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Mining Autonomous Vehicle Driving Boundary Detection on Basis of 3D LiDAR

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Abstract: Mining area is very large, and the road conditions are also very complex. It is very difficult to familiarize oneself with the environment of the mine by driving. Based on 3D LiDAR technology, this research explores a driving boundary detection method for driverless vehicles in mines based on point cloud data. Through the use of 3D LiDAR sensors to obtain point cloud data of the environment, and the use of object shape recognition, high-precision ranging, multi-angle observation and multi-sensor fusion and other technologies, the accurate detection of mine environmental boundaries is realized. The experimental results show that the boundary detection method of mine driverless vehicles based on 3D LiDAR has high accuracy and real-time. Using the point cloud data obtained by the 3D LiDAR sensor, it can quickly capture and represent the shape and contour of objects in the mine environment, and realize accurate boundary detection.

1. Introduction

Applying autonomous vehicles to mines can improve work efficiency. This article adopts a mining autonomous vehicle driving boundary detection method based on 3D LiDAR technology. Its sensors can obtain point cloud data of the environment at high frame rates and fast data acquisition speeds, thereby achieving accurate detection of mining environmental boundaries. Through techniques such as object shape recognition, high-precision ranging, multi angle observation, and multi-sensor fusion, the method proposed in this paper can quickly capture and represent the shape and contour of objects in the mining environment, achieving accurate detection of boundaries.

This article first introduces the research background and current situation of 3D LiDAR based boundary detection for unmanned mining vehicles, and elaborates in detail on the 3D LiDAR based boundary detection method used in this article, including data acquisition, real-time processing, and boundary detection algorithms. Next, this article presents experimental results and analysis, verifying the effectiveness and reliability of the proposed method. Finally, the research findings were summarized and future research directions were discussed.

2. Related Work

Many people have conducted research on unmanned driving detection, among which Tian Guohong proposed a method for detecting obstacles in front of unmanned vehicles in uncertain environments, using LiDAR to obtain LiDAR images of the vehicle's driving process. By using bilateral filtering methods to complete image denoising, a road boundary model is established based on the searched road boundary points, and obstacle features are extracted to establish an obstacle model. The classification results of spatiotemporal feature coefficients can be used to identify obstacle types and achieve obstacle detection [1]. Guo Yongcun proposed a multi-target detection model for underground electric locomotives. This model is improved based on the instance segmentation algorithm by embedding a compression excitation module in the residual block of the backbone feature extraction network ResNet, learning the importance and interrelationships of each channel, and enhancing the network's ability to select and capture features [2]. Meng Dejiang proposed the Grid Kalman Road Slope Real time Detection (GKSRD) method. This method takes three-dimensional LiDAR point clouds and INS (Inertial Navigation System) elevation angle information as inputs, and uses two-dimensional raster maps, iterative optimization algorithms for rectangular regions of interest, and Kalman filters [3]. Hu Qingsong systematically reviewed the research status of unmanned driving environment perception technology in mines. He pointed out that the special environment of the tunnel can lead to varying degrees of performance degradation of the mine vehicle mounted perception equipment, and summarized the advantages and disadvantages of various vehicle mounted perception equipment [4]. Qin Peilin proposed a 3D target detection method for unmanned trackless rubber wheeled vehicles that integrate images and radar point clouds. For the pre-processing of the obtained trackless rubber tire vehicle driving environment data, the global histogram equalization method can be used to improve the brightness of RGB images and reduce the impact of uneven underground lighting [5]. Edwards D J aimed to provide a systematic review of existing literature on the application of autonomous driving technology in the field of civil engineering, and to analyze in depth the limitations of comprehensive adoption of related barriers [6]. Bissell D called on sociologists to provide much-needed critical voices for institutions and public debate on the development of autonomous vehicle [7]. Karmakar G proposed two deep learning based models to measure the credibility of autonomous vehicles and their main onboard unit components [8]. Kabzan J applied an algorithm and system architecture for autonomous racing, integrating perception, estimation, and control into a high-performance autonomous driving racing car [9]. Engholm A believed that road freight is the first transportation sector where autonomous vehicles can have a significant impact [10]. These studies provide assistance for the algorithm implementation in this article, which can be based on 3D LiDAR technology to design unmanned mining vehicles.

3. Method

3.1 Collection of Mine Road Surface Data

3D LiDAR is a sensor technology used to obtain three-dimensional spatial information of the surrounding environment. It achieves spatial perception and distance measurement by emitting a laser beam and measuring the time and intensity of the laser beam's return [11-12]. Its sensors can be installed on mining transportation vehicles and fixed in appropriate positions, while multiple upright poles can be erected with a height of 10m. Multiple mining vehicles equipped with radar can travel back and forth, arranged with 3D LiDAR on upright poles, to ensure that sensors can cover the required road surface area. The radar can emit laser beams and receive their returned signals, forming point cloud data [13-14]. The obtained point cloud data contains noise and incomplete parts, so data processing and registration are required, including noise removal, filtering, point cloud registration, and other steps, to obtain accurate road surface point cloud data. The processed point cloud data can be used for road segmentation and extraction operations, and algorithms such as ground estimation and plane fitting can be used to separate the road surface point cloud from the entire point cloud data. Table 1 shows a collection of mining road surface data:

Table 1: Road Surface Data

Location	X Coordinate	Y Coordinate	Z Coordinate	Depth	Speed
1	10.25	15.78	6.32	2.1	25
2	8.97	19.42	5.85	3.2	18
3	12.15	13.67	7.81	1.8	22
4	9.62	17.23	6.95	2.5	20
5	11.78	14.92	6.07	2.9	19

3.2 Point Cloud Segmentation

Point cloud segmentation based on region growth can be used to divide point cloud data into different subsets or regions. This method includes steps such as data preprocessing, ground estimation, feature calculation, seed point selection, region growth, and post-processing. The original point cloud can be preprocessed, outliers removed, filtered and sampled, and ground estimation algorithms can be used to fit the ground plane model. Ground points can be separated from non-ground points [15-16]. Feature calculations can be performed on non-ground point clouds, such as normal vectors, curvature, and color. By selecting one or more seed points as the starting point for region growth, it can be manually or automatically selected. Starting from the seed point, the region growing algorithm is used to gradually add adjacent points to the same region, and the conditions can be defined based on the geometric or attribute similarity between the points. The generated segmentation results can be post-processed to remove noise points, fill segmentation gaps, merge adjacent regions, etc. The final output identifies the point cloud segmentation results for different regions. This point cloud segmentation method based on region growth can be applied to fields such as unmanned mining, providing accurate road information and environmental perception [17-18].

3.3 Road Edge Construction

This article uses collected data for feature extraction to identify and segment road edges. For point cloud data, features such as point height, curvature, and normal vectors are used to locate road edges. By setting a height threshold, points in the point cloud that exceed a certain range in height can be filtered out, as the roadside is usually higher than the road surface by a certain degree. The curvature of each point in the point cloud can be calculated using the rate of change of surface normals, and points with larger curvature often correspond to the position of the roadside. A curve fitting algorithm is used to fit the geometry of the outer edge. In order to cope with changes in the mine environment, roadside information needs to be updated and maintained, so sensors need to be used regularly to collect data on mine roads to obtain the latest point cloud data or image data [19-20]. The paper compared and matched the collected new data with the existing kerb model, identified the changing kerb area, and dynamically update the kerb model based on the detected changes, and used the new data for feature extraction and modeling to maintain the accuracy and real-time of kerb information. Through feature extraction, kerb modeling, and kerb update and maintenance, the kerb information of mine roads can be accurately constructed and maintained, and reliable navigation and safety support can be provided for unmanned vehicles.

3.4 Boundary Detection Algorithm

Gaussian smoothing of the image returned by the 3D LiDAR reduces the noise in the image and makes subsequent edge detection more accurate. It can use Canny edge detection algorithm to detect the returned image, calculate the gradient information on the smoothed image, use Sobel operator or other gradient operator to calculate the horizontal and vertical gradient values of each pixel in the image, and then calculate the gradient amplitude and direction based on these gradient values. The gradient amplitude represents the intensity of the edge, while the gradient direction represents the direction of the edge. By comparing the pixels in the gradient direction, the pixels with the largest gradient value are retained. This step helps to refine the edges and make them more delicate. According to the set high and low thresholds, the pixels are divided into three categories: strong edge, weak edge, and non-edge. A high threshold value is used to accept strong edge pixels, a low threshold value are used to exclude non-edge pixels, and the pixels in between are marked as weak edges. This step helps to filter out noise and weak edges, improve the accuracy of edge detection, and form a closed edge contour by connecting strong edge pixels and weak edge pixels connected to them.

4. Results and Discussion

The driving boundary detection system can be combined with unmanned vehicles for experimental testing at mine A. The experimental control is unmanned vehicles without a boundary detection system. The experimental group and control group each have 15 vehicles traveling back and forth in the mine. Their boundary detection accuracy, false detection rate, and delay time can be compared. In the experiment, 3D LiDAR sensors can be calibrated, including calibration of internal and external parameters, to reduce data acquisition errors.

4.1 Boundary Detection Accuracy

Accurate boundary detection can help autonomous vehicles sense the position and shape of the road. If the accuracy of boundary detection is low, it may lead to vehicles misidentifying road boundaries, resulting in deviation from the road or collision with obstacles. Boundary detection has high accuracy and can provide accurate boundary information, helping vehicles make correct driving decisions and improving driving safety. Figure 1 shows the accuracy comparison:

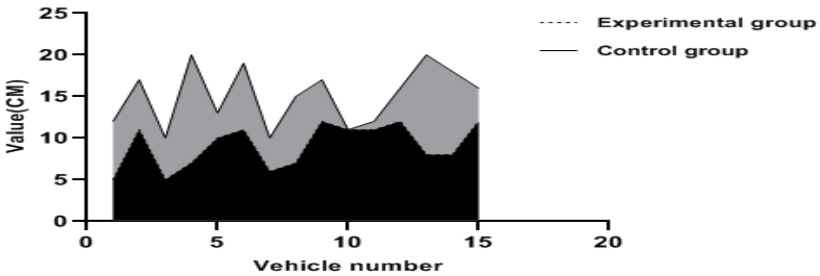

Figure 1: Boundary detection accuracy

In the accuracy test, the experimental group of 15 vehicles had an accuracy of 5-12cm, while the control group of 15 vehicles had an accuracy of 10-20cm. It can be clearly seen that the experimental group in this article has higher accuracy, with the highest accuracy performance reaching 5cm. This is because the 3D LiDAR sensor can obtain point cloud data of the environment at high resolution. It generates high-density and high-resolution point cloud maps by emitting a laser beam and measuring the time and intensity information of the returned laser points. This high resolution enables 3D LiDAR to accurately capture and represent subtle features and boundaries in the environment.

4.2 Misdetection Rate

The false detection rate refers to the frequency at which an algorithm incorrectly identifies non boundary areas or irrelevant objects as boundaries. There may be many interfering objects, noise, or other non-boundary features in the mining environment, and a high false alarm rate may lead to unmanned vehicles mistakenly identifying these areas as boundaries, thereby affecting driving safety and efficiency. Figure 2 shows the comparison results:

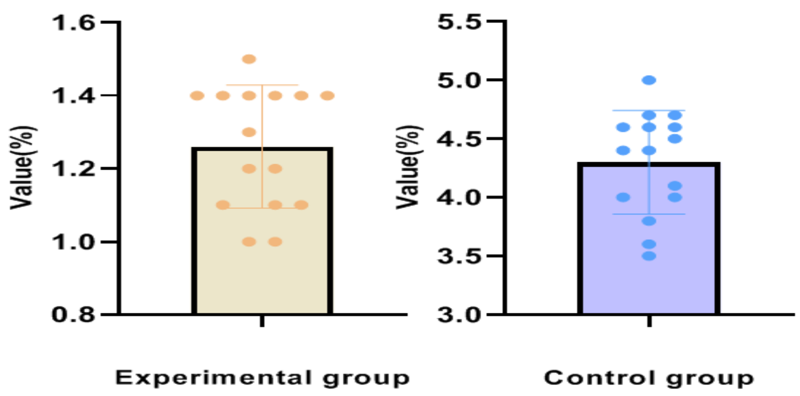

Figure 2: Misdetection rate

The level of false detection rate is important for the safety of autonomous vehicles. In the test, the maximum false detection rate of the experimental group in this article is 1.5%, and the minimum is 1%. The maximum false detection rate in the control group is 5%, and the minimum is 3.5%. 3D LiDAR can observe objects in 360 degrees and collect information from multiple sides. By integrating observation data from multiple angles, boundary detection algorithms can better understand the shape and boundaries of objects, reducing the possibility of false positives.

4.3 Delay Time

Delay time refers to the time required from the appearance or change of a boundary to the detection and processing of the change by the boundary detection system. The shorter the delay time of the boundary detection system, the faster the system can respond to environmental changes and provide real-time boundary detection results. A lower delay time can improve the real-time performance of autonomous vehicles, enabling them to perceive and respond to changes in boundaries in a timely manner, thereby improving driving safety and reliability. Figure 3 shows the comparison results:

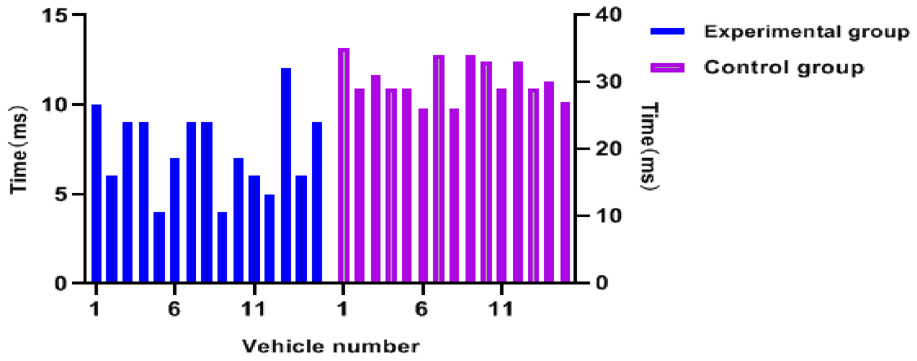

Figure 3: Delay time

The delay time test results show that the delay time of the experimental group in this article is between 4-12ms, which is a relatively low delay. The delay time of the control group is between 26-35ms, which is relatively high compared to the experimental group and prone to accidents. 3D LiDAR sensors are typically combined with high-performance processors and algorithms to process large amounts of point cloud data in real-time. This enables boundary detection algorithms to quickly analyze and interpret point cloud data, thereby quickly detecting changes in boundaries. The ability to process real-time data enables autonomous vehicles to respond to environmental changes in a short period of time, reducing the latency of algorithm processing.

5. Conclusions

After conducting experimental tests on three indicators, it can be concluded that 3D LiDAR can accurately detect the boundaries of mining environments and respond to changes in boundaries in a short period of time. The low delay time enables the boundary detection system to quickly obtain the latest environmental information and take timely obstacle avoidance measures, improving the safety and stability of autonomous vehicles. The mining autonomous vehicle driving boundary detection technology based on 3D LiDAR has broad application prospects, which can be applied in the mining industry to improve production efficiency and safety. However, in order to further improve the accuracy and reliability of boundary detection, algorithms and hardware technologies still need to be continuously improved to achieve higher levels of environmental awareness and boundary detection capabilities.

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