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Perception and Decision Optimization of Autonomous Driving System Driven by Internet of Things and Artificial Intelligence Algorithm

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Abstract. AI algorithm can also carry out self-learning and self-optimization through Machine learning (ML) and deep learning (DL), and continuously improve the perception and decision-making ability of self-driving cars. In order to build a more intelligent computer-aided driving system, this article applies the algorithms to the perception and decision optimization of autonomous driving system. In the experiment, the algorithm is verified and tested, and pictures of various scenes are used for experiments, which verifies the adaptability, stability and accuracy of the algorithm to different scenes. The algorithm in this article has a significant advantage in the accuracy of vehicle or obstacle feature detection, which is 28.64% higher than the contrast algorithm, which means that the algorithm in this article can identify the features of vehicles and obstacles more accurately and locate their edge contours more accurately. The system can realize real-time monitoring and target recognition of the road in front of the vehicle, and make decision and control of vehicle-assisted driving according to the target information and the vehicle's own information and instructions.

Keywords: Internet of Things; Artificial intelligence; Computer-aided driving; Target following
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1 INTRODUCTION

Self-driving car technology integrates cutting-edge technologies in many fields, including IoT, AI, sensor technology, etc., aiming at achieving a safe, comfortable and efficient car driving experience. The LSTM automatic encoder architecture proposed by Ashraf et al. [1] consists of three parts: encoder, decoder, and output layer. Intelligent transportation systems have become an important means of modern urban traffic management, but various abnormal events are inevitable during the operation of the system. These abnormal events may originate from various factors such as system failures, traffic accidents, and road congestion. If not detected and handled in a timely manner, it may have a serious impact on the entire transportation system. We conducted experiments on the proposed LSTM automatic encoder architecture using real intelligent transportation system data. Compared with traditional anomaly event detection methods, this architecture has improved accuracy and real-time performance. In addition, we also demonstrated the effectiveness and practicality of the architecture in practical applications. Self-driving car technology is an intelligent car driving technology based on computer, sensor, control system and other technologies. Its purpose is to realize the automatic navigation, control and driving of automobiles through technical means without human intervention. Intelligent transportation systems refer to real-time monitoring and intelligent management of road traffic conditions using various sensors, communication, and information technologies, in order to achieve safety, efficiency, and environmental protection of transportation. In intelligent transportation systems, active safe driving technology is an important research direction aimed at road safety through measures such as early warning and collision avoidance. Intelligent transportation systems use various advanced technological means, such as Chang et al., [2] to monitor and intelligently manage road traffic in real-time, improving road safety and operational efficiency. Active safe driving technology is an important technology in intelligent transportation systems, which utilizes various sensors and algorithms. Predict the traffic conditions around the vehicle, promptly identify potential safety hazards, and take corresponding measures for early warning and collision avoidance. With the continuous development of AI, IoT and other technologies, the technology of self-driving cars is also improving, from primary to advanced, and different degrees of self-driving are gradually realized. Cheng et al. [3] introduced an adaptive control system for longitudinal anti-collision and lateral stability of autonomous vehicle. The longitudinal collision avoidance control strategy of autonomous vehicles mainly involves predicting the vehicle's travel trajectory and adjusting the vehicle's speed and acceleration based on the predicted results to avoid collisions with obstacles ahead. In the design, we adopted Model Predictive Control (MPC) algorithm to achieve longitudinal collision avoidance control. Using a linearized model to describe the dynamic behavior of the vehicle, taking into account factors such as tire force and air resistance. Using vehicle models and sensor data to predict the vehicle's travel trajectory. Based on the predicted results, adjust the driving speed and acceleration of the vehicle to ensure safe obstacle avoidance. By real-time calculation and execution of control strategies, dynamic control of vehicle longitudinal collision avoidance is achieved. Through on-board sensors, GPS, high-definition maps and other means, self-driving cars can obtain a lot of environmental information, and then transmit this information to the cloud through IoT technology. The collaborative detection mechanism for distributed denial of service attacks in the Internet of Vehicles based on Amulti agent is an innovative DDoS attack detection and defense method, which fully utilizes the advantages of multi vehicle collaboration in the Internet of Vehicles. The comparative experimental results show that the vehicle network using collaborative detection mechanism has higher robustness and security in the face of DDoS attacks. To verify the effectiveness of the collaborative detection mechanism for distributed denial of service attacks in the Internet of Vehicles based on the Amulti agent, Dong et al. [4] designed a series of experiments. In the experiment, we built a simulation environment containing multiple vehicles and infrastructure to simulate DDoS attacks in real vehicle networking scenarios. By comparing the situation where collaborative detection mechanism is not used and the situation where collaborative detection mechanism is used, we can observe the advantages of this mechanism in improving attack detection accuracy and defense effectiveness. Through the processing and analysis of these data, the cloud can obtain detailed information about the surrounding environment of the vehicle, thus providing more accurate information support for the decision-making of autonomous vehicles. Information exchange is the key to improving driving safety. However, due to the complexity of the network environment and the randomness of vehicle movement, the delay estimation of data forwarding has become a challenge. Gao and Tian [5] conducted estimation research on the data forwarding delay of intelligent transportation systems based on vehicle networking technology. The Internet of Vehicles technology provides more accurate and real-time traffic information through information exchange. This information exchange is of great significance for the study of data forwarding delay estimation in intelligent transportation systems. Data forwarding delay refers to the time interval between data being sent from the source node and received by the destination node. The estimation of data forwarding delay can usually be done through model establishment and simulation testing. Among them, model establishment can establish theoretical models based on network topology, communication protocols, etc., and calculate the expected delay through theoretical calculations. Simulation testing can simulate and test data forwarding latency through actual network environments and test data. AI algorithm can identify the environment and obstacles around the vehicle and predict the behavior of other vehicles and pedestrians, thus providing more accurate support for the decision-making of autonomous vehicles. Autonomous driving technology relies on a large amount of data for learning and improvement, so the integration of autonomous driving datasets is particularly important. cet al. [6] introduced a knowledge graph-based method for integrating autonomous driving datasets. By applying knowledge map to the integration of automatic driving data sets, data can be more effectively organized and utilized, and the performance of auto drive system can be improved. Integrate LiDAR data and camera data to improve data reliability and accuracy. Finally, it is necessary to extract useful information from the data through data mining techniques, such as using clustering algorithms to classify vehicles for autonomous driving decision-making and control. In addition, the AI algorithm can also self-learn and self-optimize through ML and DL, and continuously improve the perception and decision-making ability of self-driving cars.

This article studies a target following algorithm based on computer vision, which uses image information to identify and track target objects. Firstly, by analyzing the characteristics of the target object, we use these characteristics to search and match the target in the image. Then, using the matched target information, the target is tracked and predicted, and the position and trajectory of the target object are obtained. Using the target following algorithm, the distance between the target object and the vehicle can be calculated in real time, and automatic safety distance control can be carried out according to the set safety distance threshold, so as to keep the safety distance between the vehicle and the vehicle or pedestrian in front. Deep learning models are providing strong support for safe and reliable transportation operations. Jolfaei et al. [7] analyze, and utilize data through various advanced technological means to achieve traffic flow monitoring, prediction, management, and control. Deep learning models systems due to their strong fitting and adaptive abilities. Deep learning models are providing strong support for safe and reliable transportation operations. Intelligent transportation systems collect, analyze, and utilize data through various advanced technological means to achieve traffic flow monitoring, prediction, management, and control. Due to their strong fitting and adaptive abilities. When the sudden appearance of pedestrians or vehicles in front is detected, the algorithm can send braking instructions to the control system in time to realize automatic braking control, so as to avoid collision or reduce the degree of collision. Through the target following algorithm, the following control of the vehicle in front can be realized. With the continuous development of autonomous driving technology, real-time intelligent object detection system has become an indispensable part of autonomous vehicle. Identify pedestrians, vehicles, road signs and other objects, so as to provide reliable support for decision-making and control of autonomous vehicle. Liang et al. [8] introduced collaboration. In the traditional auto drive system, the vehicle obtains the surrounding environment data through laser radar, camera and other sensors, and processes and analyzes them in the on-board computing unit. However, this approach has problems such as limited computing resources and insufficient data processing. Therefore, we will introduce the concept of edge cloud collaboration to improve the performance and efficiency of real-time intelligent object detection systems. Using the on-board camera and image processing system, the position and motion information of the vehicle in front can be obtained in real time, and the vehicle can be controlled to follow the vehicle in front. Crowdsourcing is a collaborative model that assigns work tasks to non-specific mass networks. The advantages of this model lie in reducing costs, improving efficiency, and gathering public wisdom. With the popularity of crowdsourcing, more and more enterprises and organizations begin to use this model to solve problems. Intelligent transportation system is a system that utilizes advanced information, communication, and technological means, and Lucic et al. [9] has intelligently transformed urban transportation systems. It can help traffic management departments better monitor traffic conditions, optimize resource allocation, improve transportation efficiency, and provide the public with a more convenient and safe travel experience. The advantages of intelligent transportation systems lie in improving traffic safety, reducing congestion, energy conservation and environmental protection, and have become an indispensable component of modern cities. When encountering obstacles during driving, the algorithm can calculate the path to avoid obstacles by identifying and tracking obstacles, and automatically control vehicles to avoid them. Using target following algorithm, pedestrians on the road can be detected in real time, and automatic avoidance control can be carried out according to the position and speed information of pedestrians to avoid collision with pedestrians. The main innovations of this study are as follows:

(1) This article combines computer vision technology with AI algorithm to realize fast and accurate identification and tracking of target objects.

(2) The algorithm combines the information and instructions of the vehicle itself to realize the decision and control of vehicle-assisted driving.

(3) The adaptability, stability and accuracy of the algorithm in different scenarios are verified by experiments, and the algorithm is successfully applied to the computer-aided driving system, and good application results are obtained.

In this article, an automatic driving target following algorithm based on visual perception is proposed, and the characteristics of the target are automatically learned through convolutional neural network. Compared with genetic algorithm (GA), this algorithm has higher accuracy and efficiency in target following and feature detection, which is expected to provide useful reference for the realization of automatic driving system.

2 THEORETICAL BASIS

For autonomous vehicle, radar is a very important sensor. Through radar, cars can obtain real-time information about their surrounding environment, including other vehicles, pedestrians, road signs, traffic lights, etc., in order to make accurate driving decisions. The chip/encapsulated radar further improves the performance and integration of the radar, making it more miniaturized, efficient, and low-cost. Secondly, intelligent transportation systems also need to rely on radar technology to achieve intelligent management of traffic flow. For example, radar can monitor traffic information such as road congestion, vehicle speed, and vehicle spacing, in order to reasonably schedule and divert traffic flow. Chip/encapsulated radar can better adapt to this application scenario, improve the reliability and durability of the radar, and reduce costs. Saponara et al. [10] discussed the opportunities and challenges of chip/inner package radar, the application scenarios of chip/built-in radar are very extensive. First of all, in autonomous vehicle, the chip/inner package radar can be used to detect the distance and speed between vehicles to help vehicles drive safely. In addition, it can also perform tasks such as road sign recognition and pedestrian detection, improving the automation level of automobiles. In intelligent transportation systems, chip/encapsulated radar and control of traffic flow, improving road efficiency and safety. Intelligent transportation systems have become an important means of solving modern transportation problems. Collaborative intelligent transportation system services, as a new type of intelligent transportation system, provide effective solutions for improving road safety and traffic efficiency through efficient information sharing and collaborative scheduling. Shepelev et al. [11] studied how to predict the passage time of highly automated vehicle queues based on neural networks in collaborative intelligent transportation system services. However, despite the enormous potential of collaborative intelligent transportation system services, their implementation still faces many challenges, such as information collection, data processing, communication reliability, and other issues. In terms of predicting the passage time of highly automated vehicle queues, previous research has mainly focused on time prediction based on traditional statistical and machine learning algorithms. The application of vehicle networking technology can help solve the challenges faced by traditional prediction methods. For example, by collecting and analyzing real-time communication data between vehicles, dynamic changes in traffic flow can be more accurately captured, thereby improving prediction models. In addition, through information sharing between vehicles, more efficient route planning and collision avoidance safety goals can also be achieved.

Among them, collaborative positioning technology, as one of the key technologies in the Internet of Vehicles, aims to improve the accuracy and reliability of vehicle positioning. Shi et al. [12] introduced the principle and method of multi-source and multi-objective collaborative positioning based on vehicle workshop relative vector fusion in the Internet of Vehicles. In the Internet of Vehicles, commonly used positioning technologies include satellite positioning technology, wireless positioning technology, and vehicle feature positioning technology. Satellite positioning technology utilizes satellite navigation systems such as the Global Positioning System (GPS) for positioning, which has high accuracy and a wide range of applications. Wireless positioning technology utilizes wireless communication networks to locate through base stations or wireless sensors, suitable for areas such as urban environments and tunnels that cannot be covered by satellite signals. The blockchain based privacy protection system for the Internet of Vehicles has obvious advantages. Firstly, through distributed storage and encrypted transmission technology, the system can effectively protect the privacy and security of data. Secondly, with the help of blockchain's smart contract function, automatic data management and access control can be achieved, further enhancing the maintainability and reliability of the system. In addition, the decentralized nature of blockchain technology is beneficial for reducing the risk of system centralization and improving the scalability and fault tolerance of the system. Su et al. [13] By utilizing the distributed storage characteristics of blockchain, we can decentralize and store private data on multiple nodes, thereby avoiding the risks associated with centralized data storage. Secondly, through blockchain encryption technology, we can encrypt the transmitted data to ensure its security and confidentiality during transmission. Finally, with the help of blockchain's smart contract function, we can achieve automatic data management, including access control, usage, and deletion of data.

The CAV network needs to verify the identity of network devices to ensure that only authorized devices can access the network. The data transmission between CAV vehicles and data centers needs to ensure its security to prevent data from being intercepted or tampered with. CAV vehicles and related equipment need to have sufficient security to prevent being attacked by hackers or infected by malicious software. Sun et al. [14] investigated CAV related enterprises and institutions, such as automakers, technology providers, and policy makers. A total of 500 questionnaires and 100 on-site interviews were collected through questionnaire surveys and on-site interviews. Through the analysis of survey data, it was found that there are the following main issues with CAV network security: some CAV devices did not use sufficient strength data encryption technology, resulting in the risk of data being intercepted or tampered with. With the continuous development of technology, the G space air ground integrated intelligent transportation system is becoming an important means to solve urban transportation problems. In this context, the introduction of autonomous vehicle technology plays an important role in improving traffic efficiency. However, how to further improve the traffic efficiency of autonomous vehicle? Tan et al. [15] proposed a solution to enhance traffic efficiency of autonomous vehicle speech emotion recognition based on G space air ground integrated intelligent transportation system. Using high-precision sensors and GPS positioning system, real-time position and speed information of autonomous vehicle can be obtained. Secondly, using speech emotion recognition technology, analyze the driver's speech information and determine their emotional state. Finally, according to the emotional state information, adjust the driving strategy of autonomous vehicle to improve traffic efficiency. Using machine learning algorithms for speech emotion recognition to determine the driver's emotional state. According to the analysis results, the driving strategy of autonomous vehicle is optimized to improve the traffic efficiency. With the continuous development of artificial intelligence technology, autonomous vehicle has gradually become a research hotspot. In autonomous vehicle, raindrop detection is a very critical issue, because it directly affects the safety and reliability of autonomous vehicle. Venugopal [16] introduced the concept of autonomous driving raindrop detection based on artificial intelligence, and explained its importance and application prospects. The traditional raindrop detection methods mainly include visual detection and sensor detection. Visual detection is the process of obtaining raindrops on car windows or rearview mirrors through image acquisition devices, and then detecting and analyzing them through image processing technology. Sensor detection is to install sensors outside the car to sense the size and distribution of raindrops, and then transmit them to the auto drive system for decision-making. Xiong et al. [17] proposed an autopilot service deployment adaptive method based on mobile edge computing. The core idea of the adaptive method for autonomous driving service deployment is to select appropriate adaptive methods based on actual situations and optimize service deployment. In the implementation process, it is first necessary to analyze the characteristics of autonomous driving scenarios, including large data volume and high real-time requirements. Then, according to the analysis results, select the appropriate edge computing algorithm and model for data processing and analysis. At the same time, it is also necessary to consider the optimization of service deployment, including the allocation of computing resources and the design of network topology. The hybrid application of autonomous driving and manual driving is an important research direction in this system. However, how to ensure the safety of this mixed traffic is an urgent problem to be solved. Yu et al. [18] proposed a hybrid traffic safety solution based on deep learning for autonomous and manual driving, and conducted experimental verification on it. Deep learning technology has played a crucial role in hybrid traffic safety solutions for autonomous and manual driving. Firstly, high-precision sensors and GPS positioning systems are used to obtain vehicle position and speed information, which is used as input for deep learning models.

3 PERCEPTION AND DECISION OPTIMIZATION MODEL OF AUTOMATIC DRIVING SYSTEM

Computer vision is a science that studies how to make computers get information from images or videos, understand the content and make decisions. It involves many fields, including image processing, ML, pattern recognition and so on. In the automatic driving system, computer vision is mainly used for vehicle perception and decision-making, including:

(1) Environmental awareness: Through sensors such as cameras, self-driving vehicles can obtain detailed information about the surrounding environment, including vehicles, pedestrians, road signs, traffic signals and other factors. After processing this information, a high-precision environmental map can be generated, which provides a basis for vehicle path planning and decision-making.

(2) Target recognition: Computer vision can recognize the target objects in the image, including vehicles, pedestrians and traffic signals. Through target recognition, autonomous vehicles can perceive the position, speed, orientation and other information of traffic participants around them, so as to make corresponding driving decisions.

(3) Road identification: Using computer vision technology, autonomous vehicles can identify the shape, lines, textures and other information of the road, and judge the position, direction and speed of the vehicle through this information. This is helpful to realize autonomous navigation and path planning of self-driving vehicles.

AI algorithm is an algorithm to realize intelligent decision-making and control by learning, analyzing and processing a large amount of data. In the automatic driving system, AI algorithm is mainly used in the following aspects:

(1) Machine learning (ML): Through a large number of driving data training models, AI algorithm can learn the rules and patterns of driving behavior, so as to make accurate driving decisions. For example, by learning a large number of traffic scenes, the algorithm can judge the behavior and intention of traffic participants independently.

(2) Deep learning (DL): DL is a kind of ML, which uses neural network model to process and analyze data. In automatic driving system, DL can be used for target recognition, image segmentation and other tasks. For example, through the deep neural network, the algorithm can accurately identify pedestrians and other traffic participants.

(3) Reinforcement learning (RL): RL is a ML method to learn the best behavior through the interaction between agents and the environment. In the automatic driving system, RL can be used for tasks such as path planning and control optimization. For example, by strengthening the learning

algorithm, autonomous vehicles can learn the optimal driving strategy. Due to the development of society and the progress of technology, self-driving cars have gradually become the focus of research. Self-driving car technology can realize more intelligent, efficient and safe vehicle control, which brings many benefits. For example, self-driving cars can reduce traffic accidents, improve the transportation efficiency of roads, and enhance the travel experience of pedestrians. To achieve these goals, visual perception technology is indispensable. Visual perception plays a vital role in autonomous driving. Through visual sensors, vehicles can obtain images and video information of the surrounding environment, and process and analyze this information to identify and track targets. In addition, visual perception can also provide information about the vehicle itself, such as position, speed and acceleration. This information is very important for the path planning, decision-making and control of the automatic driving system. However, the processing and analysis of visual perception is a complex and computationally intensive task.

Traditional visual perception methods usually adopt feature extraction and classifier design, which need to be optimized and adjusted independently for different tasks.

Target following algorithm is one of the key technologies of automatic driving system perception and decision optimization. This section proposes a target following algorithm based on computer vision, which includes the following steps:

(1) Target detection: the target object is detected in the image, and the target is identified by feature extraction and classifier algorithm.

(2) Feature extraction: According to the characteristics of the target object, extract effective feature vectors. These feature vectors may include color, shape, texture, etc.

(3) Establishment of motion model: According to the motion characteristics of the target object, a motion model is established, and the target object is tracked by this model.

(4) Target following: using the motion model and feature vectors, target following is carried out between consecutive image frames, and the motion model is updated in real time.

In the concrete implementation process, a target detection algorithm based on DL is adopted, and convolutional neural network (CNN) is used for feature extraction and classifier training. Moreover, according to the motion characteristics of the target object, a target following algorithm based on kinematics model is established, which realizes the accurate tracking of the target object. The algorithm consists of two basic problems, namely feature extraction and target following, as shown in Figure 1.

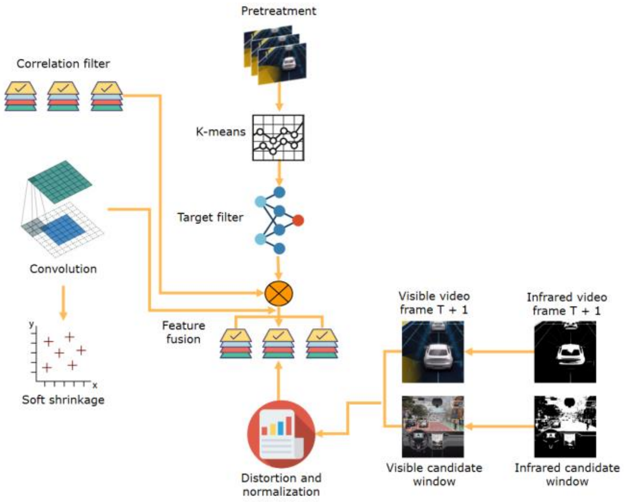

Figure 1: Automatic driving control algorithm.

Binocular imaging technology is a key technology in computer-aided driving system. By simulating the visual mechanism of human eyes, it uses two cameras to collect pictures at the same time, and obtains the pixel difference of the corresponding points of an image imaged by the left and right cameras to obtain depth information, and then obtains 3D information to realize the reconstruction of objects.

In order to ensure the consistency of the scenes shot by the left and right cameras, the binocular camera adopts the method of simultaneous acquisition. The acquired picture will change with the focal length of the camera. Increasing the optical focal length will narrow the imaging field of view and is limited by volume; Increasing the baseline distance of binocular system is not only limited by the volume of the system, but also increases the blind area of binocular imaging and increases the difficulty of calibration. The parameters of the camera include whether the lens itself is completely parallel to the image, and whether the light at the center of the lens is more curved than near the center. These factors may lead to lens deviation during lens installation and assembly, so calibration is needed to obtain accurate camera parameters. The binocular imaging principle of computer-aided driving system is shown in Figure 2.

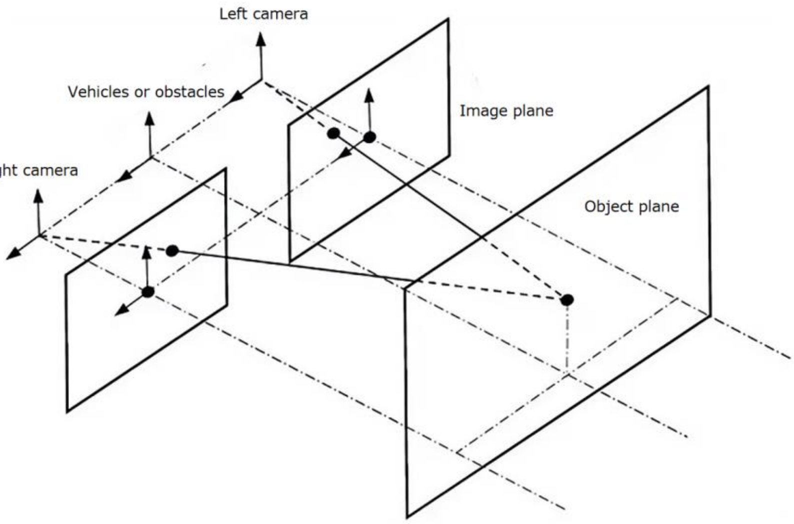

Figure 2: Binocular imaging principle.

Depth information can be obtained by calculating the pixel difference of the images obtained by the left and right cameras. The depth information is related to the position of the object in the camera coordinate system, and the 3D information of the object can be obtained after processing by a certain algorithm. Using the obtained depth information and the image information obtained by the left and right cameras, 3D reconstruction can be carried out to reconstruct the 3D model of the object.

$$\alpha_s \arg\max \alpha^T \sum \alpha$$
$$subj. \quad ubj\|\alpha\|_2 = 1, \|\alpha\|_1 \le k \tag{1}$$

$$\theta = \frac{1}{k}\sum_{j=1}^{k}\theta_{ij} \tag{2}$$

The overall framework of computer-aided driving target following algorithm can be divided into the following main parts: target detection and feature extraction: firstly, it is needed to detect the target object from the video sequence and extract its features, such as color, shape and texture. Motion model establishment: according to the motion characteristics of the target object, the motion model is established. The model can include parameters such as the trajectory, velocity and acceleration of the target. Target following: using motion model and feature vector, target following is carried out between consecutive video frames. Trajectory prediction and decision control: according to the result of target following, trajectory prediction and decision control are carried out. For example, the future position can be predicted according to the position and trajectory of the target, and the driving control of the vehicle can be carried out according to the prediction result. Figure 3 is the overall framework of the computer-aided driving target following algorithm in this article.

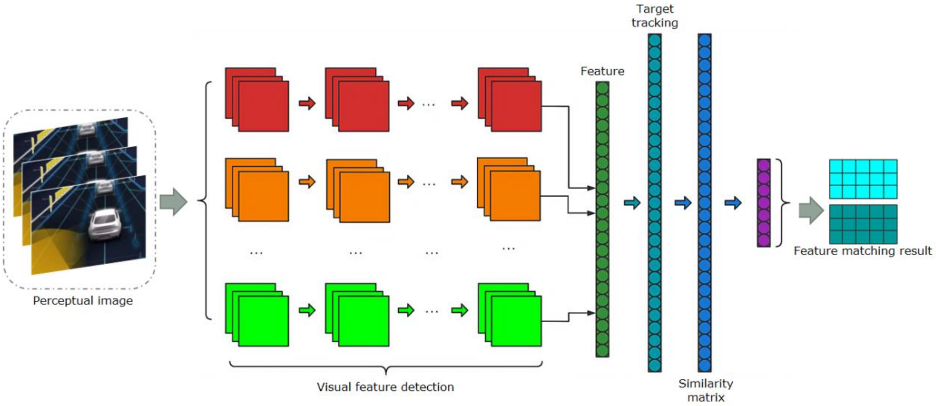

Figure 3: Overall framework of computer-aided driving target following algorithm.

$$P(z) = F(z)eB \tag{3}$$

In the process of occlusion, the target matching error is:

$$sum(\Delta x, \Delta y) = \sum_{p=1,\, p \neq q_i}^{N} S_p(\Delta x, \Delta y) \tag{4}$$

In the process of automatic driving visual perception image feature detection, cameras or other sensors are usually used to obtain image data including roads, vehicles, pedestrians and other objects. Pre-processing the obtained image, including image standardization, noise removal, color space conversion, etc., to improve the image quality and recognition effect. Using computer vision technology and DL algorithm, the feature vectors in the image are extracted. Using the results of feature extraction, target detection is carried out. According to the detected target characteristics, classification and recognition are carried out. For example, different types of things such as vehicles, pedestrians and roads can be distinguished. Multi-target following is carried out by using multi-frame information, and relevant results are output. For example, we can analyze the trajectory of the target object and predict its future position, so as to make corresponding driving decisions and operations. Based on the recognition results, decision-making and control signals are generated to control the running of the vehicle. When pedestrians are detected in front, the system will give an early warning and automatically slow down to avoid.

Assuming that the input and output functions of perceptual image feature information are expressed as R and R' respectively:

$$R' = [k, j] = \sum_{m=-p}^{p} \sum_{n=-p}^{p} B[m, n, k, j] R[k-m, j-n] \tag{5}$$

$$B[m,n,k,j]=\frac{\exp\left(-\frac{m^2+n^2}{2\sigma_\delta^2}-\frac{R[k-m,j-n]}{2\sigma_\xi^2}\right)}{R(k,j)} \tag{6}$$

Where σ represents the scale parameter of perceptual image feature information.

When processing image pixels, the basic idea of the algorithm is to randomly select two pixels to fit a straight line, and then judge whether other fitted data points are inner points or outer points according to tolerance errors. If the quantity of interior points is greater than the preset threshold, it is considered that the lane line has been found. Replace the pixel point (x,y) that needs to be processed with the average value obtained, and record the gray value of the pixel point to be processed as $g(x,y)$, that is:

$$g(x,y)=\frac{1}{N}\sum_{f\in I} f(x,y) \tag{7}$$

In the formula, the total quantity of all pixels in the template is denoted as N. Describe the model structural risk minimization function for training:

$$\beta=\min\sum_{i=1}(f(x)-y)^2+\alpha\|\theta\|^2 \tag{8}$$

The linear transformation function input to the image is:

$$\partial=\sum_i \beta_i\omega(x_i) \tag{9}$$

The coefficient ω vector can be used to represent the weight ∂ value. The image information feature samples are usually used as input variables:

$$\theta=\theta(x_i,x_j) \tag{10}$$

Detect an input image through a filter β generate after training, and calculating and display perceived image information:

$$f(y)=\sum\beta_i\theta(y,x_i) \tag{11}$$

After processing the image features, this information can be applied to autonomous driving. For example, lane line detection technology can be used to identify the location and direction of lane lines, and this information can be used in vehicle path planning and control system; The speed and time of vehicles can be controlled by traffic light recognition technology; Potential dangers can be predicted and avoided through pedestrian and vehicle detection technology.

4 ALGORITHM TESTING AND ANALYSIS

In order to verify the application effect of the algorithm, this section carries out verification and testing. In the experiment, the algorithm is applied to a self-driving prototype, and the driving of the vehicle on highways and urban roads is tested. The test results show that the algorithm can accurately track and monitor the vehicles, pedestrians and obstacles in front, and can assist the control system in emergency treatment and path planning. Moreover, the application of this algorithm also improves the safety and comfort of vehicles, thus providing better driving experience for drivers.

The algorithm in this article (Figure 5) has higher tracking accuracy than the GA model (Figure 4). In figure 4, the scatter points obviously deviate from the straight line, which means that the GA model has a large error in the tracking process. In contrast, the scattered points in Figure 5 are closer to straight lines, which shows that the algorithm in this article has higher accuracy.

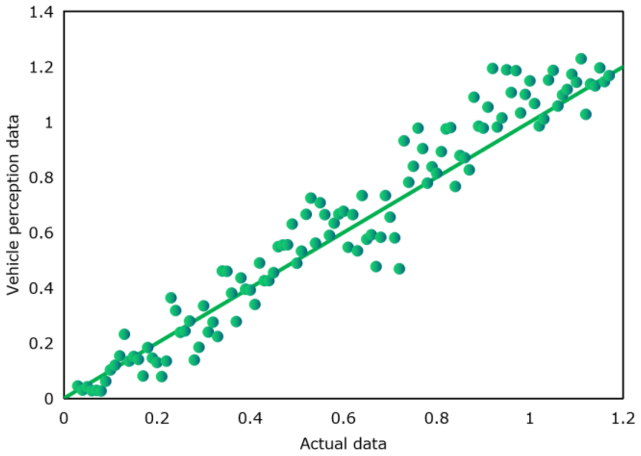

Figure 4: Target detection based on GA model.

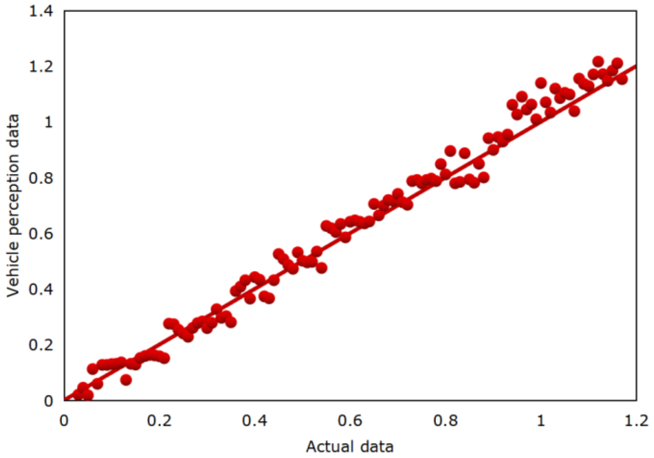

Figure 5: Target detection based on this algorithm.

GA is easily influenced by initial parameters and search space when searching for the optimal solution. If the search space is too large or the initial parameters are not suitable, the search process may fall into local optimum and the best solution cannot be found. The prediction results of GA model fluctuate greatly in time series, which may be because the algorithm has done a lot of repeated calculations when searching for the optimal solution. In contrast, the prediction results of this algorithm are smoother, which shows that the algorithm has better stability in the tracking process. This stability may be due to the adoption of a more effective optimization strategy or the use of a more efficient data structure. The algorithm may be more suitable for processing large-scale data sets, thus showing higher efficiency in real-time applications.

Compared with GA model, this method has obvious advantages in the later stage of operation, and the mean absolute error (MAE) is reduced by 37.25% (Figure 6). This result shows that this method is more accurate, more reliable and has higher accuracy and efficiency in visual perception image feature detection.

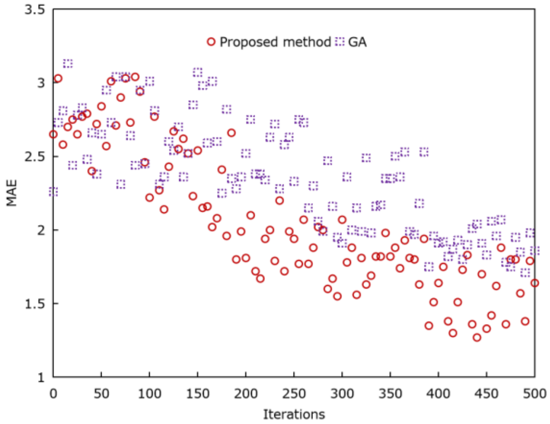

Figure 6: Comparison of MAE of algorithms.

In order to realize efficient visual perception image feature detection, it is needed to use a lot of computing resources, such as high-performance computers or GPUs, for image processing and model training. Moreover, it is needed to design efficient algorithms to reduce computational complexity and processing time and improve real-time and accuracy. Under the changing driving environment and traffic conditions, the visual perception system needs to be robust and adaptive to deal with different scenes and complex situations. This means that the system should have the ability to learn and adapt to the new environment and new situation, as well as the ability to maintain stability under adverse conditions such as noise, light change and occlusion.

As can be seen from the detection results in Figure 7, this algorithm has a significant advantage in the accuracy of vehicle or obstacle feature detection, which is 28.64% higher than the contrast algorithm, which means that this algorithm can identify the features of vehicles and obstacles more accurately and locate their edge contours more accurately.

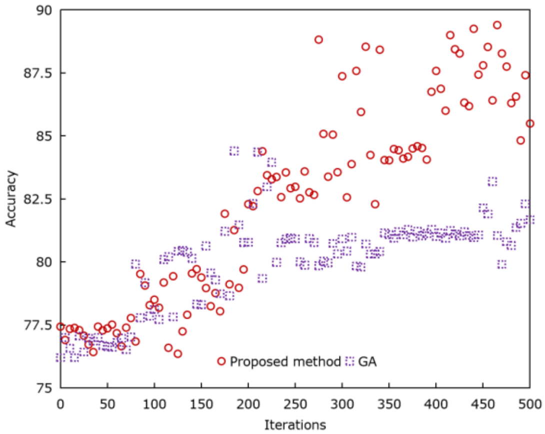

Figure 7: Comparison of vehicle or obstacle feature detection accuracy.

The shapes and sizes of vehicles and obstacles may vary greatly in different scenes. In this article, the algorithm adopts multi-scale feature extraction method, which can capture the features of vehicles and obstacles with different scales and make it more adaptable. This result is of great significance to the automatic driving system, because reliability of vehicles in complex traffic environment. Moreover, the results further verify the effectiveness and practicability of the proposed algorithm in vehicle and obstacle feature detection.

From the results, we can see that the accuracy and efficiency of the proposed algorithm are better than GA model in target following and feature detection. This method uses DL and convolutional neural network to automatically learn the characteristics of the target. Compared with traditional methods, it can better capture and understand the characteristics of the target, thus improving the accuracy of recognition. In a complex driving environment, factors such as illumination change and occlusion often affect the target recognition effect. The algorithm may reduce the influence of these factors through more effective data preprocessing and model training strategies, thus improving the robustness of recognition.

5 CONCLUSION

Self-driving car technology is an intelligent car driving technology based on computer, sensor, control system and other technologies. In order to build a more intelligent computer-aided driving system, this article applies IoT and AI algorithms to the perception and decision optimization of automatic driving system. In the field of autonomous driving, target following and feature detection are key research topics. In this article, the automatic driving target following algorithm based on visual perception is studied. By comparing GA with the algorithm proposed in this article, the performance of different algorithms in target following and feature detection is analyzed. Through experimental comparison, it is found that the proposed algorithm is more accurate and efficient than GA in target following and feature detection. In a complex driving environment, factors such as illumination change and occlusion often affect the target recognition effect. The algorithm may reduce the influence of these factors through more effective data preprocessing and model training strategies, thus improving the robustness of recognition. To sum up, the automatic driving target following algorithm based on visual perception studied in this article has higher accuracy and efficiency than GA. The algorithm can better adapt to the complex driving environment and different traffic conditions, which provides a useful reference for the realization of automatic driving system.

Although the algorithm in this article shows excellent performance in experiments, whether it can maintain this performance in a wider range of practical scenarios needs further verification. Future research can focus on the application of the algorithm in actual roads and different weather conditions to evaluate its practicability and robustness.

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