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An overview of the development of key technologies in autonomous driving technology

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Abstract. Technological advances in each of the smaller fields of automated driving technology have collectively advanced the maturity of automated driving technology. This paper describes some of the technological advances in the development of automated driving of automobiles. Firstly, it introduces the improvement of 3D target detection algorithms, the problem of 3D target detection from LIDAR point cloud, and the proposed control network to address the lack of human driving logic in the existing driverless strategy. Next, the convenience of virtual simulation technology in testing self-driving cars is presented as well as the use of high-definition maps by self-driving cars to understand the road and surroundings. Then the solution to the problem of weak feature extraction and low training efficiency when extracting data in the self-driving learning model, the path planning technology for self-driving cars, and the understanding of the scene when self-driving cars are traveling at night are presented. Finally, image target recognition based on synthetic aperture radar, image color recognition method based on deep learning, and how deep learning can be applied to the field of image recognition are presented.

Keywords: component, autonomous driving, 3D target detection, path planning, color recognition, deep learning

1. Introduction

The automobile sector stands out due to its role in passenger safety. Incidents are not permissible, leading to exceptionally stringent prerequisites for the safety and dependability of automobiles. Therefore, in the process of studying unmanned driving, there are extremely high requirements for the accuracy and robustness of sensors and algorithms. On the other hand, autonomous vehicles are commodities meant for everyday consumers, necessitating cost management. While highly accurate sensors enhance precise algorithm outcomes, their affordability has been a historical challenge. Presently, the advanced precision facilitated by deep learning technology propels the advancement of self-driving systems across pivotal domains like object detection, decision-making, and sensor implementation. Deep learning methodologies, exemplified by convolutional neural networks, are presently extensively employed in various image processing tasks, making them highly compatible with the realm of autonomous driving. Its training test samples are obtained from inexpensive cameras, which have attracted much attention as a way to reduce costs by using cameras instead of radar. In the unmanned driving system, the decisive role is the perception of the external environment, such as recognizing road signs, classifying obstacles, and accurately positioning pedestrians and vehicles. With the popularization of cars and the rapid development of industrial Internet, 5G and other technologies, the research of automatic driving technology is becoming more and more hot. The core of realizing automatic driving is making the right decision quickly according to the current vehicle state. Deep Reinforcement Learning (DRL) is a process in which the agent interacts with the environment, gives feedback to get rewards, and then makes the next action decision. The cycle repeats, and finally realizes the goal of autonomous decision making.

In this article, the authors introduce the application of deep learning in automatic driving, firstly, the authors introduce the commonly used models of deep learning and their related functions and applications, and secondly, the authors introduce how to optimize and improve the function of related algorithms in image recognition and enhance its function through algorithms. At the same time, it introduces how deep learning can improve the accuracy and practicality of scene recognition and scene interaction. For example, designing behavioral trees, PID control for optimization and optimizing algorithmic networks. All these behaviors make a valuable contribution and guidance for us to enhance the application of deep learning in autonomous driving. Finally, this paper provides an outlook and introduction of the related content in the market.

2. Relevant Techniques on Target Detection in Autonomous Driving

Cui J. investigates the environment-sensing task of self-driving vehicles in road scenarios [1]. The authors address the problems of long detection time, occlusion, unbalanced samples in the training dataset, and complex model of target detection algorithm in the current 3D target detection by clustering the taken data, performing similar shape category clustering, random sampling of vehicle target samples to enhance data training, and compressing model volume to optimize. After optimization, the improved model is compared and verified in the KITTI dataset, and Average Precision (AP) judges the target detection accuracy. The AP metrics for 3D detection were improved by 7.63%, 3.44%, and 2.12% for easy, medium, and difficult levels, respectively.

AP metrics for Bird's Eye View (BEV) detection improved by 3.09%, 2.57%, and 1.12% at easy, medium, and difficult levels, respectively. The improved target detection algorithm is evaluated in a real road environment, and the algorithm's single-frame elapsed time is improved by 21ms.

Wang L. addresses the problems, mainly the 3D target detection problem based on the LiDAR point cloud, the image-point cloud bidirectional multitask fusion problem, and the auto-vehicle-target vehicle motion state estimation problem [2]. The authors propose to use Point-Net++ to construct a 3D target detection network, which achieves the leading detection accuracy in its class in the KITTI dataset and propose a generalized neural network, PI-Net, for the bidirectional fusion of image-point cloud to solve multitasks at the same time. Evaluation results on the dataset show better performance than the existing methods in the bidirectional fusion of image and point cloud. Performance. The authors also propose the use of the neural network to simultaneously accomplish the position estimation of the external target vehicle and self-vehicle and design the reduced-order observer to observe the speed information of the target vehicle and self-vehicle and verify the effectiveness of the neural network and observer proposed in this paper in simulation and real vehicle experiments.

Lv D., Xu K., Li H.Y. and Pan M.Z. address the problem that existing driverless strategies ignore the driving logic that humans follow when driving a car, the authors impose the effect of the rule constraints of human-like driving on the successive behaviors of the intelligence in a deep reinforcement learning-based end-to-end driverless control network and build a driverless end-to-end control network capable of outputting successive ordered behaviors that conform to the logic of human-like driving [3]. The authors also reduced the output rate of dangerous behaviors of the control strategy by applying a posteriori feedback to the output. For sparse catastrophic events that are difficult to be fitted during training, the authors state a reward function that improves the steadiness of the algorithm training. The results from several different simulation environments show that the improved reward shaping approach improves the approximation of the optimization expectation of the objective function in evaluating sparse catastrophic events by 85.57% over the pre-improvement period, and improves the training efficiency by 21% over the traditional deep deterministic policy gradient (DDPG) algorithm, the rate of successfully completing tasks by 19%, and the efficiency of executing tasks by 15.45%.This shows that using the strategy proposed in this paper significantly reduces collisions and improves driving performance while ensuring driving safety.

3. Technologies Related to Image Recognition and Driving Patterns in Autonomous Driving

Yanfeng Li, Hsin Guang, Xin Jia and Chuguang Duan reported how using realistic virtual simulations can improve the testing of self-driving cars [4]. When testing these cars, creating a virtual world that closely resembles the real one is important. This involves simulating things like car movements, sensor usage, and the environment's appearance. A crucial aspect of these tests is the scenario vehicle, which is a simulated car that interacts with the self-driving car being tested. However, a problem with current scenario vehicles is that they're too cautious and only respond negatively to situations, lacking confident decision-making.

To address this issue, a recent study proposes a dynamic scenario vehicle model inspired by the behavior of real human drivers. The researchers draw on psychological theories from Maslow and Reiss to understand the motives behind human actions. They then design a simple behavior tree framework to organize the scenario vehicle's behavior. The researchers develop a 2D simulator and run experiments to test their new model. The results are promising – the scenario vehicle equipped with the new model successfully completes long drives, reaches its goals, and interacts with other vehicles just like a human driver would. This approach could help make virtual testing of self-driving cars more accurate and reflective of real-world driving behavior.

Guannan Li, Xiu Lu, Liangchen Zhou, Bingxian Lin and Guonian Lv reported the locations of various objects within streets is crucial [5]. Current methods for positioning objects in street-view images, particularly from mobile mapping systems (MMSs), often depend on depth information or matching image features. However, these methods can be expensive due to the need for additional data or face limitations when dealing with MMS data with low overlap.

Li, Lu, Lin, Zhou and Lv introduce a new positioning approach based on the "threshold-constrained line of bearing" (LOB) concept to overcome these challenges [6]. While the existing LOB method faces issues with threshold selection that can vary based on specific data and scenarios, this study proposes a "divide and conquer" strategy built on the LOB technique. In this method, the driving trajectory of the MMS is used to adaptively divide the calculation area, which restricts the effective range of LOB and reduces unnecessary computation costs. This approach leads to a more efficient screening of positioning results within the designated range, eliminating the need for extra auxiliary data. As a result, both computing efficiency and geographic positioning accuracy are improved.

An experimental area in YinCun town, Changzhou City, China, was utilized to test the proposed method. Pole-like objects were chosen as the research focus, and deep learning was employed for object detection. The study maps these objects as LOBs and achieves high-precision geographic positioning through region division and self-adaptive constraints. The outcomes of the experiments demonstrate the effectiveness of the approach. Around 6104 pole-like objects were detected through deep learning and accurately mapped as LOBs. The proposed method achieved impressive results through the combination of region division and self-adaptive constraints: a 93% recall rate (correctly identifying objects) and a 96% accuracy rate (precise positioning). Moreover, the proposed approach achieves higher accuracy

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compared to existing LOB-based positioning methods, and the threshold value is automatically adjusted to suit different road scenarios.

The ADASKY reported the significance of object detection in self-driving cars, especially in challenging weather conditions. While current systems use visible imaging, LIDAR, and RADAR, harsh weather can compromise their performance, as shown in figure 1. To address this, thermal imaging emerges as a valuable solution due to its ability to detect and recognize surroundings even in extreme conditions. Thermal images can also work well with detection algorithms like artificial neural networks. The paper delves into an analysis of how well thermal sensors perform in severely unfavorable fog conditions. The primary aim was to determine the limits of thermal camera reliability when faced with heavily degraded fog situations. The study employed two indicators – mean pixel intensity and contrast – to assess resilience. The outcomes highlighted the critical role of a thermal camera's angle of view (AOV) in foggy scenarios. Notably, the results indicated that cameras with AOVs of 18° and 30° prove effective for object detection even when confronted with thick fog conditions (meteorological optical range of 13 meters). These findings were further verified through object detection software, which demonstrated that both the 18° and 30° cameras achieved a detection rate of over 90% for pedestrians. The article underscores the importance of object detection for self-driving cars, particularly in challenging weather like fog. Thermal imaging emerges as a robust solution, especially when paired with suitable camera parameters, and the study's findings offer valuable insights for enhancing the reliability of self-driving car perception systems under adverse conditions.

Figure 1. Use of the ADASKY LWIR camera to improve visibility on roads.[3]

4. Techniques on Target Recognition and Driving Patterns in Autonomous Driving

Meiling Chen presents a deep reinforcement learning method based on a self-attention mechanism, aiming at the problems of weak feature extraction ability and low training efficiency when a reinforcement learning model is used to extract high-dimensional data [7]. A deep reinforcement learning method based on an information bottleneck is proposed to solve the problem that the reinforcement learning algorithm only completes the policy update according to the reward size while ignoring the influence of the feature extraction ability of the model on the strategy learning. Using the information bottleneck method, the model can retain the key features related to the task as much as possible and discard the redundant information unrelated to the task. This chapter mainly uses the model that has been trained for about 20,000 rounds for model validation, by analyzing the model's performance under the influence of weather, driving scenarios, noise and other factors. The experiments on the simulation platform show that the proposed deep reinforcement learning method based on information bottleneck can obtain higher rewards than the traditional method and the deep reinforcement learning method based on a self-attention mechanism in the process of completing the automatic driving decision-making task.

Ouyang Keke argues that self-driving cars promise to improve traffic safety while increasing fuel efficiency and reducing congestion [8]. This paper mainly studies the path planning of autonomous vehicles in traffic. Based on deep learning and reinforcement learning, a network model based on the Markov decision process is designed to complete the path planning of curve driving and lane keeping in the simulation environment. A simulated driving environment model was established according to the real environment. The model applied the optimal automatic driving strategy trained by deep learning. Finally, the simulation experiment verified the method. Under the four weather conditions, the average reward obtained by the model as a whole can be maintained at a high level, and the average reward obtained can be maintained at more than 8. The experimental results show that the proposed method can reduce the lateral tracking error, improve the model's generalization performance, and reduce the over-dependence problem.

Ruan Yu, Sun Shaoyuan, LI Jiahao and WU Xueping aims to enhance the understanding of the surrounding scene when the autonomous vehicle is driving at night so that the car or the driver can make corresponding adjustments in time, applying deep learning to the scene prediction of night vision images [9]. A predictive coding network is used to predict the scene changes of night vision images. The structure is adjusted somewhat based on the traditional deep convolution-recurrent neural network. The errors between the predicted and actual images are transmitted forward through the network, and the errors are constantly updated to adjust the prediction results. The test results show that the trained scenario prediction model can predict the reasonable future after 0.4s of night driving scenarios and improve the ineffective problem in long-term prediction tasks, with good accuracy and real-time performance.

Li P. reported visual target identification based on synthetic aperture radar (SAR) has been a popular research topic in the field of radar image interpretation [10]. The presence of adversarial examples in the context of deep learning algorithms applied to Synthetic Aperture Radar (SAR) image target recognition remains a topic that has yet to be definitively addressed. The first paper attacks the recognition accuracies of three classical deep learning algorithms for SAR image target recognition, AlexNet, VGGNet, and ResNet models, which are labeled with BMP2, by generating adversarial examples using three mainstream algorithms with 96.45%, 97.94%, and 98.77% recognition accuracies, respectively, for test samples labeled with BMP2. The experiments involve publicly available real synthetic aperture radar (SAR) images, and 550 experiments are conducted against white-box and black-box attacks. The results show that under targeted white-box attacks, the experimental results indicate that the adversarial examples are more aggressive under the condition of mastery of the structure. Under targeted black-box attacks, the experimental results show that the adversarial examples are somewhat more aggressive. Therefore deep learning based synthetic aperture radar image target recognition algorithm is possible. Therefore, the deep learning based synthetic aperture radar image target recognition algorithm is at risk of being attacked by the adversarial example

Huang and colleagues presented a method rooted in deep learning for enhancing image color recognition, along with an optimization approach in tackling the challenge of image color recognition as shown in Figure 2 [11]. This involved the creation of a post-processing framework utilizing a bag-of-words (BOW) model. The framework integrated convolutional neural network (CNN) features and computed the similarity of these features. Groups of highly similar images were then directed into an image classifier that had been trained through the BOW clustering model. This classifier initiated the retrieval process, determining the category with the most matching images. The conducted experiments revealed that when compared to a CNN-based image retrieval algorithm, the framework achieved a 90.4% accuracy rate in image retrieval on the same dataset and classification categories, signifying a 10% improvement. To conclude, the study emphasized the significance of aligning image color to the desired retrieval image.

Fujiyoshi H. reported numerous image recognition tasks within the realm of image analysis have been successfully completed by merging manually crafted local image attributes (referred to as handcrafted features) with machine learning techniques [12]. After 2010, many image recognition methods using deep learning were proposed. Image recognition methods using deep learning are far superior to the methods used in general object recognition competitions before the advent of deep learning. Therefore, the third article will describe how deep learning can be applied to image recognition and describe the latest trends in deep learning-based autonomous driving. Highlights - Convolutional Neural Networks for Object Detection and Semantic Segmentation - Visual Interpretation for Decision

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Making for Autonomous Driving through End-to-End Learning - End-to-End Learning for Autonomous Driving.

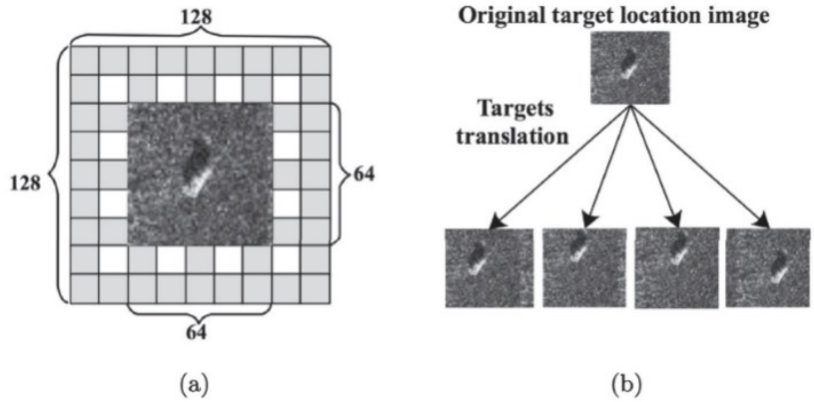

Figure 2. An example of the target translation steps. (a) Computing target translation; (b) Result of target translation [11]

5. Conclusion

Based on deep learning image recognition technology applied to the field of automatic driving, the collection of relevant experimental data to find the most suitable algorithms to solve the problem, to build a network to achieve effective detection of their own vehicles and the speed of the surrounding vehicles. Based on the virtual simulation scenario to solve how to better simulate the real scene optimization, the researchers used laser advanced technology to collect a large amount of road information to draw high-definition maps to increase the reliability of automatic driving. Based on the psychological theories of Maslow and Reis, the researchers used the "behavioral tree" to create a model to make changing car behavior become more consistent with human thinking. In Deep Learning-based Autonomous Driving, researchers proposed a deep reinforcement learning method based on information bottlenecks, which solves the problem of reinforcement learning algorithms completing policy updates based only on the size of rewards. To improve the performance of nighttime autonomous driving, the researchers used predictive coding networks for scene changes, improving the ineffectiveness problem in long-term prediction tasks. In terms of images, the researchers optimized and improved the algorithm's effectiveness based on synthetic aperture radar to optimize the algorithm's accuracy. Meanwhile, for the problem of image color recognition, a method of image color recognition and optimization is proposed, and a post-processing framework is designed, which greatly improves the color matching between the image color and the color of the image to be retrieved. The neural network-based PID control algorithm introduces an enhanced BP algorithm study to improve the control efficiency and performance of the PID control system. With the wider application of deep learning in the field of automated driving, the related industries will produce more perfect and better performance products related to automated driving. More products in the market will be seen in the future.

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