Improved Vehicle Detection Method Using Feedback-AdaBoost Learning

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Abstract—**With the increase in traffic, the demand for driver assistance systems (DAS) has increased. To predict and prevent vehicle accidents, vehicle detection is an essential component of DAS. Vision is the most commonly used human sense while driving and vision sensors (CCD/CMOS) are cheap. Therefore, vision research applied to DAS has been done. In vision research, most vehicle detection methods have database learning (training) as classification algorithms. Well-trained classifiers will have a strong vehicle detection performance. This article presents an improved database learning method for vehicle detection. We use the AdaBoost classifier's results for feedback input training data. The false-positive results were added to negative training images and true-positive results were added to positive training images. In the experiment results, we proved that our proposed method is better than the existing AdaBoost classifier performance.**

Index Terms—**Adaboost, vhicle dtection, dtabase taining, har-like feature, fedback.**

I. Introduction

Driver Assistance Systems (DAS) are the most important part of intelligent automotive research. DAS prevent traffic accidents and support the safety of the driver. Currently, DAS using a radar sensor are common. However, drivers mainly rely on their visual sense while driving. According to these principles, DAS using an image processing sensor (CCD/CMOS) has attracted attention in recent years. Like the human visual system, the image processing sensor provides visual information to the driver. Vehicle detection algorithms are based on this visual information.

In the field of computer vision research, a vehicle detection algorithm has been based on the general object detection algorithm, which is composed of three phases. The first step is feature extraction, which is defined as the mathematical characteristics of objects. The next step is classifier learning. In this step, the classifier is trained by extracted features. The final step is object detection, which uses the trained classifier. These three steps are combined sequentially. Examples of existing feature extraction algorithms are SIFT [1], SURF [2], HOG [3], Haar-like [4], LBP [5], etc. Also Neural Network [6], SVM [7], AdaBoost [8] are widely used for classifier algorithm.

The general vehicle detection algorithms are based on the face detection algorithm [4]. In the field of face detection research, the Haar-like feature and AdaBoost classifier have been mainly applied since a combination of these algorithms is comparatively good at face detection. However, the characteristics of vehicle images are different from those of facial images. Vehicle images are highly variable due to the kind of vehicle, the color of the vehicle, the surrounding environment, etc. These elements cause difficulties for vehicle detection processing, especially in a general assessment since the AdaBoost classifier has drawbacks that create numerous false-positives.

In this framework, we tuned the face detection algorithm for the vehicle detection. We discuss how to configure the database and improve the AdaBoost learning method. To obtain good quality data, we extracted the vehicle database images from sequence images we took directly. We collected vehicle images taken from behind, and normalized the database image size. The AdaBoost classifier was trained with these vehicle database images. Then, we input the sequence test images for the AdaBoost classifier training. The AdaBoost classifier output true-positive results and false-positive results. Using these results we reconstructed the vehicle database. The positive database was reconstructed using the true-positive results, and the negative database was reconstructed using the false-positive results. The repetition of database reconstruction processing improved the detection algorithm performance.

This paper is organized as follows. In Chapter II, we introduce the database image extraction method and the database construction method. In Chapter III, we introduce AdaBoost classifier learning, and in Chapter IV, using this AdaBoost cascade classifier, we detect the vehicles on road images and reconstruct the database inputs. In Chapter V, the experiment results, we prove that the proposed learning algorithm results are better than existing AdaBoost learning algorithm results. Chapter VI is the conclusion.

II. Database

A. Vehicle Images Extraction

We took a sequence of photos that represented the vehicle driving environment. For this, we used a CCD sensor that takes gray-image photographs. Black and white photographs have less data than color photographs, which is an advantage in the processing time. As Fig. 1. shows, we took photos of vehicles driving in the same direction. From these photos, we only extracted the rear appearance of the vehicles. These extracted photos constituted the training database for the positive image part.

B. Vehicle Image Normalization

We cropped the vehicle images based on the endpoints of both tires, as shown in Fig. 2. We set the row size of the image equal to the column size of the image, so the rate of the row and column was the same. We also normalized the image

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size, since the same size configuration is easier for AdaBoost learning. We defined the image size as 256-256 pixels.

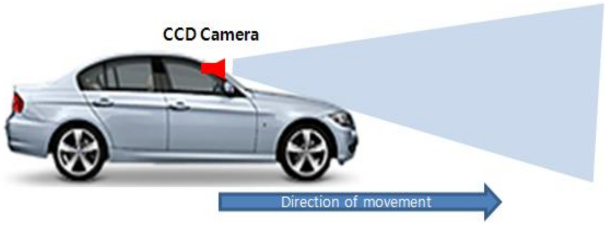

Fig. 1. Camera position.

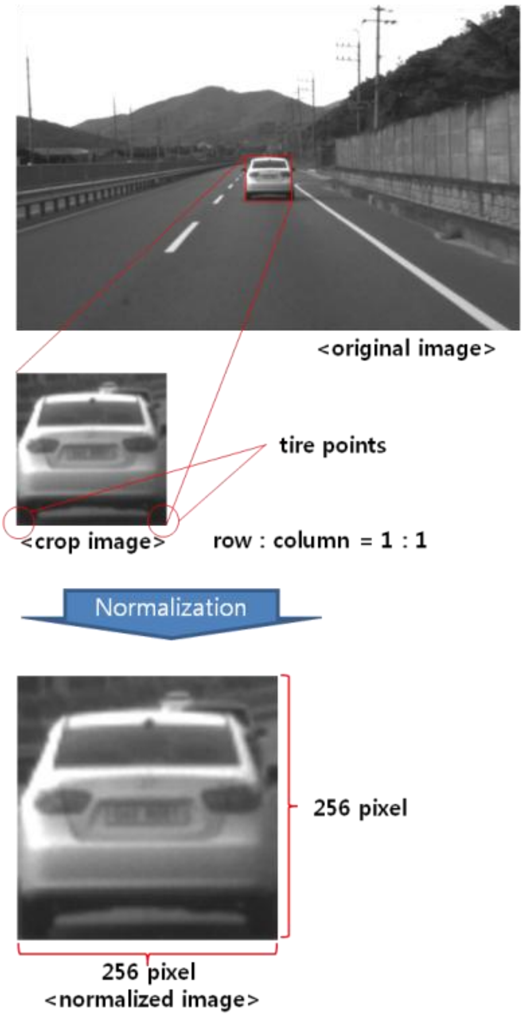

Fig. 2. Vehicle image extraction & normalization.

C. Negative Image

We defined the positive images to the patch including the vehicle appearance, while the negative images were defined as background images. That is, a random image patch of the road which did not have a vehicle image.

III. Learning

A. AdaBoost Learning

The AdaBoost classifier learned from the database that we extracted from the road images. The AdaBoost classifier that we usd was based on Viola's methods [4]. Fig. 3. shows more information on this classifier.

- Given example images $(x_1, y_1), \ldots, (x_n, y_n)$
  where $y_i = 0, 1$ for background images and vehicle images respectively.
- Initialize weights $\omega_{t,i} = \frac{1}{2m}, \frac{1}{2n}$ for $y_i = 0, 1$ respectively,
  where m and l are the number of background images and vehicle images respectively.
- For $t = 1, \ldots, T$:
  ① Normalize the weights,
  $$\omega_{t,i} \leftarrow \frac{\omega_{t,i}}{\sum_{j=1}^{n} \omega_{t,j}}$$
  so that $\omega_{t,i}$ is a probability distribution.
  ② For each feature, j, train a classifier h_j which is restricted to using a single feature.
  The error is evaluated with respect to $\omega_{t,i}$,
  $$\epsilon_j = \sum_i \omega_i |h_j(x_i) - y_i|.$$
  ③ Chose the classfier, h_j, with the lowest error ϵ_j.
  ④ Update the weights :
  $$\omega_{t+1,i} = \omega_{t,i} \beta_t^{1-e_i}$$
  Where $e_i = 0$ if example x_i is classified correctly, $e_i = 1$ otherwise, and $\beta_t = \frac{\epsilon_t}{1-\epsilon_t}$.
- The final strong classifier is :
  $$h(x) = \begin{cases} 1 & \sum_{t=1}^{T} \alpha_t h_t(x) \geq \frac{1}{2} \sum_{t=1}^{T} \alpha_t \\ 0 & \text{otherwise} \end{cases}$$
  where $\alpha_t = \log \frac{1}{\beta_t}$

Fig. 3. AdaBoost learning.

IV. Vehicle Detection

A. Cascade Classifier

As Fig. 4. shows, we detected the vehicles using a cascade classifier. Each cascade had one strong classifier, which was represented by the detection window. This detection window has the selected Haar-like features, and conducted full size input image searching. The input image was constructed by a scale-space image. The scale-space of the image could cope with the changing scale of the object. The rescale rate of the scale-space affects the detection performance; the dense rescaling makes detection performance better, but the processing time is long. On the other hand, if the scale-space is sparsely constructed, the detection performance is degraded but the processing speed is increased. In our experiment results, we prove the performance effects according to the rate of scale-space. During detection processing, background images are rejected by the detection window, and the vehicle images were delivered to the next cascade.

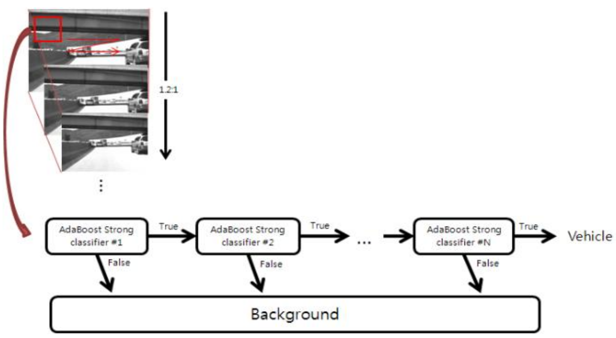

Fig. 4. Cascade classifier.

B. Feedback Input

Fig. 7. represents the key point of our paper. We input the

test road image sets into the AdaBoost classifier. The AdaBoost classifier output the detection results which were divided into positive images and negative images. We used these results for feedback input. As Figure 8 shows, the positive database was reconstructed with the positive results of the earlier stage. However, the negative database was reconstructed with the negative results of the earlier stage. The negative results constituted image patches of road, such as guard rails, traffic signs, road signs, etc. The infrequent image patches of general road such as outdoor billboards, buildings, sky, etc. were excluded. To create an accurate classifier we re-trained the classifier using the earlier stage output. Whenever the database was reconstructed, the classifier performance was better than the earlier stage.

V. Experiment Results

The experiment was conducted on general roads and highways. To get feedback inputs, we used approximately 5200 random road images. For performance evaluation, we used two image sets. One set constituted 400 images of general roads while the other set constituted 400 images of highways. We had 1327 vehicles in these test image sets which were the ground truth results. The random road images for feedback input and the performance evaluation road images did not overlap.

A. Detection Rate

Fig. 5. shows the relative proportion of true-positive results and false-positive results. This is the Receiver Operating Characteristic (ROC) curve. This result is represented by the scale-space rescale rate.

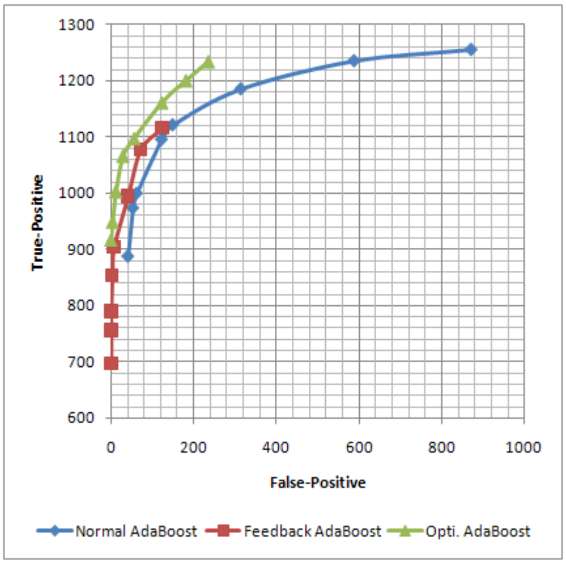

Fig. 5. Receiver operating characteristic curve.

The blue line of the graph shows the results of the existing method, while the red line shows the results of using feedback input. The reconstructed database is used in a one time repetition. The green line is the optimized results. For these results, we conducted the database reconstruction three times. After that, we experimented with more repetition of the database reconstruction, but do not obtain significantly better results than the green line results. In these experiment results, we obtained the best performance when more feedback input was included in the database.

B. Recall-Precision Curve

For more exact analysis, Figure 6 represents the recall-precision results. The recall value and precision value are defined below.

$$Recall = \frac{True\,Positive}{True\,Positive + False\,Negative}$$

$$Precision = \frac{True\,Positive}{True\,Positive + False\,Positive}$$

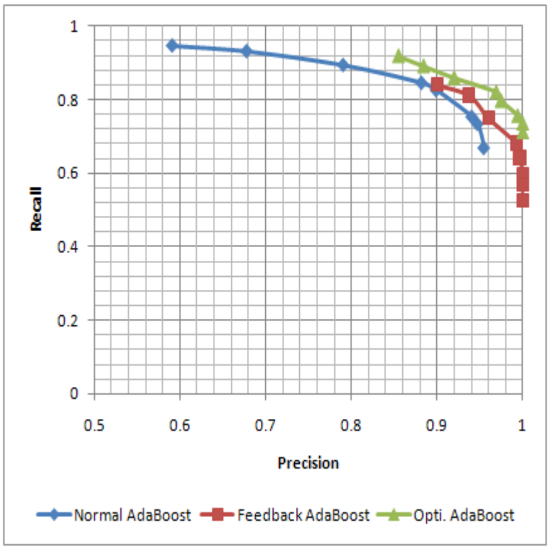

Fig. 6. Recall-precision curve.

The so called recall value is the correctly detected vehicle component rate on existing vehicles, also the precision value is the detected vehicle rate on the detection result outputs. Combined with previous results, the results of the reconstructed database show a better performance than earlier results.

C. Results

Fig. 8. is the final result images. The upper two results are from highways and the lower two results are from the general road. The processing speed was 20 frames/sec for the highway images, and 14 frames/sec for the general road images. The general road images had more obstacles and occlusion than highway images, which increased the cascade classifier processing time. A simulation of these results is shown on YouTube website [9].

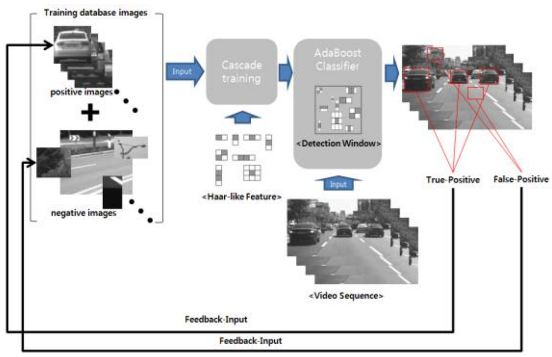

Fig. 7. Proposed Algorithm.

Fig. 8. Results.

VI. Conclusion

In this framework, we introduced a classifier learning method and database construction method for vehicle detection. We obtained better performance when more feedback input was included in the database. The configuration and quality of the database play very important roles in classifier learning. Like a human learning, if we train the classifier with a well configured database we obtain a strong detection performance.

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