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Child Identification Optimization Algorithm for AEB System of Autonomous Vehicle based on Machine Learning

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Abstract: With the development of cities and the extension of roads, related concepts such as smart cities and intelligent transportation are coming out. The child recognition (CR) algorithm of autonomous vehicle (AV) AEB system has played an important role in road traffic safety. Based on machine learning (ML) technology, this paper studies and analyzes the optimization algorithm of CR in AV AEB system. This paper briefly analyzes the working principle and basic control logic of the automatic emergency braking system (AEB) system, discusses the auto drive system, and applies it to the CR optimization algorithm of the AV AEB system by analyzing the ML technology.

1. Introduction

With the rapid development of economy, motor vehicles have become the main means of transportation in modern society, and the frequency of traffic accidents is also high. The research shows that the AEB system of AV is of great significance for the reduction of traffic accidents. The AEB system is designed to provide the final physical intervention in an emergency to prevent or mitigate potential collisions. According to the actual driving situation of the vehicle when a dangerous scene occurs, the AEB system can automatically activate the brake action of the vehicle or adaptively supplement the driver's brake pedal input, so as to achieve the goal of quickly making full use of the vehicle's braking potential to avoid collisions. Therefore, it is of great significance to research and develop the optimization algorithm for CR of AV AEB system based on ML to improve traffic conditions and ensure road traffic safety.

Many scholars at home and abroad have studied and analyzed the optimization algorithm of CR of AV AEB system based on ML. Prajapati A used Australian in-depth investigation accident data (including rear end collision, pedestrian, frontal collision, right angle side collision, right turn accident, fixed object accident) to evaluate the effectiveness of several emergency braking systems [1]. According to the motion characteristics of long headed vehicles and pedestrians in the real road, Gamba SR established a mathematical model to study the influence of automatic braking system parameters such as detector detection angle, maximum braking deceleration, braking advance time, braking coordination time on reducing pedestrian casualty risk [2].

This paper mainly starts with the vision system of AV, and mainly studies the optimization algorithm of children recognition in AEB system of AV based on ML. A new auto drive system is proposed. Once applied, it will greatly improve the efficiency of highway transportation and reduce the accident rate. This paper studies the CR and positioning technology of the AV AEB system, which improves the detection quality in detail. This precision positioning method is also a new inspiration for image segmentation. The good results of our detection module ultimately benefit from these innovative work [3-4].

2. AEB System of AV

2.1. Operating Principle of Automatic Emergency Braking (AEB) System

Based on the actual requirements of vehicle assembly of AEB system, the following requirements are put forward for AEB system: real-time acquisition of the vehicle information meeting certain accuracy requirements without additional equipment. Such as engine output speed, wheel speed of four wheels, brake master cylinder pressure, etc. Relatively economical sensors can be used to obtain traffic scene information in a certain range in front of the vehicle. For example, whether there is a vehicle in front, the distance between this vehicle and the vehicle in front, and the speed of the vehicle in front; Based on the selected sensors, a reasonable recognition algorithm is designed to quickly and accurately identify the effective targets within the detectable range, eliminate the interference, and give consideration to the real-time performance on the premise of ensuring the recognition success rate; Avoid system misoperation, fully consider the system mistriggering scenario, and design a certain suppression mechanism to suppress the system's role when necessary; It has both effective collision avoidance and occupant comfort, and can control the driving state and body posture of the vehicle after the active intervention of braking, making it as close as possible to the operation process of human driver braking; The normal driving behavior of the driver shall not be disturbed, that is, the time for system braking intervention shall not be too early, and the time for the driver to actively control the vehicle to avoid collision after receiving the alarm shall be reserved [5-6].

In order to achieve the above functional requirements, the AEB system first needs to collect the information of the vehicle during driving through a series of sensors. These sensors do not need to be reinstalled on the vehicle, but can be obtained by using the sensors of other systems already equipped on the vehicle. In addition, it is also necessary to obtain the traffic environment information around the vehicle, especially the movement state of the target in front of the vehicle in the driving direction. These sensors need to be additionally installed [7].

At present, the types of sensors that can meet the demand include millimeter wave radar (24GHz or 77GHz), laser radar (single line or multiple lines), and camera (single or dual eyes) [8]. Each of the three types of sensors has its own focus on performance, so one can be selected separately, or multiple sensors can be used at the same time to complement each other, that is, through multi-sensor data fusion, further improve the accuracy of information acquisition and expand the scope of application of the system [9]. On the test vehicle studied in this paper, 77GHz long range millimeter wave radar is used to detect the traffic environment ahead. See Table 1 for performance parameters.

Table 1. Radar performance parameters

Parameter name	Parameter Details
Dimension (width × height × Thickness)	100×80×31(mm)
Working voltage	DC9~16(V)
Detection range	0.5~150(m)
Relative speed detection range	±200(km/h)
Range of heading angle	±15(°)
Vertical beam width	±2(°)

2.2. AEB Basic Control Logic

The AEB system adopts a two-layer hierarchical control structure. The upper controller will transmit the relative speed and distance data between the vehicle and the obstacles in front obtained from the radar to the controller ECU after data filtering and coordinate system conversion. ECU integrates radar data and vehicle intrinsic sensor data, classifies the movement state of environmental targets, and grades the safety state of the current vehicle: if the current vehicle state is judged as safe, the brake actuator will not be triggered; If it is determined that the current vehicle motion status is maintained and there is a possibility of collision with obstacles in front (vehicle or stationary object), the brake actuator will be activated for automatic braking [10-11]. The lower controller controls the vehicle braking system to respond according to the expected deceleration output by the upper controller. Specific to the way of braking intervention and the confirmation of the required braking intensity, it is necessary to identify whether the driver has stepped on the brake pedal, and determine whether it is partial braking or full braking according to the estimated collision speed and the vehicle speed [12].

Braking strategy: when designing the braking strategy of the AEB system, it is necessary to comprehensively consider the three factors of vehicle dynamics, driver behavior and passenger riding experience. On the assumption that the system judges the danger degree of the current traffic environment of the vehicle correctly and reasonably, and the driver does not respond to the alarm signal in time (braking or steering), the AEB system intervenes [13]. The discussion is divided into two situations:

(1) The driver makes a brake response to the current scene at a later time and steps on the brake pedal. However, due to the delayed response of the brake system or the insufficient travel of the brake pedal imposed by the driver due to human physiological limitations, the braking deceleration generated by the vehicle cannot meet the demand for collision avoidance. In this case, the system needs to provide additional brake pressure. Generally, vehicles equipped with ESC are equipped with BA function, which determines whether it is necessary to release all brake pressure according to the speed or force of the driver stepping on the pedal [14-15].

(2) The driver does not respond to the current scene by braking or steering lane change, and the AEB system controller is required to send a braking command to the brake actuator (ESC). At this time, the brake pressure is completely dependent on the brake strength issued by the ECU, that is, the target deceleration requirement.

2.3. Automobile Auto Drive System

2.3.1. Hardware Architecture

The auto drive system of the automobile is a set of comprehensive systems integrating automatic control, computer graphics, machine vision, pattern recognition, operating systems, embedded systems and other disciplines. This paper completes the design of direction control in the auto drive system through the organic combination of various technologies [16]. The system uses the GPS system to locate the current position of the vehicle, and realizes the automatic control of steering in the auto drive system of the vehicle through the identification of road signs, traffic signs, front and rear vehicles and signal lights. The hardware system is divided into four parts: image acquisition and processing system, GPS receiving and positioning system, steering servo system and central control system [17]. Figure 1 shows the overall structure of the system hardware.

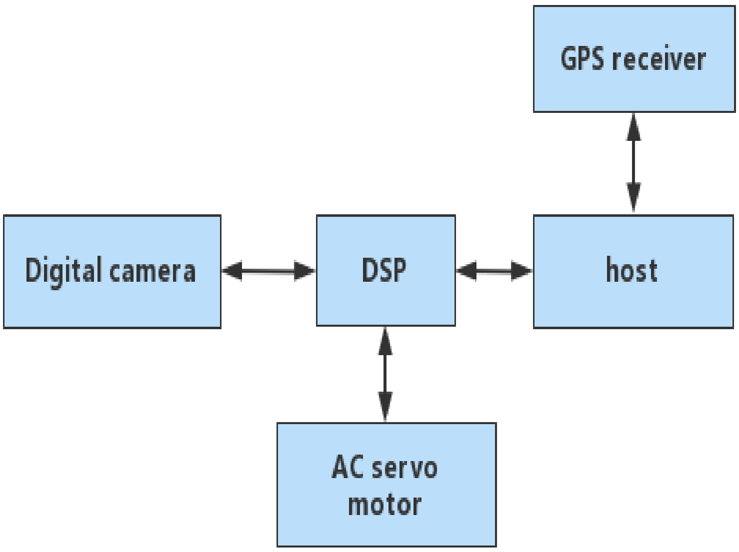

Figure 1. Overall hardware structure diagram

In Figure 1, the host is a small PC with dual core processor, which is enhanced for the on-board use environment and adopts Windows XP system. The host is the core of the whole system, and path planning, image recognition, decision-making, steering action control, etc. are all completed by the host. DSP is the second core of the system, and the images acquired by the camera are processed by DSP. DSP appears as a PCI interface card in the whole system, which is connected to the PCI interface of the host for high-speed and efficient data/instruction transmission [18].

2.3.2. Image Processing System

This module is mainly composed of CMOS sensor, DSP and its peripheral circuits. After DSP further processes the image, it transmits the obtained data to PC through PCI bus so far the system has completed a work cycle. The system structure is shown in Figure 2.

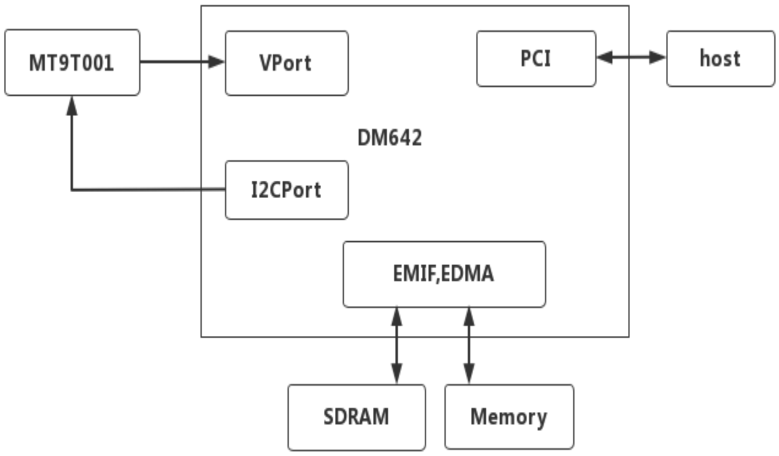

Figure 2. Structure of image acquisition and processing system

3. ML algorithm

3.1. Information Entropy

According to the training process of decision tree, the key of decision tree learning is how to select the optimal partition attribute in the attribute set. In general, we hope that during the training process of the decision tree, with the growth of the decision tree, the remaining sample categories in each node should be more and more consistent, or that the "purity" of this node is higher and higher. Generally, the "information entropy" measure is used to measure the "purity" of a sample set. Now, suppose there is a sample set D, in which there are k types of samples, and the proportion of each type of sample in the overall sample is pk (k=1,2,..., | y |), then we define the information entropy of set D:

$$E(D) = -\sum_{k=1}^{|y|} p_k \log_2 p_k \tag{1}$$

Here, the smaller the value of E (D), the higher the "purity" of set D.

3.2. Information Gain

Now a discrete attribute a in the attribute set has V values {a1, a2,..., aV}. If the sample set D is divided according to the value of a, then V sub nodes will be generated. The samples in the v sub node are all the examples in the original sample set D where the value of property is, which are recorded as Dv. The information gain is defined as the difference between the amount of information before and after all examples are separated.

$$Gain(D,a) = E(D) - \sum_{v=1}^{V} \frac{|D^v|}{|D|} E(D^v) \tag{2}$$

Generally speaking, we need to select the attribute with the largest information gain among multiple attributes as the current partition attribute. As the amount of information becomes smaller and smaller after the entire sample set is "diverted", we can more and more determine the category to which each child node is most likely to belong. Because of its intuitive and reliable principle, information gain has become one of the most common criteria for decision tree generation.

4. Optimization Algorithm Analysis of AV AEB System CR Based on ML

4.1. System Model Analysis and Simulation Verification

This summary analyzes and verifies the CR model of AV AEB system before and after optimization, mainly from four aspects: recognition accuracy, recognition efficiency, reliability and stability. Among them, recognition accuracy is measured by classifier classification accuracy Acuuracy; The identification efficiency is measured by Timecos, which is a long running model; Reliability and stability are measured by sensitivity Acc (+), specificity Acc (-), G-mean structure mean and generalization error OOB generalization error.

UCI dataset is used to build and simulate the model before and after optimization with matlab. Before the model is transplanted to the system platform, various performance indicators of the identified model are verified and guaranteed.

4.2. Model Accuracy and Efficiency Verification Analysis

In order to ensure the authenticity and universality of the experimental test, 8 groups of ML validation data from UCI database are used for the comparative test. The data length, data feature dimension, classification label category, positive and negative data proportion and other information of the data are shown in Table 2.

Table 2. UCI data test table

Serial no	Data name	Data length	Data characteristic dimension	Number of categories	Positive negative data ratio
1	Twonorm	300	20	3	1.0979
2	Statlog	200	13	2	0.8
3	Spectf	244	39	2	7.133
4	Images	2000	784	9	0.8382
5	Heart	294	13	2	0.367
6	Egg	14980	14	3	0.8142
7	Hearts	11500	178	5	1.5
8	Blood	748	5	2	0.32

In Table 1, as far as the data length is concerned, there are 14980 pieces of data at most for EGG and 200 pieces of data for Stalog; As far as the feature vectors of data are concerned, there are 784 feature vectors of images, and at least three feature vectors of blood. As far as classification is concerned, there are four groups of binary data and four groups of multi category data. As far as the positive and negative ratio between data is concerned, there are asymmetric data and symmetric data. In conclusion, the data of validation experiment is universal.

The classification accuracy of random forest is an important indicator to measure the classification results. The detection accuracy of random forest is defined as:

$$Accuracy = \frac{T_{correct}}{T_{all}} \tag{3}$$

In Formula (3), Tcorrect is the number of correct data for random forest classification in the test set and tall is the data length of all test sets. The classification efficiency of random forest refers to the total time for testing and classifying through the training time of decision tree in random forest and the model after training:

$$tim_{\cos t} = tim_1 + tim_2 \tag{4}$$

In Formula (4), tim1 is the training time of random forest, and tim2 is the testing time. Generally, after the random forest training is completed, the testing time of tim2 is very small, which can facilitate the rapid use of the model.

4.3. Simulation Verification of Model Accuracy and Efficiency

The CR models of the AV AEB system before and after optimization were simulated and verified using eight sets of data sets, of which PSO-RF was the CR model optimized by ML in the paper, OR-RF was the original CR model not optimized, and ML methods were used to build decisions. The decision tree construction range was 10 to 500 trees, increasing by 5 trees each time. The experimental environment of the two was completely consistent. Within the range of 400-500 decision trees, the mathematical expectation is used as the recognition result to obtain the system recognition accuracy and efficiency shown in Table 3 and Figure 3.

Table 3. System identification accuracy and efficiency

Category	Data name	Accuracy		Time cost (s)	
		Or-fr	Pso-rf	Or-fr	Pso-rf
Second classification	Statlog	70%	85%	3.23	3.2
	Spectf	75%	77%	4.0	3.5
	Heart	73%	80%	2.3	2.3
	Blood	84%	87%	4.6	4.4
Multi classification	Twonorm	96%	98%	3.2	3.12
	Images	82%	85%	10.2	9.4
	Egg	78.2%	83.4%	12.4	10.3
	Hearts	76.2%	85.3%	120	60.2

It can be seen from the above chart that the recognition accuracy and detection efficiency of the optimized PSO-RF model have been significantly improved. For multi classification and unbalanced data, the optimized model has good recognition performance. Compared with the original OR-RF random forest model, the optimized recognition system model has the following advantages:

When the number of decision trees is the same, the classification accuracy of the optimized PSO-RF model is generally improved, indicating that proper pruning of redundant decision trees and optimization of random forest parameters are helpful to improve the classification accuracy of subsystems in practical applications; Pruning the decision tree improves the efficiency of the model, reduces the share of resources, and makes the optimized recognition model have good real-time performance; The optimized random forest PSO-RF model improves the recognition accuracy and training efficiency when dealing with multi label data

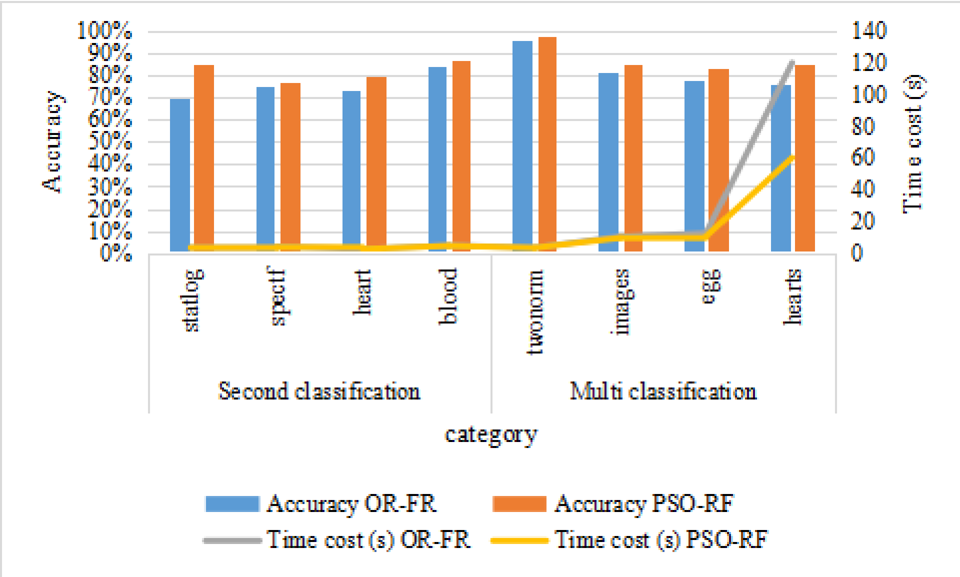

Figure 3. Data chart of recognition accuracy and efficiency

To sum up, we summarized the characteristics of the optimized PSO-RF model of random forests as follows: improve the classification accuracy and efficiency of random forests; improve the classification accuracy and reliability of the random forest model for asymmetric data; the random forest itself has a good performance in dealing with multi category label data; the optimized model improves classification accuracy, model reliability and classification efficiency when processing large amounts of data, the classification efficiency of the optimized random forest model is significantly improved, and the confidence and classification accuracy of the random forest are improved, which can effectively reduce the generalization error of the random forest.

5. Conclusion

This paper mainly studies the CR algorithm of AV AEB system, and analyzes the application of ML related theories; To overcome the limitations of the single information recognition method and realize the complementarity of advantages, the ML algorithm is used to build a CR model, and with the help of high-performance embedded processors, infrared cameras, smart bracelets and other devices as the support platform, a ML based optimization system for AV AEB system CR based on ML is designed and developed, which can be used for real-time, accurate and efficient recognition and early warning. However, there are also shortcomings. There are many ML algorithms, and this paper only briefly analyzes one of them. Therefore, the optimization algorithm for children recognition of AV AEB system based on ML needs further research.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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