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Obstacle Detection Technology for Autonomous Driving Based on Deep Learning

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Abstract. With the rapid growth of artificial intelligence (AI) technology, traditional obstacle detection equipment faces multiple challenges such as high cost, low real-time performance, non normalization, dependence on manual operation, and time-consuming and labor-intensive. To address these shortcomings, this article proposes a deep learning (DL) based obstacle detection technology for autonomous driving on the road surface. As a complex system that integrates multiple key components such as environmental perception, positioning and navigation, path planning, and motion control, one of the core technologies of autonomous vehicles is accurate perception of the surrounding environment. In practical applications, autonomous vehicles often face complex and variable road environments, which may lead to a decrease in the quality of images captured by cameras, resulting in blurry and unclear phenomena. The DL method, especially the object detection algorithm, has shown unique advantages in visual perception and recognition in autonomous driving scenes. This paper deeply studies the obstacle detection technology of automatic driving road based on DL, aiming to achieve efficient and accurate obstacle recognition, improve the safety and reliability of auto drive system, and promote the further growth of automatic driving technology.

Keywords: Deep learning, autonomous driving, road obstacle detection.

1. Introduction

With the rapid growth of DL technology, as a key branch of computer vision, obstacle detection technology has received widespread attention and research in both academia and industry [1]. Especially in the field of intelligent driving in automobiles, the application prospects of obstacle detection technology are very broad [2]. The core technologies of autonomous vehicle include environment awareness, positioning and navigation, path planning, motion control, etc., of which the environment awareness system plays a crucial role [3]. The main task of the environmental perception system is to accurately identify the road environment, including obstacle detection and classification, traffic signs and signals recognition, pedestrian and vehicle detection and tracking, etc., in order to provide accurate environmental information for vehicles to support subsequent decision-making and planning [4]. Therefore, obstacle detection has become an important and indispensable part of intelligent transportation systems.

However, the application of autonomous vehicle to actual complex road traffic scenes still faces many challenges [5]. Firstly, the variability and uncertainty of road environments make obstacle detection and classification exceptionally difficult [6]. For example, changes in lighting conditions, weather effects, blurring or occlusion of road signs, and other factors may all affect the recognition performance of the model [7]. In addition, dynamic obstacles such as pedestrians, non motorized vehicles, and construction equipment also pose additional challenges to environmental perception. In order to solve the above problems, DL based autonomous driving road obstacle detection technology has emerged. DL models, especially Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have powerful feature extraction and classification capabilities, and can automatically learn the features of obstacles from input images, thereby achieving efficient obstacle detection. Through training and optimization, the DL model can accurately identify various traffic elements, including lane lines, traffic signs, pedestrians, vehicles, etc., and classify and locate them [8].

Compared to traditional methods, DL technology has higher accuracy, real-time performance, and robustness, and can better adapt to complex and changing road environments. The application of DL based obstacle detection technology in the field of intelligent driving has many advantages. Firstly, it can greatly improve the accuracy and real-time performance of obstacle detection, reduce false positives and missed detections, and thus ensure driving safety. Secondly, DL technology can automate obstacle detection, greatly reducing the workload of inspectors and improving work efficiency. In addition, the DL model also has strong generalization ability, which can adapt to various situations such as different road environments, lighting conditions, and types of obstacles, making obstacle detection more intelligent and automated. DL based obstacle detection technology for autonomous driving is an important research direction in the field of intelligent driving. With the continuous growth and improvement of DL technology, it is believed that obstacle detection technology will become more mature and efficient in the future, providing strong guarantees for the safe operation of intelligent driving vehicles.

2. DL Related Theories

DL, as a subfield of machine learning, is dedicated to exploring more complex and abstract data representations [9]. It is based on a large amount of labeled data and learns and extracts the inherent patterns and patterns in the data through a progressive network structure. In this process, the model will gradually abstract high-level feature representations that are closer to human perception from the original low-level features (such as pixel values), thereby achieving more accurate classification, recognition, or prediction. The power of DL technology has been validated in multiple scientific research fields. In medical image engineering assisted diagnosis, DL models can analyze medical images such as X-rays, CT, and MRI, helping doctors more accurately identify abnormal conditions such as tumors and lesions. In the field of facial recognition, DL technology makes applications such as phone unlocking and access control systems more secure and convenient. In terms of natural language processing, DL models can understand and generate natural language texts, and achieve functions such as machine translation and intelligent question answering. In the field of image processing, DL also plays a crucial role, from simple image classification to complex object detection, all cannot do without its support [10].

Among numerous DL algorithms, CNN has emerged as a powerful tool in the field of object detection in recent years. CNN is particularly skilled at handling data with grid structures, such as images. It can automatically extract local and global features from images through structures such as convolutional layers and pooling layers, thereby achieving efficient object detection and recognition. The excellent performance of CNN is attributed to its powerful feature extraction ability and end-to-end training method, which enables the model to directly learn effective feature representations from the original images, greatly improving the accuracy and efficiency of object detection. Figure 1 shows the basic structure of CNN.

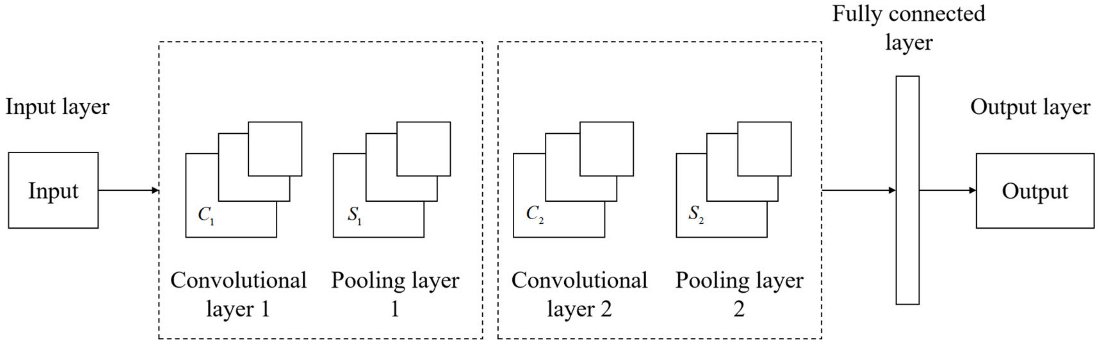

Figure 1. CNN structure

3. The Application of DL in Obstacle Detection on Autonomous Driving Roads

Accurate detection of obstacles is crucial to ensuring driving safety in autonomous driving scenarios. In recent years, DL technology has made significant progress in this field, especially in processing point cloud data obtained from LiDAR scanning. Laser radar, as an active sensor, can measure the distance, speed and angle of objects in the environment with high accuracy, so it plays a vital role in the auto drive system. The 3D object detection based on DL mainly utilizes point cloud data obtained from vehicle mounted LiDAR scanning. Point cloud data is a collection of a large number of discrete points, each containing information such as the position and reflection intensity of an object. Through the DL model, we can extract useful features from these point cloud data, thereby achieving accurate detection and classification of obstacles. In practical engineering applications, DL models are usually combined with traditional signal processing techniques to fully utilize the depth information obtained from LiDAR. At the same time, the video information collected by the camera also provides important supplements for object detection. By integrating point cloud data with video information, object detection and recognition algorithms such as CNN can be used to more accurately obtain the location and classification information of obstacles in traffic road scenes.

4. DL Based Obstacle Detection Technology for Autonomous Driving on Road Surface

4.1. Algorithm Principle

In CNN, convolutional and pooling layers do not have strict requirements for the size of the input image. Convolution operations extract features by sliding the convolution kernel over input data, while pooling operations are used to reduce the spatial size of the data, both of which can handle inputs of different sizes. Therefore, even if the size of the input image changes, the convolutional and pooling layers can still effectively extract features. However, the fully connected layer is different. The fully connected layer is usually located in the last few layers of the network in CNN, used to map the features extracted from the previous layers to the sample label space. Due to the fact that each neuron in the fully connected layer is connected to all neurons in the previous layer, it requires that the size of the input data be fixed. The core operation of fully connected is the product of matrix vectors, as shown in equation (1).

$$Y = W \times X \tag{1}$$

In the formula: X is the pixel matrix of the input image; Y is the pixel matrix of the output image; W is a fixed invariant matrix.

The projection based laser point cloud processing method is a commonly used data processing technique, mainly used to extract useful information from the raw point cloud data obtained from laser scanning equipment. The core steps of this method typically include coordinate system conversion and projection operations. The coordinate system transformation is represented as rotation and translation in three-dimensional space, as shown in formula (2):

$$\begin{pmatrix} x_w \\ y_w \\ z_w \\ 1 \end{pmatrix} = \begin{pmatrix} R_{3\times3} & \vec{t} \\ \vec{0}^T & 1 \end{pmatrix}_{4\times4} \begin{pmatrix} x_l \\ y_l \\ z_l \\ 1 \end{pmatrix} \tag{2}$$

In the formula, $R_{3\times3}$ represents rotation in three-dimensional space, and $\vec{t}$ represents translation.

The loss function is an indispensable module, designed as follows:

$$Loss = L_{pro} + L_{reg} \tag{3}$$

In the formula, L_{pro} represents the region score loss function module, i.e. the classifier; L_{reg} is the target candidate region position module, which is the regressor.

4.2. Result Analysis and Discussion

In the field of autonomous driving, the performance of DL models is crucial, and high-quality datasets are the foundation for training these models. In autonomous driving traffic scenarios, pedestrians and vehicles are the main obstacles, and accurately identifying these obstacles is of great significance for ensuring driving safety. Therefore, selecting the appropriate dataset for training is crucial. This article selects the COCO dataset as the training set. This dataset covers various object categories, including pedestrians, bicycles, motorcycles, cars, buses, etc., and is very suitable for obstacle detection tasks in autonomous driving traffic scenes.

Figure 2 shows the comparison of obstacle recognition rates between DL based road obstacle detection methods and traditional detection methods. From the graph, it can be seen that under various road environments and weather conditions, DL based detection methods have shown higher recognition rates. Especially in complex backgrounds and situations with significant changes in lighting, its advantages are more pronounced. This is due to the powerful feature extraction and adaptive ability of the DL model, which enables it to better adapt to different road environments and weather conditions. This provides strong support for the growth of autonomous driving technology, which helps to improve the safety and reliability of vehicles.

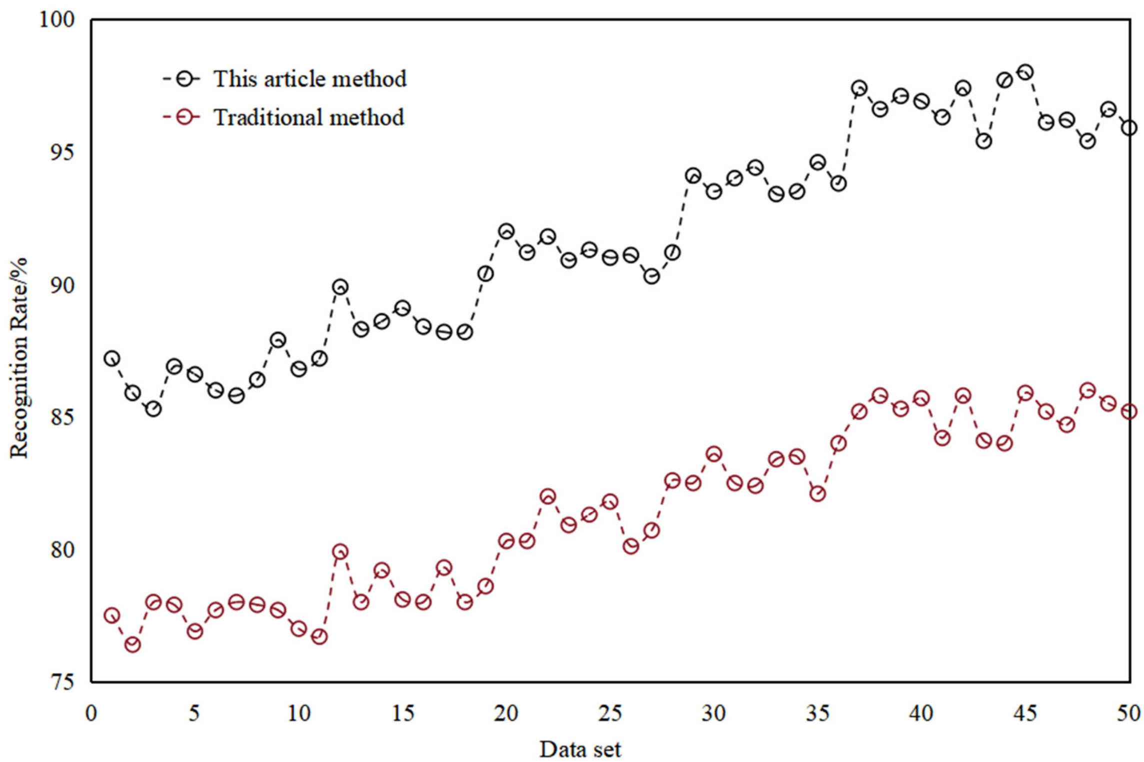

Figure 2. Comparison of recognition rates

Figure 3 shows the comparison of the loss function between the proposed method and the traditional method during the training process. The loss function is a key indicator in the optimization process of machine learning models, used to measure the difference between the predicted results of the model and the actual labels. The descent rate and stability of the loss function can reflect the convergence rate and generalization ability of the model. From the graph, it can be seen that the method proposed in this article exhibits a fast convergence speed in the early stages of training. Its loss function rapidly decreases in the early stages of training and maintains a stable downward trend throughout the entire training process. This indicates that the DL method can learn effective feature representations faster, thereby achieving high-precision recognition of obstacles. In contrast, the loss function of traditional methods decreases slower and experiences fluctuations and oscillations in the later stages of training. This may be due to the insufficient feature representation ability of traditional methods in dealing with complex and variable road environments and weather conditions, making it difficult for the model to further optimize.

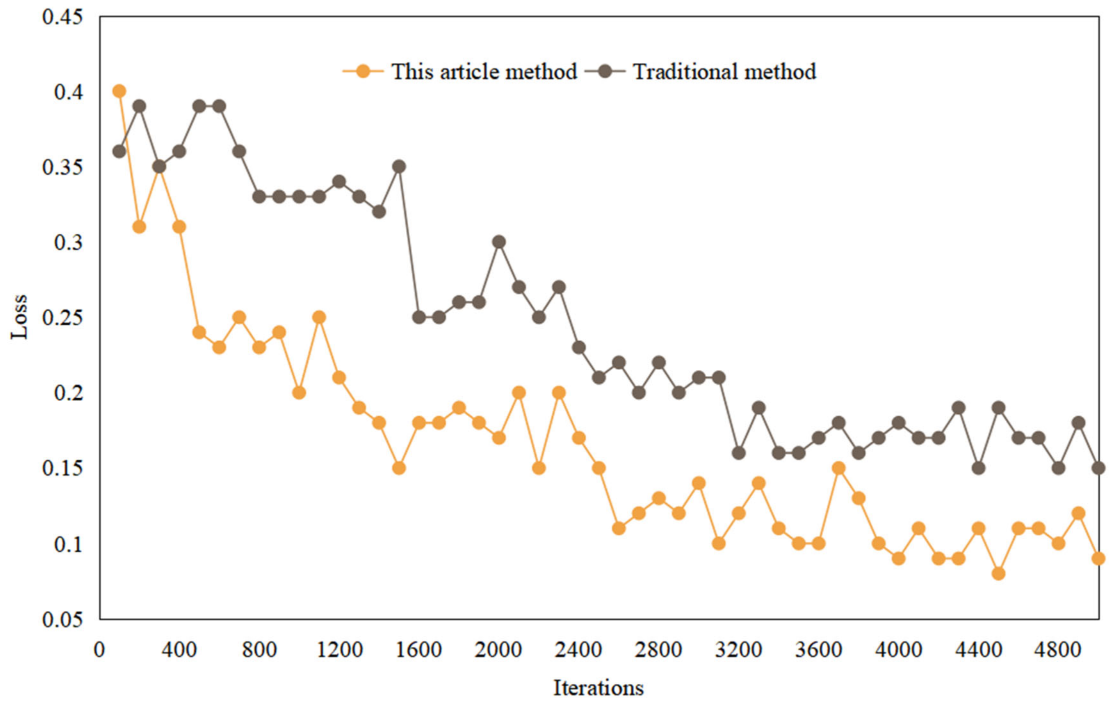

Figure 3. Comparison of loss functions

5. Conclusions

With the continuous evolution of computer vision algorithms and technology, autonomous driving technology has made significant progress. Especially in object detection and recognition, current technologies have been able to achieve a considerable degree of automation in complex traffic scenes. This significant progress not only marks a new milestone in the field of autonomous driving, but also provides higher levels of environmental perception capabilities for autonomous vehicles, significantly enhancing their safety. The core research of this article focuses on DL based obstacle detection technology for autonomous driving roads. The original intention of this technology is to achieve efficient and accurate obstacle recognition, which is crucial to ensure the safety and reliability of the auto drive system. Through the DL model, vehicles can analyze the road environment in real time, accurately identify pedestrians, vehicles, road markings, and other potential obstacles, thereby making fast and safe driving decisions. The growth of autonomous driving technology will undoubtedly drive human society towards a more intelligent, efficient, and safe transportation future.

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