Research on Vehicle Detection Technology of Blind Spots at Night Based on CAdaBoost Algorithm

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Abstract: Aiming at the problem of vehicle video detection in blind areas at night, a method of vehicle detection in blind areas at night based on CAdaBoost algorithm is proposed. Since night vehicles and daytime vehicles have different illumination, visibility, vehicle edge characteristics, vehicle contours, etc., the test image is first grayed out and ROI is determined. Then, because the features of the car head and wheels at night are more obvious than other features, a parallel method is used to train multiple weak classifiers offline at the same time, mainly to train the Haar-like features of the car head and wheels of the test image. In the meantime, in order to improve the accuracy of detection, the weighted parameter is introduced to determine the role of the weak classifier in the final strong classifier. Then, the offline trained model is used to match the Haar-like features of the test vehicle's car head and wheels respectively, and finally realize the real-time detection of vehicles in the blind area. The results show that, for vehicle detection in blind spots at night, the algorithm has a high detection accuracy and low detection time.

1. Introduction
At present, in the advanced driving assistance system, the blind spot vehicle detection based on monocular vision is a technical bottleneck. Because the limited computing power of the on-board DSP, the real-time requirements for vehicle detection in blind spots have become more demanding, especially for vehicle detection in blind spots at night. Through the research of daytime vehicle detection algorithm[1] in recent years, it is found that in the daytime environment, vehicle detection has high detection accuracy, low time-consuming and low false alarm rate. However, the shadows, edges, contours and other features of vehicles in the blind area become inconspicuous at night. After referring to related literature[7], it is found that the car head and wheel characteristics of vehicles in blind areas at night are more obvious. Based on the algorithm of AdaBoost[8], a method of vehicle detection in blind areas at night based on CAdaBoost algorithm is proposed. The main idea of the algorithm is that firstly a parallel strategy is used to train multiple weak classifiers offline at the same time. Then, extracting the Haar-like features of the car head and wheels of the test vehicle online. At last, the trained model is used to match the Haar-like features of the car head and wheels of the test vehicle in real time.

2. Material and Methods
2.1. AdaBoost Algorithm
Freund and Schapire[10] improved the Boosting algorithm in 1995 and proposed the AdaBoost algorithm. AdaBoost adopts iterative idea, the core principle is to train different weak classifiers for the same training data set, then combine these weak classifiers into a strong classifier. In particular, the algorithm is implemented by changing the data distribution, that is, the weight of each sample is determined...
according to whether the classification of each sample in each training set is correct. Because the algorithm is simple and has high detection accuracy, it is widely used in the field of vehicle detection.

The execution process of the AdaBoost algorithm is shown in Figure 1, where D is the training data set, \( w_i \) is the initialization weight, \( e_j \) is the weak classifier error, \( \alpha_j \) is the weak classifier weight, and \( G_j \) is the weak classifier, \( G \) is the strong classifier, where \( j = 1, 2, \ldots, M \).

**Figure 1. Schematic diagram of AdaBoost algorithm.**

1) Given the training data set \( D \), initialize the weight distribution of each sample in \( D \) to \( 1/N \).

2) Training multiple weak classifiers in an iterative manner, which trains \( m \) rounds, where \( m = 1, 2, \ldots, M \).

3) Normalize the weight of the training sample set, which is marked as \( w_m(i) \).

4) Using the training sample set \( w_m(i) \) to learn, and get a weak classifier \( h_m(x) \). Then, calculate the error \( e_m \) of its corresponding feature and the weight coefficient \( \alpha_m \) of the weak classifier \( h_m(x) \).

5) After \( M \) iterations, \( M \) best weak classifiers are generated, which are linearly formed into a strong classifier.

\[
H_d(x) = \text{sign}(f(x)) = \text{sign}(\sum_{m=1}^{M} \alpha_m h_m)
\]

(1)

In Equation (1), \( H_d(x) \) is strong classifier, \( f(x) \) is the linear combination of weak classifiers. In addition, the AdaBoost algorithm’s predetermined goal is to minimize the exponential loss of \( f(x) \) on the training data set \( T \).

\[
h_m = \arg \min_h \sum_{i=1}^{N} w_m(i) \text{sign}(y_i h(x_i))
\]

(2)

In Equation (2), \( y_i h(x_i) \) is the predetermined target, \( N \) is number of samples in \( D \).

2.2. **Parallel AdaBoost algorithm**

According to the entire execution process of the AdaBoost algorithm, it can be seen that reducing the offline training time of the weak classifier is the key to improving the detection rate of the algorithm. Based on the AdaBoost algorithm, this paper uses parallel strategy and weighted parameter idea to train model.

2.3. **Vehicle detection in night blind spots**

2.3.1. **Process of vehicle detection in night blind spots**

The whole detection process is divided into two parts, training data and test data. The training data is mainly used to train the CAdaBoost model offline, and the test data is mainly to detect the input test images. The specific flow chart of vehicle detection in blind spots at night is shown in Figure 2.

**Figure 2. Flow chart of vehicle detection in night blind spot.**
2.3.2. Grayscale processing
Since the edges, shadows, contours and other features of the night vehicle are not obvious, it is necessary to perform grayscale processing on the test vehicle image.

2.3.3. Determination of the region of interest
This paper uses the method of detecting different features according to the distance to determine the region of interest (ROI). The wheels are detected in the red area within 5 meters of the test vehicle. And according to the rectangular area 5 meters away from the test vehicle, the car head is detected.

2.3.4. Parallel processing of weak classifiers
In order to shorten the offline training time, this paper uses a parallel strategy to train multiple weak classifiers. In addition, this paper introduces weight parameter based on the weight coefficients of AdaBoost method to accurately describe the role of the selected weak classifier in the final strong classifier, as shown in Figure 3.

![Figure 3. Schematic diagram of parallel processing of weak classifiers.](image)

Specific steps are as follows:
1) Selecting \( h_m \) according to the above Equation (2), and use the training sample set with the weight distribution function \( \omega m(i) \) to learn, and obtain the parallel combination form of multiple weak classifiers for:

\[
E_m(x_i) = \text{sign}(\sum_{j=1}^{p} \varphi^j h_m^j(x_i))
\]  

(3)

\( \varphi^j \) is the training accuracy of the weak classifier, and \( \sum_{j=1}^{p} \varphi^j h_m^j(x_i) \) is the decision function of \( p \) parallel classifiers, where \( j=1, 2, ..., P \), where \( m=1, 2, ..., M \).

2) Calculate the error of the weak classifier corresponding to each feature:

\[
\varepsilon_m = P[h_m(x_i) \neq y_i] = \sum_{h_m(x_i) \neq y_i} \omega_m(i)
\]  

(4)

3) Update weight parameters.

\[
\alpha_m = \frac{1}{2} \ln \left( \frac{1 - \varepsilon_m}{\varepsilon_m} \right) + Ke^{\varepsilon_m}
\]  

(5)

Among them, \( K \) is a constant, \( Ke^{\varepsilon_m} \) is an increasing function of \( \varepsilon_m \).

2.4. Haar-like characteristics of vehicles in blind spots
The vehicle features collected in the blind area at night are divided into two categories: car head detection features in the blind area where the distance between the camera and the target vehicle is greater than 5 meters, and wheel detection features in the blind area where the distance between the camera and the target vehicle is less than 5 meters. In addition, this paper uses integral images to calculate Haar-like features.

3. Results and Discussions

3.1. Source of experimental data
In this experiment, the vehicle detection data in the blind area at night is divided into two parts: offline training picture set and test picture set. This paper uses a monocular camera installed under the rearview mirror of the vehicle to shoot 10 video clips with a resolution of 720*480, whose target scene of the test is an urban road. And 6,000 pictures are collected from it, including 1,480 positive samples for the car head of car, 1,520 positive samples for wheels, and 3,000 negative samples for training, as shown in Figure 4.

![Figure 4. Example of training samples.](image)

3.2. Experimental Results
In order to verify the reliability and effectiveness of the algorithm, this paper tested the actual vehicles in the blind area at night. Figures 5-6 show examples of the results of detecting the car head and wheels of the car.

![Figure 5. Vehicle head detection results.](image)

![Figure 6. Vehicle wheels detection results.](image)

It can be seen from Figures 5-6 that the detection accuracy of the car head and wheels of the blind area at night is still relatively high. In addition, this paper mainly adopts detection rate and single frame time (unit: ms) as the detection indicators for the car head and wheels of vehicles in blind areas at night. Specific as shown in Table 1.

| Detection algorithm | Statistics number of frames | Wheel detection rate (%) | Car head detection rate (%) | Single frame time-consuming for wheel detection (ms) | Single frame time-consuming for car head detection (ms) |
|---------------------|-----------------------------|--------------------------|----------------------------|------------------------------------------------------|------------------------------------------------------|
| Daytime             | 405                         | 91.5                     | 90.6                       | 29.2                                                 | 32.4                                                 |
| Night               | 405                         | 90.4                     | 89.8                       | 32.6                                                 | 34.3                                                 |

It can be seen from Table 1 that the wheel and car head detection in the blind area at night meets the real-time requirements, with an average of 33.45ms per frame. Moreover, the average detection rate of the car head and wheels reached 90.1%, which is almost the same as during the day. However, the false detection rate is a bit high and needs to be improved in the future.

4. Conclusions
Aiming at the problem of vehicle detection in night blind spots, a vehicle detection method in night blind spots based on CAdaBoost algorithm is proposed. Compared with the daytime, vehicle in blind Areas at night have weak light and low visibility, and features such as Vehicle edges, textures, contours are not obvious, which cannot be detected using daytime algorithms. The CAdaBoost algorithm proposed in this paper firstly preprocess the input image. Then, training multiple weak classifier in parallel to improve the offline training speed. Next, targeting the blind area of different regions of interest, extracting the Haar-like features of the car head and wheels of vehicle, and using the offline...
trained model to match the extracted car head and wheel features. Experimental results show that the algorithm has a high detection accuracy rate for vehicles in night blind spots, and the detection time is low.

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