograms, which have high robustness under different rotations, scales and illuminations.

Machine learning involves extracting target features from the images for training. The classifier derived from machine learning is then used to match the image to be recognized and the recognition results are obtained. Its common features include edge features and their variants HOG [9], Harr [10], and DTB [11], and FFT shape features [12]. The common machine learning classifiers are: Support Vector Machine (SVM), Extreme Learning Machine (ELM), Random Forest (RF), etc. Stallkamp [13] achieved a recognition accuracy of 95.68% in German public data sets, using directional gradient histogram features combined with a linear discriminant analyzer. Boi F [14] developed a shape-based classification model using SVM. Based on SVM, it used grid search and simulated annealing search, making it possible to classify speed limit signs with an accuracy greater than 99%. Most of the early target detection algorithms were constructed based on manual features, which failed to meet the requirements in terms of speed and accuracy despite the use of a large number of complex feature representations and network gas pedals.

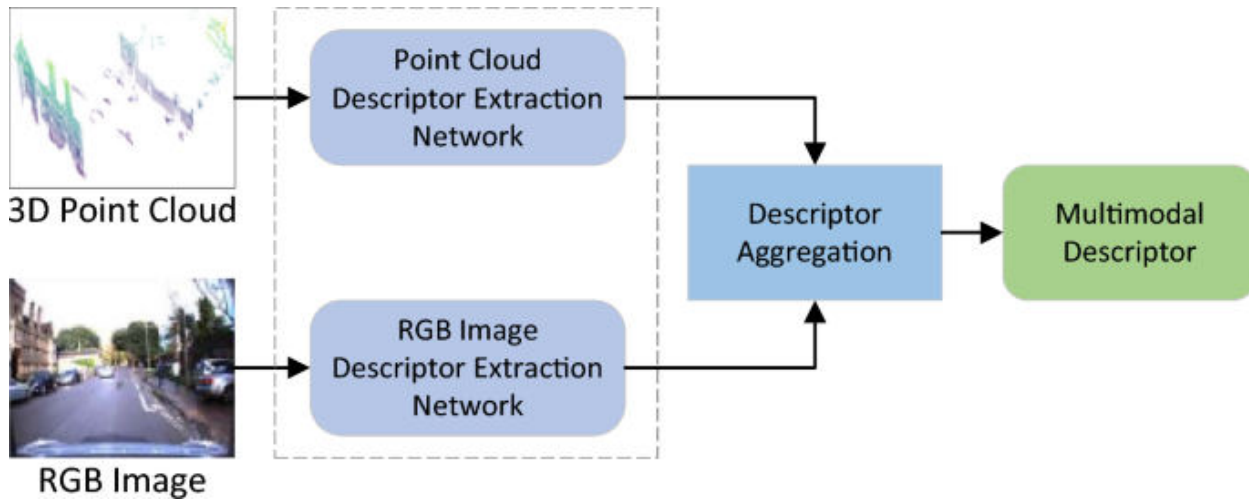


Fig 1: 3D point cloud-based place recognition

The most mainstream method for target recognition is Convolutional Neural Networks (CNN). There are many precedents for using this method for detection. Y. Ma adjusted the convolutional kernel to 3×3 size and added dropout and convolutional layers to the AlexNet model, which achieved an accuracy of 96.875% on the German GTSRB public dataset. Ciresan [19] used a multi-column deep convolutional neural network, reaching an accuracy of 99.46% after testing on the GTSRB dataset. Dan C [20] added and subtracted two standard deviation average pixel intensities on RGB three channels and performed histogram equalization to greatly expand the dataset. Then, he combined HOG features and SVM extraction to achieve an accuracy of 99.15% in GTSRB. Yawar Rehman [21] learned features by gathering semantic information, which reduced the use of sliding window in traditional target detection and relied on color changes to find areas with a higher possibility of traffic signs, achieving an accuracy of 100% on the GTSRB dataset. The deep learning method requires prior training of features from a large amount of sample data. Compared with the traditional manual method, accuracy and robustness are greatly improved, making it is less likely to be undetectable due to lighting, angle, and occlusion.

II.RELATED WORK

In this paper, we binarized 8 bits of intensity to 1 bit. In the case of intensity, it is possible to express an image in gray scale, as shown in Figure 2, because it provides information with 8 bits. Thus, the intensity can be regarded as the brightness of the



image, and binarization is possible by applying the threshold. For binarization, it is necessary to set the threshold value of the intensity. To solve this, Otsu's thresholding method is used. Otsu thresholding is a method to find the optimal threshold using the brightness distribution of all pixel values in the image. Using this method, we can find the threshold even if the intensity is changed in every scene.

However, even when scanning the same road marking, there is a difference in intensity among the vertical layers of the 3D LIDAR. Figure 3 shows the intensity of the same road marking scanned by a 3D LIDAR for each vertical layer. The vertical layer means the number of vertically scanned 3D LIDAR channels. In this research, we used 32-channel 3D LIDAR and 12 channels are used for scanning the road marking. As shown in this figure, intensity values are different depending on the vertical layer. Thus, if we binarize to the threshold of the entire layer, the road marking cannot be extracted properly. Therefore, we applied thresholding and binarization to each layer.

A global map is essential for localization. In addition, a precise vehicle trajectory is required to generate a precise global map. In general, when using simultaneous localization and mapping (SLAM), errors accumulate as the vehicle progresses. Therefore, when a global map is generated, the road marking does not match.

Figure 5 shows the binary road marking grid map generated by using the GPS (RTK)/INS (NovAtel RTK/SPAN system) trajectory. As shown in this figure, it can be confirmed that the road marking is not consistent. Therefore, we performed graph optimization using graph SLAM. Graph optimization is a method of setting constraints for each node and optimizing the trajectory using edge relationships between nodes. The incremental pose information outputted from the ICP scan matching algorithm was used as the edge measurement of the graph.

III.METHODS

Traffic signage has the following characteristics in the point cloud data: (1) traffic general signage is suspended from the pole, above the ground, and perpendicular to the ground. (2) Traffic signage belongs to the façade, with a regular geometric shape, generally rectangular or triangular. (3) In order to ensure the safety of traffic, the state requires the surface of traffic signs to be sprayed with high-reflectivity materials, and the national safety production standard has a minimum value of reflectivity for traffic sign equipment, including poles.

Combining the above characteristics, this paper adopts the point cloud traffic sign extraction by combining intensity features and morphological features. Although the atmospheric attenuation and laser acquisition incidence angle will affect the reflection intensity of the point cloud data, this feature can still be used to distinguish the traffic sign from most of the features.

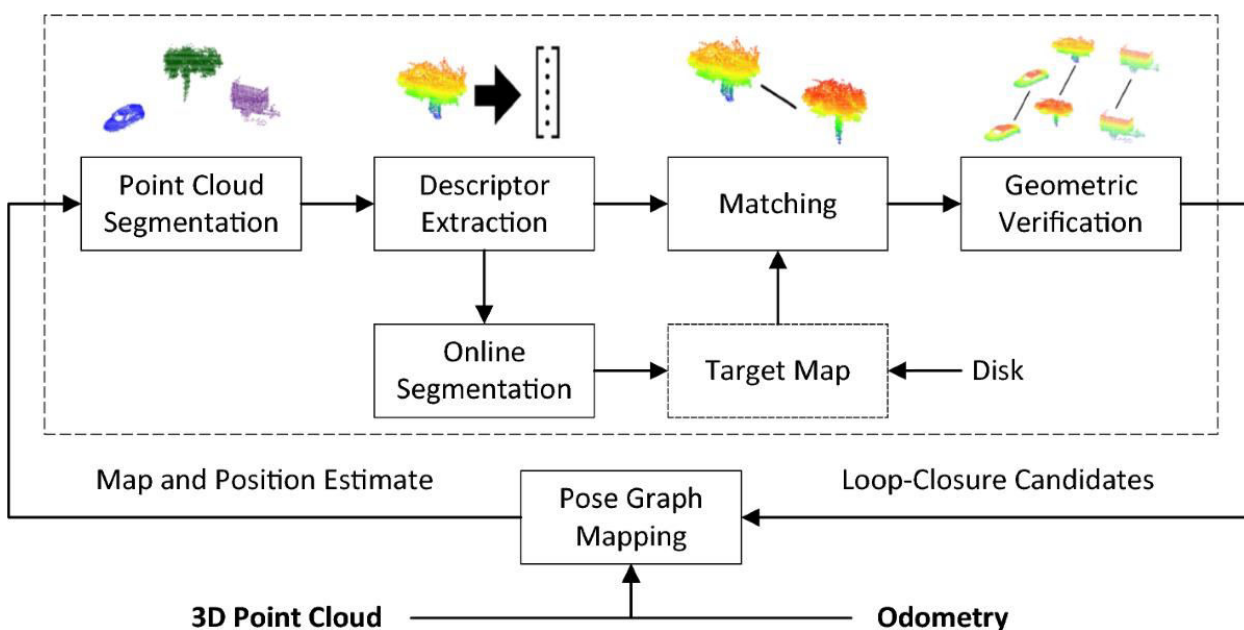


Fig 2: 3D point cloud-based work flow

The high precision conversion of pixel coordinates to point cloud coordinates is a prerequisite for making full use of image detection results. Next, we will introduce the transformation process from pixel coordinates to point cloud coordinates in detail, and carry out crude extraction of traffic signs based on this. The vehicle-mounted laser measurement system is equipped with a panoramic camera that continuously captures images during travel. Meanwhile, in the LIDAR radar system, the laser range scanning unit continuously emits microwaves to obtain distance information, the Differential Global Position System (DGPS) obtains position information, and the Inertial Measurement Unit (IMU) obtains attitude information. The geometric relationship between the camera coordinate system and the corresponding ground points in the geodetic coordinate system can be determined from the internal and external orientation elements of the image. The image acquired by the camera can be matched with the point cloud to give color information. In the process of loss function calculation of the network, the GIOU of the prediction frame and the standard reference frame are regarded as positive samples when it is greater than a certain threshold and negative samples when it is less than that threshold. However, the traffic sign data usually come from panoramic images or surveillance equipment, and the proportion occupied by the signage in the image is generally much smaller than the background proportion.

IV.RESULT ANALYSIS

In this paper, the reflection intensity-based extraction method and RANSAC-based extraction method are used for comparison. The reflection intensity-based extraction method extracts traffic signage based on the manually set intensity range; the RANSAC-based extraction method goes to extract the faceted area as traffic signage based on the manually set area region. The comparison experiments in this paper are divided into two aspects: whether to combine images and different traffic signage extraction methods. Therefore, there are five groups of experiments: (1) extraction based on reflection intensity for the whole point cloud; (2) extraction based on RANSAC for the whole point cloud; (3) extraction based on reflection intensity method combined with image positioning; (4) extraction based on RANSAC method combined with image positioning; (5) using the method of this paper.

In **Table 3**, Method I and Method III, Method II, and Method IV can form two sets of control tests, illustrating that locating traffic signs by image detection before performing traffic sign extraction can bring a huge improvement to the accuracy and recall rate. This is due to the elimination of most other easily confusing objects after establishing a reasonable target area. Method III and Method V, and Method IV and Method V can form two more sets of control tests, which illustrate that the traffic sign extraction method proposed in this paper has a better extraction effect compared with the reflection intensity-based method or the RANSAC method.

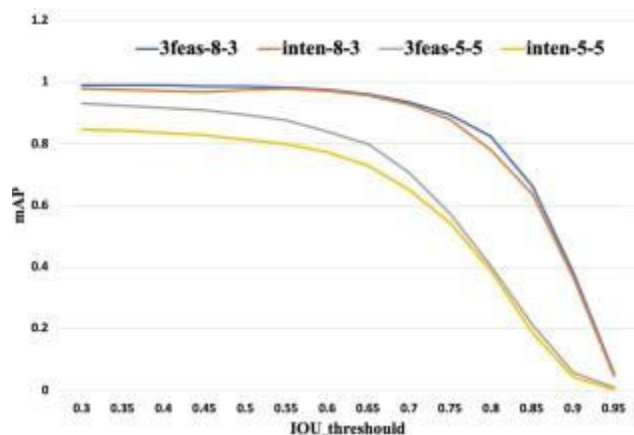


Fig 3: Result analysis

In this section, the original training set is reprogrammed using an improved Yolo network, and the panoramic images collected by the laser system on the South Fourth Ring Road of Beijing are used as an expanded dataset to include more indication signs on top of the original dataset. The overall process of the proposed method to extract traffic signage in the target point cloud range goes through several steps, including region growth clustering segmentation, ground point removal, intensity filtering, and dimensional feature screening. After processing in the previous sections, traffic signs and other features can be distinguished in most scenes. To further increase the accuracy, our paper uses the principal component analysis to calculate the dimensional features. Principal Components Analysis (PCA) is a common method of dimensionality reduction, which aims to determine the variables that are not linearly related to each other by the correlation between data with the help of mathematical operations. Additionally, it is arranged in order of decreasing variance. While keeping the total variance constant, each group of variables is called the first principal component, the second principal component, and so on. The variables between each principal component are not correlated.

V.CONCLUSION

Traffic signs play an important regulatory role in the process of road driving, and the correct identification of traffic signs is an important guarantee for driving safety. Extracting traffic signs accurately in complex and changing road scenes is a difficult problem. In this paper, we analyze the existing traffic sign extraction methods and propose a traffic sign extraction method that combines image detection and point cloud segmentation. In order to improve the signage detection accuracy in images, three aspects of the YoloV3 detection model are improved: network structure, prediction frame size, and loss function. The model is validated using domestic public road traffic datasets, and the experiments prove that the model has higher accuracy compared with the original model.

However, there are still some problems that need to be improved or solved. The method in this paper is harsh on data acquisition, which needs to rely on the external parameters of each panoramic photo derived from the conversion of the inertial guidance system. These parameter files are used as the initial data to realize the whole process, which has high



requirements on data acquisition, cannot be realized solely by point cloud data, and the universality needs to be enhanced. Our method relies on visual detection results to extract point cloud, and the final accuracy is affected by the deep learning algorithm. Manually marking traffic signs in a 3D scene takes time and effort. The point cloud data extracted in this paper can provide a dataset for extracting traffic signs directly from 3D data.

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