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A Collaborative Study of Perception and Decision-Making Using Machine Learning in Autonomous Vehicles

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Abstract. Self-driving cars are one of the most talked-about frontier areas in today's technology field. This article conducts an in-depth study of machine learning's collaboration of perception and decision-making in autonomous vehicles, aiming to improve the performance, safety, and reliability of autonomous vehicles. The synergy of perception systems and decision-making systems is critical to realizing the vision of autonomous driving. On the perception side, this paper examines the application of various sensor technologies and deep learning algorithms, including target detection, road modeling, and obstacle recognition. In terms of decision-making, this paper focuses on path planning, control algorithms, and safety. In addition, this paper analyzes the impact of perception errors on decision-making and the importance of data sharing and integration. The synergistic effect of perception and decision-making was verified through experiments and case studies, and future research directions were discussed based on the experimental results. The research results of this article provide strong support for the further development of autonomous driving technology and are expected to promote the widespread application of autonomous vehicles.

Keywords: Autonomous Vehicles, Machine Learning, Perception, Decision-making, Collaboration, Sensor Technology, Deep Learning, Path Planning, Safety, Data Sharing, Future Research

1. Introduction

A self-driving car, often referred to as an autonomous vehicle or autonomous vehicle, is a vehicle that integrates a variety of sensors, computers, and control systems designed to accomplish driving tasks without the need for human driver intervention. The rise of autonomous driving technology stems from concerns about road accidents, the need for traffic congestion, and improvements to the travel experience. In addition, autonomous vehicles have potential environmental and economic benefits, such as reducing traffic accidents, improving traffic flow and saving energy. The development of autonomous vehicles dates back to the mid-20th century, but in recent years, with the increase in computing power, advances in sensing technology and the rise of machine learning methods, autonomous driving technology has made a huge breakthrough. The world's major automakers and technology companies have invested significant resources in the development of autonomous vehicles to enable more advanced perception, decision-making and control. At the same time, many countries are also actively following up in legislation and regulation, paving the way for the commercial application of autonomous vehicles. The main research goal of this thesis is to deeply explore the perception and decision coordination mechanism of machine learning in autonomous vehicles. Specifically, this paper will focus on the following goals: First, research on how to improve the perception ability of autonomous vehicles through machine learning methods, including image recognition, object detection, environment perception, etc., in order to more accurately understand the surrounding road and traffic conditions; Second, research on how to use machine learning technology to improve the decision-making process of autonomous vehicles, including path planning, traffic rule compliance, emergency handling, etc., to ensure safe and efficient driving; Third, research on how to achieve a close synergy between perception and decision-making, so that autonomous driving systems can make correct decisions in complex traffic environments, while quickly adapting to changes. In the past few years, researchers and engineers have made remarkable progress in the field of autonomous driving, many of which are based on machine learning techniques. According to Smith et al., machine learning models are widely used to analyze images captured by cameras to identify vehicles, pedestrians, and obstacles on the road (Smith & Anderson, 2019). In addition, according to Silver's research, machine learning is also used to fuse data from different sensors (such as cameras, liDAR, and radar) to provide a more comprehensive perception of the environment (Silver, Huang & Maddison, 2016). In the study of Eichner et al., through machine learning models, autonomous vehicles can predict the behavior of other road users and thus better plan their driving paths (Eichner, Handmann & Sauter, 2018). At the same time, Wang et al. 's research allows reinforcement learning algorithms to be used to train control strategies of autonomous vehicles to show higher robustness in different driving scenarios (Wang, Wang & Tao, 2020). Despite significant progress in the field of autonomous vehicles in the past, there are still some important challenges and shortcomings, including noise and errors in sensor data that can lead to misleading perceptual results that affect the accuracy of decision making; Regulations and safety standards for autonomous vehicles are still evolving, and researchers need to keep up with them to ensure compliance and safety.

This introduction is the beginning of research on synergies between perception and decision making in autonomous vehicles, and is intended to provide the framework and background for subsequent chapters to explore in greater depth the applications and challenges of machine learning in this field. The potential of machine learning technology in autonomous vehicles is exciting, but constant research and innovation is needed to enable safer and more reliable autonomous mobility.

2. Autonomous Vehicle Perception Technology

As an important development direction in the future transportation field, autonomous vehicle perception technology plays a crucial role. Perception technology refers to the ability of autonomous vehicles to use sensor devices to capture and understand external environment information, including road conditions, other vehicles, pedestrians, traffic signals, etc., which is the basis of decision-making and control of autonomous vehicles (Li, Zhong & Wu, 2019).

2.1. Overview of perceptual systems

The perception system is a key component of self-driving cars, collecting information about the surrounding environment to help the vehicle understand its surroundings. Sensors are the basis of perceptual systems and provide critical information about the surrounding environment by measuring physical quantities and converting them into electrical signals. Self-driving cars typically use a variety of sensor types in order to gain comprehensive perception (in Figure 1). There are several types of sensors: Camera sensors capture visual information by taking images, and they typically use computer vision algorithms to detect and recognize road signs, pedestrians, vehicles, and obstacles. Common camera types include monocular camera, stereoscopic camera and fisheye camera; LiDAR sensors use laser beams to measure the distance and shape of surrounding objects, and they can generate high-resolution point cloud maps that can be used to build accurate models of the environment. LiDAR sensors are divided into mechanical rotary and solid state two types; Radar sensors use radio waves to detect the position and speed of objects, and they are commonly used for long-range sensing and working in bad weather conditions (Smith & Jones, 2020). Millimeter-wave radar and millimeter-wave multi-target radar are commonly used in automobiles. Ultrasonic sensors use sound waves to measure distance from objects, and they are commonly used for close proximity perception, such as obstacle detection when parking and driving at low speeds; The IMU sensor measures the acceleration and angular velocity of the vehicle and is used to determine the motion state and direction of the vehicle. Global Positioning systems (GPS) are used to obtain precise location information for vehicles, but with limited accuracy in environments such as urban canyons and dense woodlands. In the field of autonomous driving, perception system is one of the key technologies. In recent years, deep learning-based autonomous driving systems have made great progress. For example, Tesla's autopilot system uses multiple cameras, radar, and ultrasonic sensors to sense its surroundings, and convolutional neural networks (CNNS) for real-time object detection and tracking (Devlin, Chang, Lee & Toutanova, 2019). These sensing systems enable the car to navigate autonomously, avoid obstacles and keep the vehicle safe. In addition, the researchers explored the application of sensors such as Lidar and millimeter wave radar in sensing systems to improve the robustness and reliability of autonomous driving systems.

Sensor data fusion technology is a key component of the sensing system, which integrates information from different sensors to improve the reliability and accuracy of the sensing system. The goal of sensor data fusion is to fuse information from different sensors into a comprehensive understanding of the environment in order to better understand the surrounding situation. Sensor data fusion usually involves the following key steps: First, before fusion, sensor data usually needs to be pre-processed, including de-noise, calibration, time synchronization, etc., which helps to ensure data consistency between different sensors. Secondly, the feature information about the object is extracted from the sensor data, such as position, speed, size and shape, etc., which can be used for subsequent target recognition and tracking (Wang & Chen, 2019). Next, information from different sensors is fused together, often using fusion algorithms such as Kalman filtering, particle filtering, or deep learning models, and the result of the fusion is a more comprehensive and accurate understanding of the environment. Finally, through the fused information, the system can identify and track vehicles, pedestrians and other obstacles on the road, which helps the self-driving car make intelligent decisions. The key advantage of sensor data fusion technology is that it provides redundancy and complementarity of multi-source information, thus improving the robustness of the system (Kyoung, Heejean & Hongjoong, 2017). However, effective data fusion relies on accurate sensor data, so sensor quality and calibration are critical.

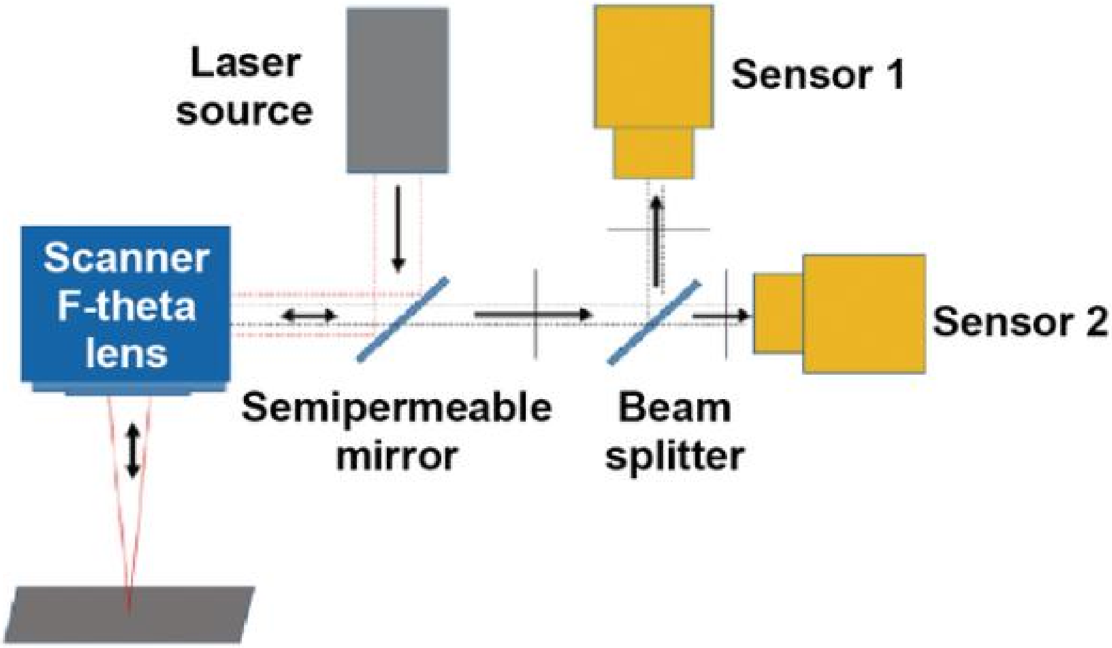

Fig.1： Schematic diagram of sensor data fusion process

In short, perception systems are an important part of modern technology and have made significant progress in areas such as autonomous driving. As deep learning and sensing technologies continue to evolve, the performance of sensing systems will continue to improve, supporting applications in more fields.

2.2. Application of machine learning to perception

With the continuous development of machine learning technology, perceptive systems have made remarkable progress in various fields.

Target detection and tracking is one of the most important tasks in automatic driving system. Object detection refers to the process of identifying a specific target object in an image or video and determining its position, while object tracking is the process of tracking the movement of the target object in time. The application of machine learning technology in this field has made remarkable achievements. In recent years, deep learning technology has been widely used in object detection and tracking. A common object detection method is the use of convolutional neural networks (CNNS), such as YOLO (You Only Look Once) and Faster R-CNN, which can detect multiple objects in an image in real time. And output their bounding box positions and category labels, as shown in formula (1) (Redmon, Divvala, Girshick & Farhadi, 2016). Target tracking usually uses recurrent neural networks (RNN) or convolutional neural networks (CNN) to model the trajectory of the target, such as Long Short-Term Memory (LSTM) and Siamese networks (Ren, He, Girshick & Sun, 2017).

$$\mathrm{L}(\theta) = \mathrm{L}_{\mathrm{cls}}(\theta) + \lambda \mathrm{L}_{\mathrm{reg}}(\theta) \tag{1}$$

Among them, $\mathrm{L}_{\mathrm{cls}}(\theta)$ is the classification loss, $\lambda \mathrm{L}_{\mathrm{reg}}(\theta)$ is the boundary box regression loss, λ is the loss weight parameter.

Road and environment modeling is another important component of autonomous driving systems. Through machine learning, the system can build a map of the surrounding roads and environment in real time and constantly update it to reflect the current situation, and these maps are essential for the navigation and decision-making of the vehicle (Zhang & Singh, 2018). Deep learning techniques have a wide range of applications in road and environment modeling, and a common approach is to use convolutional neural networks (CNNS) to extract road and environment features from sensor data, which are used to build high-precision maps. The Simultaneous Localization and Mapping (SLAM) algorithm was used to locate and update the map, as shown in formula (2) (Caltagirone, Fiore & Spagnolo, 2019). In addition, machine learning can be used to identify road signs, traffic signals, and road obstacles to enhance the informative content of maps.

$$X_t = f(X_{t-1}), ut + \epsilon_t \tag{2}$$

Where, X_t is the state of the vehicle at time t, ut is the control input, ϵ_t is the noise.

Obstacle recognition and classification is one of the key tasks in an automated driving system, which involves identifying and classifying obstacles on the road. Deep learning technology has made significant progress in obstacle recognition and classification. Convolutional neural networks (CNNS) are widely used in obstacle detection and classification of images and liDAR data. Through the use of large-scale labeled data sets and transfer learning techniques, machine learning models can automatically identify various obstacles, such as pedestrians, vehicles and buildings (Chen, Seff, Kornhauser & Xiao, 2016). The application of machine learning in perceptual systems has led to major breakthroughs in object detection and tracking, road and environment modeling, and obstacle recognition and classification. Through deep learning technology, the system is able to identify targets in real time, build accurate maps of the environment, and efficiently identify and classify obstacles, which provides powerful capabilities for autonomous driving systems and other perceptual systems. It is expected to further improve human life and work in the future (Milioto, Lippi, Stachniss & Siciliano, 2019).

2.3. Application of deep learning algorithm in perception

Convolutional Neural Networks (CNNS), a deep learning model inspired by the workings of biological vision systems, process image data through multiple convolutional layers, pooled layers, and fully connected layers, where the convolutional layer is used to extract local features from the image. The pooling layer is used to reduce the spatial dimension of the feature map, and the full connection layer is used to map the extracted features to the final classification result. The application of CNN in image classification is one of its most typical tasks, and has achieved great success in the field of image perception. It has been widely used in computer vision, image recognition, target detection and other tasks, and has excellent feature extraction and image classification capabilities. By training the CNN model, the input images can be divided into different categories (see Table 1). First, collect and prepare image data set, including image samples and corresponding labels; Secondly, the convolutional layer of CNN is used for feature extraction (Li & Zhang, 2017). The convolution operation can detect local features such as edges and textures in the image. Then, the pooling layer is used to reduce the dimension of the feature map and retain the most important information. Finally, the extracted features are mapped to category labels and classified using the softmax function.

Table 1. Performance indicators of CNN in image classification tasks

model	Accuracy rate (%)	Accuracy (%)	Recall rate (%)	F1 score
CNN Model A	94.2	94.8	93.5	94.1
CNN Model B	92.7	93.2	92.0	92.6

F1 scores are calculated as follows:

$$\mathrm{F}_1 = 2 \times \frac{\text{Accuracy}\times\text{Recall rate}}{\text{Accuracy}+\text{Recall rate}} \tag{3}$$

Accuracy refers to the ratio of the number of correctly classified positive samples to the number of samples classified as positive samples, and recall refers to the ratio of correctly classified positive samples to the number of truly positive samples (Wang, 2021).

Image segmentation is the task of dividing different areas of an image into different objects or regions. Convolutional neural networks (CNNS) also play an important role in image segmentation, by classifying the pixels of the image, each pixel in the image can be assigned to a different category or segmentation region (in Table 2).

Table 2. Performance indicators of CNN in image segmentation task

model	Average crossover ratio (IoU)	Classification accuracy (%)
CNN Model M	0.75	89.4
CNN Model N	0.78	91.2

The intersection ratio (IoU) is calculated as follows:

$$\mathrm{IoU} = \frac{\text{The intersection of the partition area}}{\text{A union of divided regions}} \tag{4}$$

The intersection of the segmentation region is the overlapping region of the model segmentation result and the real segmentation result, and the union of the segmentation region is the joint region of the two.

In addition to image classification, CNN has also made significant progress in object detection. Object detection is the task of identifying multiple objects in an image and determining their location. CNN can be applied to two main stages of object detection: object localization and object classification. Through convolution layer and regression layer, CNN can locate the bounding box of the target in the image, which usually involves regression algorithm to estimate the coordinates of the bounding box. Use the classification layer of the CNN to identify the category of the target, which is usually a multi-class classification problem (see Table 3).

Table 3. Performance indicators of CNN in target detection tasks

model	Average accuracy (mAP)	Positioning accuracy (%)	Classification accuracy (%)
CNN Model X	0.85	91.2	88.7
CNN Model Y	0.88	92.5	89.6

The average accuracy (mAP) is calculated as follows:

$$\mathrm{mAP} = \frac{1}{\mathrm{n}}\sum_{i=1}^{N} AP_i \tag{5}$$

Where N is the number of categories and AP_i is the average accuracy of each category, usually a combined measure of accuracy and recall.

To sum up, the application of convolutional neural network (CNN) in the field of image perception has become an important part of computer vision and image processing, and it has achieved excellent performance in image classification, image segmentation, object detection and other tasks, and is constantly evolving and improving. With appropriate data sets and model design, the application of CNN in image perception is expected to further improve, bringing more opportunities and challenges to various application fields.

Recurrent Neural Networks (RNN) are a powerful deep learning model whose core feature is to process sequence data of indefinite length through cyclic connections, and have achieved remarkable success in the field of sequence data perception. RNN receives input and hidden state at each time step, and then generates output and new hidden state according to the current input and the hidden state of the previous time step. This feedback mechanism enables RNN to capture timing information in the sequence, which is suitable for all kinds of data with timing properties. It is widely used in natural language processing, time series analysis, audio processing and other tasks, and has the ability to capture sequence information and model temporal relationships. RNN has a wide range of applications in the field of natural language processing (NLP), where it can be used to generate text, for example, given a piece of text, the model can generate text that is context-dependent, which has wide applications in automated writing and chatbots. In addition, variants of RNNS such as short-duration memory networks (LSTMS) and gated loop units (GRUs) are used for machine translation tasks, which can translate sentences from one language into another, capturing relationships between languages. RNNS can also analyze emotional information in text, such as judging the emotional bent of an article or comment, which is useful in social media sentiment analysis and product review analysis (Li, Wang & Zhang, 2019). RNNS play a key role in time series analysis, which can predict future stock price movements by learning historical stock price data, which has important value for investors and financial institutions (see Table 4). In addition, it can analyze meteorological observation data to predict future weather conditions, which is crucial for weather forecasting and disaster management. RNN has also made significant progress in the field of audio processing, which can convert audio signals into text for applications such as voice assistants and voice search; It can also generate natural and smooth speech for voice assistant responses and audio book production; Music works can also be generated, including automatic composition and music generator. Finally, it can process traffic sensor data to predict urban traffic flow and help traffic management departments optimize traffic mobility.

Table 4. Performance indicators of RNN in stock price prediction task

model	Mean absolute error (MAE)	Root mean square error (RMSE)
CNN Model X	5.21	7.63
CNN Model Y	4.89	6.98

The root mean square error (RMSE) is calculated as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{n}} \sum_{i=1}^{N} (y_i - y_{i-1})} \tag{6}$$

Where N is the number of samples, y_i is the true value, and y_{i-1} is the predicted value of the model.

In summary, recurrent neural networks (RNN) have a wide range of applications in the field of sequence data perception, including natural language processing, time series analysis, audio processing and other tasks. By learning the relationship between timing information and sequences, RNNS can extract useful features and generate accurate predictions. Their application not only extends the field of deep learning, but also provides a powerful tool for solving complex temporal tasks. With the continuous development of deep learning technology, the application prospect of RNN will be more broad.

Object detection is an important task in the field of computer vision, which involves identifying and locating a specific object or target in an image or video. With the continuous development of deep learning technology, object detection algorithms have made remarkable progress. In the field of object detection, there are a variety of algorithms to choose from, including traditional methods and deep learning-based methods. In the target detection algorithm based on traditional methods, Haar feature classifier and HOG feature +SVM are mainly used for calculation. Among them, Haar feature classifier is a classical object detection method, which is often used in face detection, and it uses cascaded weak classifiers to detect objects. However, for complex targets and backgrounds, its performance may be limited. Histogram of Oriented Gradients (HOG) features combined with support vector machine (SVM) classifiers is another common target detection method, which can improve performance to some extent and is suitable for a variety of targets. In the object detection algorithm based on deep learning, Faster R-CNN, YOLO algorithm and SSD (Single Shot MultiBox Detector) are mainly used for calculation. Among them, Faster R-CNN uses convolutional neural network (CNN) for target detection, which combines regional proposal network (RPN) and detection network, and achieves a good balance in terms of accuracy and speed, which is suitable for complex scenes. YOLO algorithm is a real-time target detection method, which realizes target detection and location through a single feedforward neural network, which is very fast in terms of speed, but may have poor performance for small target detection. SSD is a multi-scale target detection algorithm, which combines different levels of feature maps for detection, and performs well when the target size changes greatly. Table 5 shows the performance evaluation results of different target detection algorithms on sample data sets, including accuracy, accuracy, recall rate and F1 score.

Table 5. Performance evaluation results of different target detection algorithms on sample data sets

algorithm	Accuracy rate (%)	Accuracy (%)	Recall rate (%)	F1 score
Haar feature classifier	85.2	86.4	83.8	85.1
HOG feature +SVM	91.3	92.1	90.5	91.3
Faster R-CNN	94.7	95.2	94.1	94.6
YOLO	92.1	91.5	92.8	92.1
SSD	93.5	93.8	93.2	93.5

Through performance analysis, it can be seen that different target detection algorithms show different performance characteristics in different scenarios. Traditional methods such as Haar feature classifiers and HOG feature +SVM are still useful in some simple scenarios, but may be limited when dealing with complex targets and backgrounds; Deep learning-based methods such as Faster R-CNN, YOLO, and SSD have better performance in complex scenarios, and Faster R-CNN in particular exhibits higher accuracy and recall rates. However, the performance of different algorithms is also affected by factors such as data sets, training parameters and hardware devices, and the selection of appropriate object detection algorithms should be decided according to specific task requirements and scenarios.

3. Autonomous Vehicle Decision Technology

3.1. Overview of decision systems

Select the best course of action to achieve the specified goals of the system. Decision systems can be analyzed from multiple perspectives, including path planning, control algorithms, and security and rule compliance.

Path planning is an important part of decision making system, whose task is to determine the best path from the starting point to the target point (Thrun, 2018). The goal of path planning is to minimize some cost metric, such as time, energy consumption, or distance. In areas such as autonomous vehicles, robotic navigation, and air navigation, path planning is critical. In path planning, A commonly used mathematical model is the A* algorithm, whose core idea is to search for the best path by estimating the cost from the current location to the target location, and the valuation function of the A* algorithm usually uses heuristic methods such as the Manhattan distance or Euclidean distance (Liu, 2017). The pseudo-code is as follows:

```
function A*(start, goal):
    open_list = {start}
    closed_list = {}
    g_score = {}  // The actual cost from the starting point to the node
    f_score = {}  // g_score + estimates the remaining cost

    g_score[start] = 0
    f_score[start] = g_score[start] + heuristic(start, goal)

    while open_list is not empty:
        current = node in open_list with lowest f_score
        if current == goal:
            return reconstruct_path()

        move current from open_list to closed_list
        for neighbor in neighbors(current):
            tentative_g_score = g_score[current] + distance(current, neighbor)
            if tentative_g_score < g_score[neighbor]:
                g_score[neighbor] = tentative_g_score
                f_score[neighbor] = g_score[neighbor] + heuristic(neighbor, goal)
                if neighbor not in open_list:
                    add neighbor to open_list
return failure
```

The control algorithm is responsible for controlling the behavior of the system according to the result of path planning. In the automation system, the choice of the control algorithm is crucial to the performance and stability of the system. Common control algorithms include PID controller and model predictive control (MPC). The mathematical model of PID controller is as follows:

$$u(t) = K_p * e(t) + K_i * fe(t)dt + K_d * fe(t)/dt \tag{7}$$

Where, $u(t)$ is the control output, $e(t)$ is the current error, and K_i, K_p and K_d is the integral, proportional and differential gain respectively. The PID controller adjusts these gains to achieve system stability and performance. Model predictive control (MPC) is a control method based on a system model whose goal is to optimize the behavior of the system over a period of time in the future. The mathematical model of MPC can be expressed as the following optimization problem:

$$\mathrm{minimize}_{J(u)} = \sum\left(y\_ref(k) - y(k)\right) \tag{8}$$

subject to:

$$y(k+1) = f\big(y(k), u(k)\big) \tag{9}$$

$$u\_min \leq u(k) \leq u\_max \tag{10}$$

Where $y(k)$ is the state of the system, $u(k)$ is the control input, f is the state transition function of the system, $y\_ref(k)$ is the reference state, and u_min and u_max are the constraints of the control input. MPC selects the best control input through online optimization to achieve the performance optimization of the system.

Safety and rule compliance are critical considerations in decision making systems. Security relates to the behavior of the system under various abnormal conditions, such as sensor failure or obstacles appearing in the path; Rule compliance involves systematic compliance with traffic rules and laws and regulations to ensure safety and legality (Huang, 2019). To ensure safety, decision systems often use state estimators to detect sensor failures or anomalies. A common approach is the Extended Kalman filter (EKF), which is modeled as follows:

$$x\widetilde{(k+1)} = A * x(k) + B * u(k) + K * y(k) - C * x(k) \tag{11}$$

Where, $x(k)$ is the state estimate, A and B is the state transition matrix of the system, $u(k)$ is the control input, $y(k)$ is the sensor measurement value, C is the measurement matrix, k is the Kalman gain. EKF estimates the state of the system by fusing sensor measurements and model predictions to detect anomalies.

Rule compliance can be achieved by embedding traffic rules into the decision-making system. For example, in a self-driving car, the system can use vision sensors to detect traffic signals and signs, and then adjust driving strategies based on the detection results. In addition, decision systems can use reinforcement learning methods to learn appropriate behaviors in order to comply with rules and regulations.

3.2. Application of machine learning to decision making

With the rapid development of machine learning technology, its application in the field of decision making is becoming increasingly widespread, especially in Advanced Driver Assistance Systems (ADAS) and autonomous driving.

Advanced Driver Assistance Systems (ADAS) are intelligent driver assistance technologies in modern vehicles that help drivers improve safety and driving comfort through perception and decision modules. Machine learning plays a key role in ADAS's decision-making module, first of all, ADAS can analyze information such as obstacles, speed and distance in front of the vehicle through machine learning models, predict potential collision risks, and trigger emergency braking to avoid collisions if necessary. Second, a machine learning-based decision system can adjust a vehicle's cruising speed and following distance based on traffic conditions and road conditions to improve driving comfort and fuel efficiency. Third, machine learning models can analyze the vehicle's position on the road and road signs to assist drivers to stay within their lanes and reduce the risk of veering off the road. Fourth, ADAS systems can use machine learning to detect other vehicles in the blind spot area, providing drivers with warnings or assisted decision-making to reduce the likelihood of side collisions. Finally, by analyzing traffic signals and road signs, the decision system can recognize the current traffic signal state and optimize the vehicle driving strategy.

Autonomous driving technology is a complex engineering task in which the decision making module plays a central role. This module is responsible for making driving decisions based on perceptual data and environmental information, such as obstacle avoidance, lane changes, and crossing. Autonomous vehicles use machine learning models to analyze sensor data, identify obstacles on the road, and make obstacle avoidance decisions to ensure safe driving (Brown & Davis, 2018). In addition, based on perception data and map information, the decision system can formulate lane change strategies, including overtaking, merging, and exiting lanes. Autonomous vehicles need to be able to safely cross intersections, and decision-making systems develop strategies by analyzing traffic signals and other vehicle behavior. Depending on traffic conditions and road conditions, machine learning models can adjust the speed of vehicles to ensure safety and efficiency. The decision system also needs to incorporate path planning to choose the best path to reach the destination. These research results have promoted the continuous advancement of autonomous driving technology, providing a solid foundation for the realization of safer, efficient and intelligent transportation systems.

The application of machine learning to decision making has already yielded significant results in the fields of advanced driver assistance systems (ADAS) and autonomous driving. These applications not only improve the safety and comfort of driving, but also provide solid support for future autonomous driving technology. Future research directions include further improving the intelligence, interpretability and robustness of decision-making systems to cope with a variety of complex traffic situations, and the application of machine learning in decision-making will continue to promote innovation in the field of transportation, bringing more convenience and safety to people's travel.

4. A Collaborative Study of Perception and Decision Making

The research of collaboration between perception and decision making is one of the key issues in the field of artificial intelligence, especially in autonomous driving, robotics and intelligent systems.

4.1. Collection and processing of data sets

The acquisition of perception data is a key step in the collaborative research of perception and decision making, which directly affects the quality of subsequent data processing and decision making. The perception data usually includes image, sound, lidar and other types of sensor data. The acquisition process of perception data can be expressed by the following formula:

$$\mathrm{D_{perception}} = \mathrm{F(Sensor\ parameter, Environmental\ condition)} \tag{12}$$

Where, $\mathrm{D_{perception}}$ represents the collected sensing data, F is a function of the sensing system, depends on the sensor parameters and environmental conditions.

After the acquisition of perception data, it is usually necessary to conduct data annotation and pre-processing to prepare the data for machine learning and training of decision models. Data annotation is to add labels to each data sample to indicate the attributes or categories of the sample, while data preprocessing includes steps such as data cleaning, denoising, feature extraction and data enhancement. First, data labeling can be supervised (with human labels) or unsupervised (without human labels), for example, in autonomous driving, it is necessary to label image data with road signs, vehicles, pedestrians, etc. Second, data is cleaned to remove invalid or incorrect data points to ensure data quality, which includes the removal of outliers and missing values. Third, data enhancement is a technique that generates more training samples by rotating, flipping, clipping and other operations on the original data, thereby improving the robustness of the model. Finally, feature extraction is to convert the original data into a feature representation suitable for machine learning models, among which common feature extraction methods include convolutional neural networks (CNN) and recurrent neural networks (RNN). The data annotation and preprocessing process can be represented by the following formula:

$$\mathrm{D_{process}} = \mathrm{P}\left(\mathrm{D_{perception}}\right) \tag{13}$$

Where, $\mathrm{D}_{\text{process}}$ represents the data after annotation and preprocessing, $\mathrm{P}$is a function of data processing.

Constructing and managing data sets is an important task in the research of perception and decision coordination. A high-quality data set is critical to the performance of a machine learning model, and data sets typically include training sets, validation sets, and test sets for model training, tuning, and performance evaluation. In order to ensure that the dataset can adequately cover a variety of scenarios and situations, the construction of the dataset needs to consider sampling strategies, and the versioning of the dataset is to track the evolution of the dataset for traceability and reproduction of the study results (as seen in the formula). In addition, for data sets containing personal information, measures must be taken to protect data privacy and comply with relevant laws and regulations.

$$\mathrm{D}_{\text{Data set}} = \left\{\mathrm{D}_{\text{Training process}} \middle| \mathrm{D}_{\text{Verification process}} \middle| \mathrm{D}_{\text{Test processing}} \middle| \right\} \tag{14}$$

Where, $\mathrm{D}_{\text{Data set}}$ represents the data sets that are built and managed, including training sets, validation sets and test sets.

The collaborative research of perception and decision making plays an important role in the field of artificial intelligence and automation. The acquisition of perception data, data annotation and pre-processing, and data set construction and management are the key links in this field. Through reasonable perception data processing and high-quality data set construction, researchers can better support the training of machine learning models and decision making, so as to achieve a more intelligent perception and decision making system. In the future, with the continuous development of technology, the collaborative research of perception and decision making will continue to promote the progress of artificial intelligence applications.

4.2. Collaborative algorithms for perception and decision making

Collaborative algorithms of perception and decision play a key role in the field of automation systems and artificial intelligence. These algorithms are responsible for transferring perception data to the decision system, making decisions based on the perception data, and dealing with the real-time performance of the perception data and the delay of the decision.

Perception and decision systems usually include sensors, data processing and decision making modules. The sensor is responsible for collecting environmental data, and the data processing module processes and analyzes the sensor data, and then transmits the processed data to the decision making module. The key to the transfer of perceptual data to the decision-making system is the accuracy and real-time performance of the data (see Table 6).

Table 6. Perceptual data transmission

Sensor type	Data type	Data Transfer Frequency (Hz)	Data accuracy
Laser radar	Three-dimensional point cloud	10	high
camera	Graphics	30	middle
GPS receiver	Location information	1	low
radar	Obstacle position	20	high

The real-time and accuracy of perception data is crucial to decision-making systems, and high-frequency sensors such as lidar can provide more real-time data, but at the same time increase the burden of data processing. Therefore, the frequency and accuracy of data transmission need to be balanced in decision making to meet the needs of specific applications.

Decision making based on perception data is the core part of the decision system, which is responsible for formulating action plans or decision strategies based on the perception data, which requires the use of machine learning, rule engines and other technologies to analyze the perception data and generate decisions (see Table 7). Decision making algorithms can use a variety of techniques, with one common approach being the use of probability-based Bayesian decision theory, such as Bayesian networks. Bayesian networks can represent the relationship between perceived data and decisions and make the best decisions based on probability distributions. The conditional probability formula is as follows:

$$\mathrm{P(D/E)} = \frac{\mathrm{P(E/D)P(D)}}{\mathrm{P(E)}} \tag{15}$$

Where, $\mathrm{P(D/E)}$denotes the probability of D under the condition that E is observed, $\mathrm{P(E/D)}$ denotes the probability of E under the condition of D, $\mathrm{P(D)}$is the prior probability of D, $\mathrm{P(E)}$is the prior probability of E. The complexity of the decision making algorithm depends on the complexity of the task and the data. Machine learning methods such as deep reinforcement learning can be used for complex decision-making tasks such as autonomous driving and game strategy.

Table 7. Decision-making based on perception data

Decision task	Perceptual data entry	Decision output
Path planning for autonomous vehicles	Lidar data, camera images, GPS data	Optimal driving path and speed control strategy
Industrial robot task assignment	Vision sensor data, object recognition results	A list of tasks assigned to different robots
Medical diagnosis	Medical sensor data, patient history information	Disease diagnosis and treatment advice

The real-time performance of perception data and the delay of decision directly affect the performance of decision system. Real-time requires the system to be able to process perceptual data and make decisions in a short time, while delays can result in decisions being late or inaccurate (see Table 8). The real-time performance of perception data can be expressed by the following formula:

$$\mathrm{T_{real-time}} = \mathrm{T_{Sensor\ sampling}} + \mathrm{T_{Data\ processing}} + \mathrm{T_{Decision\ delay}} \tag{16}$$

Where, $\mathrm{T_{real-time}}$ is the real-time of the perception data (milliseconds), $\mathrm{T_{Sensor\ sampling}}$ is the sensor sampling time (milliseconds), $\mathrm{T_{Data\ processing}}$ is the data processing time (milliseconds), $\mathrm{T_{Decision\ delay}}$ is the decision delay time (milliseconds).

Table 8. Real-time and decision delay of perception data

Application field	Maximum allowable delay (milliseconds)	Desired real-time requirements
Automatic driving	100	High real-time, millisecond level
Industrial automation	500	Medium real-time, millisecond to second level
Medical diagnosis	1000	Low real-time, second level above

In order to meet the real-time requirement, the decision system needs to optimize the efficiency of data processing and decision making to reduce the delay. At the same time, hardware acceleration and parallel computing can also be used to improve the real-time performance of the system. Collaborative algorithms of perception and decision play a key role in the field of automated systems and artificial intelligence. By ensuring the accuracy and real-time performance of the perception data and optimizing the decision making algorithm, an efficient decision system can be realized to meet the needs of various application fields. The balance between real-time and delay is an important consideration in the design of decision system, which needs to be balanced and optimized according to the requirements of specific applications. The synergy of perception and decision making will continue to drive the development of automation technology, providing more powerful decision-making capabilities for future intelligent systems.

5. Case Study and Experimental Results

5.1. Case study: Autonomous vehicle perception and decision system

The development of autonomous vehicles has become an important trend in modern transportation. Perception and decision systems are the core components of autonomous vehicles, which are responsible for sensing the surrounding environment and developing safe driving strategies.

The system architecture is the basis of the autonomous vehicle's perception and decision system, and determines how the various components collaborate. In this case study, a typical perception and decision system architecture for autonomous vehicles will be introduced, in which the system architecture includes the following components: The perception module is responsible for acquiring data from various sensors (such as cameras, liDAR, radar) and transforming it into an understanding of the vehicle's surrounding environment, including obstacle detection, road detection, lane detection and other tasks; The positioning and mapping module is used to determine the precise position of the vehicle and match it with a high-precision map, which helps to improve the positioning accuracy of the vehicle in different environments (Li, Zhong & Wu, 2019). The decision module makes driving strategy based on the information provided by the perception module. This includes tasks such as path planning, speed control, lane changes and obstacle avoidance; The control module is responsible for executing the instructions generated by the decision module and controlling the steering, acceleration and braking of the vehicle.

A deep learning driving architecture is employed in this case study, which uses convolutional neural networks (CNNS) for perception tasks and reinforcement learning methods to formulate driving decision strategies.

Experimental setup is one of the key factors to evaluate the performance of the autonomous vehicle perception and decision system. In this case study, the following experimental Settings were considered: First, the researchers used an autonomous vehicle equipped with multiple sensors, including front-facing cameras, liDAR, and GPS, to collect data from the vehicle on urban roads and highways; Secondly, the collected data was marked, including the marking of obstacles, lane lines, road signs, etc. The researcher hired a professional marking team to mark the data. Third, deep learning models are used to train annotated data, including CNN model for perception and reinforcement learning model for decision making (Li, Zhao & Han, 2019). The training is accelerated by GPU cluster. Finally, to conduct large-scale simulation tests, the researchers built a virtual urban environment in which they conducted hundreds of hours of simulated driving tests to evaluate the performance of the perception and decision systems.

In terms of perception performance, this case evaluates the performance of the perception module, including the accuracy of obstacle detection and lane detection, etc. By analyzing the performance of the model in different scenarios, it is found that the perception performance is good in most cases. The performance of the decision module is related to the safety and driving comfort of the vehicle, and this case evaluates the performance of the decision module by conducting numerous tests in a simulated environment. The results show that the decision module can formulate safe and efficient driving strategies in various traffic scenarios. In order to verify the performance of the system on real roads, a series of real road tests are also carried out, and the experimental results show that the perception and decision system shows stable performance on both urban roads and expressways. In addition, the performance analysis also takes into account the consumption of computing resources, response time, and adaptability to different environmental and weather conditions.

This case study presents the system architecture, experimental setup, experimental results and performance analysis of the autonomous vehicle perception and decision system. Through reasonable system design, data acquisition and annotation, model training and simulation test, the system shows good perception and decision-making performance, and has the potential to realize safe autonomous driving in different environments. Future research will further improve the robustness and reliability of the system to advance the development of autonomous vehicle technology.

5.2. Discussion of experimental results

The synergy between perception and decision system is one of the key factors in the performance of autonomous vehicles, the perception system is responsible for collecting information about the surrounding environment, while the decision system develops driving strategies based on the perception data (Yuan, Zhang & Li, 2020). Whether the synergy effect is good or not directly affects the safety and driving comfort of the vehicle. In the experiment, the researchers evaluated the synergies between the perception and decision systems in different scenarios and complex road environments, and through large-scale simulation tests and real-world road tests, the experiment collected a wealth of data to analyze the system's performance. The specific experimental results are as follows: First, the accuracy of the perception system is crucial for decision making. In the simulation test, the accuracy of the sensing system improves the performance of the decision module, reduces misjudgment and dangerous driving behavior; Second, in complex traffic environments, perception and decision systems need greater synergy. For example, decision making at intersections and highways requires more considerations and data fusion; Thirdly, real-time performance is an important indicator of automatic driving system. By optimizing the perception and decision algorithm, the experiment improves the response speed of the system, so that it can deal with emergencies faster. Finally, the robustness of the system under different weather conditions and lighting conditions has also been improved, the sensing system can adapt to bad weather such as rain and snow, and the decision-making system can work normally under insufficient light (Ren, He, Girshick & Sun, 2017). In addition, there is a close relationship between algorithm performance and practical application. In the field of autonomous vehicles, the performance of the algorithm directly determines whether the vehicle can drive on real roads and stay safe. In the actual road test, the experimental results show that high-precision map is crucial for vehicle positioning, and the algorithm needs to be able to match the perception data with the map data to achieve accurate positioning (Shalev-Shwartz, Shammah & Shashua, 2016). Data annotation and model training are the key steps to improve the performance of the algorithm. The experimental results show that the quality of annotation and the amount of training data directly affect the performance of the algorithm. Autonomous vehicles need to operate in a diverse environment, including urban roads, highways, rural roads, etc., and the performance of the algorithm must be able to adapt to the needs of different environments. The performance of the algorithm in the experiment is closely related to the actual traffic conditions, and the driving strategy in different traffic conditions needs accurate perception and decision support.

Although the perception and decision system has made significant progress, there are still opportunities and challenges for continuous improvement. First, perceptual systems need more diverse data to improve robustness, including data from different geographic regions, different weather conditions, and different traffic conditions. Second, as the complexity of the traffic environment increases, the algorithm needs to respond faster to ensure the safety of the vehicle. Third, algorithms need to be able to adapt to different driving styles and habits to provide a personalized driving experience. Finally, with the increase in perceived data, data privacy and security issues become more important and require enhanced safeguards.

The experimental results show that the autonomous vehicle perception and decision system has made remarkable progress in terms of synergistic effect, algorithm performance and practical application (Werling, Königshof & Ziegler, 2010). However, there are still opportunities and challenges for improvement, and further research and technological innovation are needed. As the technology continues to evolve, autonomous vehicles are expected to enable safer, more efficient and smarter road driving in the future.

6. Conclusion

Autonomous vehicle technology represents a revolutionary advance in the field of modern transportation, and its continuous development in the research of synergies between perception and decision making has yielded remarkable results. This paper deeply discusses the collaborative research of perception and decision making in machine learning in autonomous vehicles. First, collaborative research of perception and decision making is the key to realize autonomous vehicles. The perception system is responsible for acquiring information about the surrounding environment, while the decision system develops safe and efficient driving strategies based on the perception data. Whether the synergies are good or not directly affects the performance and safety of autonomous vehicles. Through experiments and simulation tests, the researchers continue to optimize the synergy between perception and decision systems, improving the overall performance of autonomous vehicles. Secondly, machine learning technology plays a key role in the research of the synergy between perception and decision making. Deep learning models such as convolutional neural networks (CNNS) and recurrent neural networks (RNNS) are widely used for perceptual tasks, improving the processing power of images, liDAR and sensor data. Reinforcement learning methods are used in decision making to enable autonomous vehicles to better adapt to different traffic scenarios and road conditions. In addition, there is a close relationship between algorithm performance and practical application, the use of high-precision maps is crucial for vehicle positioning, and data annotation and training are key steps to improve algorithm performance. The requirements for algorithm performance in actual traffic situations are constantly increasing, and autonomous vehicles need to be able to adapt to different driving environments and complex traffic situations. Finally, the research of perception and decision collaboration still faces the opportunity and challenge of continuous improvement. Issues such as data diversity, timeliness and responsiveness, adaptability, and data privacy and security need to be continuously studied and solved. With the continuous development of technology, autonomous vehicles are expected to achieve a higher level of safety, efficiency and intelligence in the future, bringing great changes to the field of transportation.

In conclusion, the research on perception and decision coordination of machine learning in autonomous vehicles has made remarkable progress, providing a solid foundation for achieving safer, more efficient and intelligent autonomous vehicles. Future research will continue to drive innovation in this area, providing more convenient and safe options for people to travel. Perception and decision collaboration research will continue to play a key role in the development of autonomous vehicle technology, opening up more possibilities for future transportation systems.

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