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Research on Unmanned Obstacle Recognition Based on Computer Vision

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Abstract: *With the deepening of sensing technology and deep learning, unmanned driving technology has been greatly developed. The purpose of this paper is to sort out the development status of unmanned obstacle recognition, summarize the technical points of obstacle recognition in the field of computer vision, and summarize the problems and defects of existing obstacle recognition technology and put forward relevant development suggestions.*

Keywords: *Driverless Technology; Computer Vision; Obstacle Recognition*

1. Introduction

In the past three decades, both academia and industry have steadily increased their research efforts on driverless car technology. This is due to the recent development of sensor technology and deep learning, as well as the potential impact on people's automobile traffic and the expected social benefits: in 2019, there were 193 traffic accidents in China, accounting for 41.59% of the safety accidents in that year. In 2019, there were 665 traffic deaths, accounting for 43.04% of the deaths caused by safety accidents in that year, of which 15.40% were caused by traffic accidents due to failure to comply with regulations; Traffic accidents caused by driving in violation of traffic signals accounted for 7.43%; Traffic accidents caused by speeding accounted for 4.83%. In order to ensure the safety and comfort of driving, people are eager to develop a new kind of vehicle, As far as possible, an intelligent driving mode that allows cars to perform driving tasks autonomously, and at the same time, autonomous vehicles will create a series of high-tech jobs for the society and gather wealth for the country while completing driving changes. Therefore, in the era of intelligent driving, how to accurately and efficiently identify obstacles in driving environment is very important.

2. Overview of Unmanned Driving

2.1 Domestic Unmanned Development

As early as the 1980s, the research on unmanned driving began in China. In the same year, the first unmanned vehicle ATB-1 in China was jointly developed by Tsinghua University, National Defence Science and Technology University, Beijing Institute of Technology, Zhejiang University and Nanjing University of Science and Technology. In the demonstration experiment in 1996, the autonomous driving speed of the vehicle in straight line was up to 21km/h, and that in curved road was up to 12 km/h, it marks that China's unmanned driving industry has entered an exploration period. Later, during the Ninth Five-Year Plan period, the ATB-2 unmanned vehicle was developed on the basis of ATB-1, and its performance was greatly improved. In 2005, ATB-3 unmanned vehicle was successfully developed, and its environmental awareness, target recognition and tracking based on multi-sensor fusion and all-weather navigation were further improved.

Internet giants BAT (Baidu, Alibaba, Tencent) actively integrate resources and promote the research and development and industrialization of high-precision map technology in the core industry chain of intelligent driving; Alibaba and Tencent Shenzhen have seized the leading power of the entrance of car networking through taxi software and other applications. Baidu's research on driverless cars has formed a complete set of automatic driving technology scheme, and in December 2015, it realized the fully automatic driving test under the mixed road conditions of cities, loops and expressways.

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In order to meet the new era of intelligent driving, the traditional automobile industry has also begun to enter the field of intelligent driving. SAIC has designed MG IGS intelligent driving assistant car, which can realize autonomous cruising and overtaking in the speed range of 60 ~ 120 km/h. 2015 Geely Borui 1.The 8T flagship model is equipped with ADAS functions such as ACC (adaptive cruise control), SVC (panoramic camera), LDW (lane departure warning system), BDS (parallel auxiliary system), FCW (front collision warning system or active braking system), and AP (automatic parking).

2.2 Overseas Unmanned Development

As early as 1980s, intelligent driving was concerned by many foreign universities, research institutes and companies, the most famous of which was the DARPA Grand Challenge held by DARPA three times. In 2004, the first Challenge was held in the Mojave Desert of the United States, requiring self-driving cars to complete 142 miles of desert crossing within 10 hours. But all the participating cars broke down in the first few miles and were forced to abandon the race. In 2005, DARPA Grand Challenge was held again; requiring self-driving cars to cross flat and dry lake beds and mountain passes, including three narrow tunnels and more than 100 sharp turns, driving for 132 miles, and Stanford University's automobile Stanley (Thrun et al., 2006) won the first place. Carnegie Mellon University's automobile sandstorm and H1ghlander won the second and third place respectively. The third competition, called DARPA City Challenge, was held in California, USA in 2007. This challenge requires self-driving cars to complete a 60-mile route in 6 hours together with other manual driving cars in a simulated urban environment. And follow California's traffic rules, and finally, 6 vehicles completed the route within the specified time. Auto Boss of Carnegie Mellon University won the first place, Junior of Stanford University won the second place, and Odin of Virginia Tech University ranked third. Although these challenges are much simpler than actual traffic, they do lay the foundation for the development of autonomous driving.

Since DARPA Challenge, many non-automobile manufacturing industries have joined in the research and development of autonomous vehicles. For example, the teams of Stanford and Carnegie Mellon University began to cooperate and develop Google driverless cars with the help of Google, and started to test the actual urban road environment in Las Vegas in 2010.In 2016, Uber Technology Company in Silicon Valley of the United States conducted a test on the streets of Pittsburgh, Pennsylvania, and provided unmanned driving services to the public. From 1987 to 1995, the "VaMP" and "VaMoRs" driverless cars jointly developed by the Federal University of Munich and Mercedes-Benz Motor Company can automatically avoid obstacles and realize autonomous overtaking. In 2011, the MRG team of Oxford University announced to the outside world for the first time the first self-driving car "Wildcat", which can also drive autonomously on rugged mountain roads.

With the joining of Internet companies such as Google, and the feasibility of driverless cars being gradually verified, more and more foreign traditional automobile manufacturers have started to develop their own intelligent vehicles, and have increased their investment to speed up the pace of research and development. Toyota announced that it will launch driverless cars that can drive in prescribed lanes around 2020.As a leader in automobile safety, Volvo has proposed to ensure that its self-driving cars will not have major traffic accidents around 2020. BMW announced that it will cooperate with Intel, the chip manufacturer, and Mobileye, the developer of ADAS, to speed up the development of driverless cars, and plans to build a brand-new driverless system, which will achieve mass production in 2021.

3. Unmanned Obstacle Recognition

3.1 Teaching Neural Network

In 1990, K.F. Kraiss first proposed a method of teaching neural network to guide vehicles to avoid obstacles. He designed an experimental model, in which vehicles need to pass through the door next to obstacles in the shortest distance from the starting point and drive to the end point. Mathematically correct test behaviour is used to determine the best path planning strategy, and vehicle distance d and direction error φ are taken as net inputs. The vehicle turning signal is taken as the output, and the error is reduced to a certain low level range by the reverse error propagation algorithm, and the test is terminated, thus obtaining the best driving route. However, because only the path information is added in the model, the ability to deal with unexpected events in real life is poor, resulting in poor generalization performance, so it has not been widely used.

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3.2 Linear Stereo Vision

In 1992, J.L. BRUYELLE and J.G. POSTAIRE first proposed a vehicle obstacle detection method based on computer vision. In the project, two linear cameras were used instead of video cameras to generate a linear stereo image sequence, thus reducing the data flow to be processed. By designing specific linear stereo correction and combining Canny differential operator, the selected segments in the left and right images are correlated with each other. The model can detect dynamic or static obstacles.

In 1994, according to the existing stereo vision theory, F. Thomanek equipped the system with four cameras, facing the front and rear of his own vehicle. By combining the shadow under the vehicle with the 3D geometry and the 3D dynamic scene, the obstacle features are extracted step by step.

In 1995, Yassine Ruichek and Jack-Gerard Postaire proposed a neural system based on linear stereo vision to detect obstacles in front of the vehicle in real time. The system first used recursive smoothing filter to remove noise and preserve edges, then used convolution smoothing signal and the first derivative of smoothing operator to detect edges, and finally obtained the optimal solution by Hopfield neural network. After testing, the system can detect pedestrians about 50 meters in front of the car when driving at a speed of 100 km/h. Compared with the previous implementation method, the system can improve the efficiency by 45%.

In 2006, Iyadh Cabani proposed a fast adaptive stereo vision system for road obstacle detection. Firstly, the system extracted vertical edge points by using the operator's color reduction rate, and then used dynamic programming based on geometry, irreversibility, uniqueness and color luminosity constraints to associate the vertical edge points. At last, the three-dimensional edges of obstacles are extracted, and v disparity map and u disparity map are adopted. And use the box to divide the boundary of obstacles. The performances of segmentation, matching and obstacle detection are discussed. It is pointed out that even if the code is not optimized, the processing time of obstacle detection is too long, and the future work will focus on reducing the input number of color matching.

In 2007, Guanglin Ma proposed a real-time obstacle and pedestrian detection algorithm, which used inverse perspective mapping to obtain a "virtual stereo system" to detect obstacles above the ground. The image collected by the monocular camera at t1 and the image collected at t0 are subjected to gray subtraction, because the gray value information of the ground will not change in a short time interval, However, the gray difference of obstacles on the ground is non-zero, so the area of obstacles can be obtained by marking the non-zero gray. Pedestrian detection is to calculate the binary edge image of defined ROI by using Sobel edge detection operator and then applying threshold. The method greatly improves the detection rate, At the same time, in the actual detection process, most pedestrians are detected reliably, and only a few errors are reported. However, because the algorithm is based on the condition of smooth road surface, on the actual road surface, the pitching of vehicles will lead to inaccurate kerb space, and the left side and the end are also marked as obstacles.

In 2011, Intae Na proposed a new visual obstacle detection and tracking system based on stereo vision. Robust stereo matcher, obstacle detector and tracker module are implemented and tested under actual driving conditions. Inputting the collected stereo images into a stereo matcher to generate a disparity map,The disparity map is analyzed in the target detector to detect obstacles, and the average correct detection rate of the final test result is 82.4%. However, it is easy to be affected by the illumination environment, resulting in the problem of false detection.

In 2014, Alexandru Iloie described a system for detecting obstacles in front of vehicles and dividing them into pedestrians and non-pedestrians. It uses a pair of low-cost grayscale stereo cameras to capture traffic scenes. In order to obtain high-density and high-precision stereo reconstruction points, Sort-SGM stereo reconstruction technology is adopted. Firstly, the road plane is calculated by using the V-direction disparity map, Then, obstacles are determined by analyzing the U-direction disparity map. Each pedestrian hypothesis is described by size correlation and direction gradient histogram based on gray features. Principal component analysis of features is used for feature selection and projection in correlation space. Considering the related features of pedestrian and non-pedestrian image sets, different support vector machine classifiers are trained. Finally, they are compared to select the one with the best classification score.

However, because linear stereo vision requires the level of two linear cameras to be highly unified, a specific correction level system is set, and the image information is ignored and the linear path is used instead, the effect of dealing with small obstacles is poor.

3.3 Machine Learning and Deep Learning Method

In 2002, Feiden D and Tetzlaff R summarized the traditional obstacle detection based on statistical methods, that is, using monocular camera to record video sequences, then searching for prominent image areas, calculating the estimated value of gray gradient in limited image areas, and making edges more prominent, then carrying out displacement vector estimation and 3D motion estimation, and finally carrying out motion compensation and obstacle detection. In this paper, the traditional edge detection method is improved. CNN is directly used for edge extraction, and the threshold value processed by CNN and the extracted image are iteratively annealed and optimized, and finally the parameters are obtained. This method improves the traditional edge detection method, which makes the processing speed of the network faster and more robust. However, only the results of edge detection are given in this paper. The accuracy of obstacle detection is not explained.

In 2009, Hern ́an Badino built a method called stixel-world to divide obstacles into adjacent rectangular bars with a certain height and width. SGM algorithm was used to calibrate dense stereoscopic images, and the depth changes of pixels were expressed in color, and the expected driving path of vehicles was marked in blue. The polar coordinates occupy the depth information of network obstacles and divide the free space, Using the same dynamic programming scheme as free space computing, the disparity images of foreground and background are segmented, and the height of stixels is obtained. That is, Stixel can be used to calibrate the position of obstacles.

In 2010, Qi Wu proposed a framework for obstacle detection which is different from the traditional method. Firstly, a perspective film was generated, and a 9x25 rectangle was used in coordinates to define a clear candidate path area in front of the vehicle for feature extraction. Then, the probability estimator of support vector machine was used to estimate the initial probability of the patch corresponding to the clear path for the selected features. Finally, the initial estimation is improved by probabilistic patch smoothing based on spatio-temporal constraints, so as to improve the detection performance.

In 2017, Sebastian Ramos built a visual system that used appearance, context and geometric clues to detect small target obstacles on the road, used the variant of fully rolled neural network to predict free space, combined with Stixel to mark unexpected obstacles on the road and semantic at pixel level, and used Bayesian framework to fuse semantic and stereo detection results. In the end, the relative performance is improved by 50% on the Lost and Found data set, and the detection rate can reach more than 90% at the test distance below 50 meters.

In 2017, Gowdham Prabhakar used PASCAL VOC image data set to train regional convolution neural network ZF Net, and used Fast-RCNN to detect and classify objects on roads. It showed good performance in detecting KITTI, Iloads and Indian road images, and even detected animals walking on roads, and basically processed image data with different resolutions at a frame rate of 10fps.However, the average accuracy (AP) of the system for motorcycle detection under the video shot of kitti_drive005 is 0, and the average accuracy for bus detection in the 50 images of Chennai Road data set is 0.62, which is rather poor.

In 2018, Penghua Li used region growing algorithm combined with morphological operation to extract obstacle regions, and used CNN neural network improved based on AlexNet network combined with RPN network to extract target features. Finally, in order to reduce the degree of over-fitting, Dropout layer was used to reduce training samples, and the model was obtained through Pascal VOC 2007 training set and Pascal VOC 2012 test set. The vehicle real-time video was tested and found, Under complex conditions, the detection accuracy of the model is more than 60%, and most of them are about 90%. However, the accuracy of the model is poor under complex lighting conditions and needs to be improved.

In 2019, Jing Lian proposed an obstacle detection and recognition method based on stereo vision and convolutional neural network. At first, the disparity map is obtained by semi-global stereo matching, and the obstacle candidate region is obtained by Stixel calculation. Then, we use U-Disparity Map to extract target obstacles from candidate regions. Finally, a new CNN convolutional neural network is proposed to identify target obstacles. Experimental results show that the proposed convolutional neural network improves the real-time performance (GPU memory and network computing load) by 69% when the recognition accuracy decreases by 4.9%.

Hsiang-Y u Han proposed a novel semantic segmentation network EdgeNet, which includes a class-aware edge loss module and a channel-based attention mechanism, with the aim of improving the

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accuracy without affecting the reasoning speed. The Edgenet is evaluated on the urban landscape data set. The experimental results show that the mIOU of this method in the urban landscape test set can reach more than 70%,Average IOU on GTX Titan X(Maxwell)GPU can reach above 30FPS.

The enhanced YOLOv3+ network proposed by Chintakindi Balaram Murthy in 2020 aims to realize accurate and real-time detection of smaller pedestrians in complex environments. In the proposed network, K- means clustering is applied before training to select the best K bounding boxes. The improved YOLOv3+ network introduces the inverse residual module to improve the feature extraction ability, and improves the loss function to reduce the bounding box loss error. In terms of detection accuracy, Compared with the existing network, the AP reaches 79.86%, but when detecting smaller pedestrians, the detection speed decreases slightly.

Lei Sun proposed a real-time fusion semantic segmentation network, RFNet, which can effectively utilize deep complementary features. Multi-dataset training and deep flow in the architecture enable the network to effectively detect unexpected small targets. Compared with ERF-PSPNet and SwiftNet, the tested network has significantly improved the tests on roads, sidewalks, buildings, walls, fences, poles, traffic lights and traffic signs.Furthermore, RFNet can even effectively avoid the features such as manhole covers which are easily mistaken for obstacles. However, the performance of RFNet network in detecting sidewalk, wall, motorcycle and other features is poor, only about 60%.

Finally, The remaining SE blocks applied after each convolution layer will be explained, and the edge loss module will be used to obtain higher MIOU without affecting reasoning. two different data sets will be used to verify the accuracy of the network. after verification, it is found that the EdgeNet built by ourselves has a significant improvement on MIOU compared with other networks, but the average accuracy of detecting walls, buses, trains and motorcycles is lower. It is mentioned that training samples can be increased to improve the accuracy, and this method can achieve the same accuracy as the most advanced method, with an acceleration ratio exceeding 5 to 40 times.

It can be seen that machine learning and deep learning methods use visual information such as color and depth to detect targets, which has significantly improved the accuracy of obstacle recognition. However, due to the increased complexity of visual information, the operation speed of the image processor is required to be higher, and the calculation time and cost are also increased. At the same time, due to the lack of pedestrians, motorcycles, The recognition accuracy of complex obstacles such as buses is only about 60%, and the deep learning method is greatly influenced by illumination.

4. Conclusion

Since 1990s, the concept of obstacle recognition has been proposed for the first time. The typical representative is the teaching neural network. Its principle is only to design a path from the starting point to the target to bypass the set known obstacles, so its generalization is poor. With the development of sensing technology, people gradually realize that obstacles can be recognized by binocular or multi-camera combined with disparity map. The vehicle can independently analyze the road ahead and make corresponding judgments, but linear stereo vision only extracts the path information from the visual information, ignoring other information such as color, depth, contour, etc., which makes the recognition accuracy of this kind of system low when dealing with small and changeable obstacles. With the gradual increase of the operation speed of image processor and the gradual development of deep learning technology, people gradually use CNN, EdgeNet, YOLOv3 and other networks instead of linear vision methods for target detection, which significantly improves the accuracy of obstacle recognition, but at the same time, problems such as operation time, real-time performance and cost need to be improved. The recognition accuracy of small and complex obstacles such as motorcycles is low, so we can build a special road data set for this kind of obstacles to improve the recognition accuracy. At the same time, the laser radar, acoustic radar and other sensors are used to assist the camera to improve the problem that the image information is greatly affected by illumination.

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