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An Approach to Vehicle Recognition using Supervised Learning

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Abstract

To enhance safety and traffic efficiency, a driver assistance system and an autonomous vehicle system are being developed. A preceding vehicle recognition method is important to develop such systems.

In this paper, the vision-based preceding vehicle recognition method, based on supervised learning from sample images is proposed. And the improvement for Modified Quadratic Discriminant Function (MQDF) classifier that is used in the proposed method is also shown.

In the case of the road environment recognition including the preceding vehicle recognition, there are many reports, in which evaluations are done with a few images, but a quantitative evaluation with large number of images has rarely been done. We prepare over 1,000 sample images for passenger vehicles, which are recorded on a highway at daytime, and evaluate the proposed method with those images.

The evaluation result shows that the performance in a low order case is improved from the ordinary MQDF. The feasibility of the proposed method is proved, due to the result that the proposed method indicates over 98% as classification rate.

1 Introduction

To enhance safety and traffic efficiency, a driver assistance system and an autonomous vehicle system are being developed. In these systems, a vehicle should have the function to recognize road environment such as a road lane, a preceding vehicle and another obstacle. Machine vision is considered as one of the road environment recognition methods.

Preceding vehicle recognition is one of the most important functions to develop such systems. It is difficult for machine vision because vehicles have various appearances, due to their various shapes and colors. And appearance is changed when lighting changes.

The preceding vehicle recognition method using vertical and horizontal edge detection are reported[1][2][3], they are based on the fact that there are significant vertical and horizontal edges in the differential images of back faces of passenger vehicles such as a sedan, a coupe and a station wagon. But in a real road environment, various kinds of vehicles run as well as passenger vehicles, and they have to be recognized. A motorcycle is an example of them, it should be difficult to be recognized using the above method, because it has no significant vertical and horizontal long edges in the back face.

Thus, we consider that the recognition method using supervised learning from samples is necessary in order to recognize various vehicles. We have already proposed the preceding vehicle recognition using supervised learning, and proved the feasibility of the proposed method with small number of images for passenger vehicles and motorcycles[4].

In this paper, in order to reconfirm feasibility of the proposed method, the quantitative evaluation with large number of images for passenger vehicles, and the improvement for MQDF classifier that is used in the proposed method are shown[5].

2 Outline of proposed method

The proposed preceding vehicle recognition method has the following characteristics.

1. It order to recognize various vehicles, the special features suited for special object are not used, but the gray level pixel values are used for features instead (called "appearance based" generally).
2. Two classes (the vehicle class and the non-vehicle class) are assumed. And not only vehicle samples (the images cropped from the windows(rectangle regions) fitted to outlines of vehicles) but also non-vehicle samples (the images cropped from the windows not fitted to outlines of vehicles) are given, in order to define the boundary of the vehicle region in the feature space automatically.

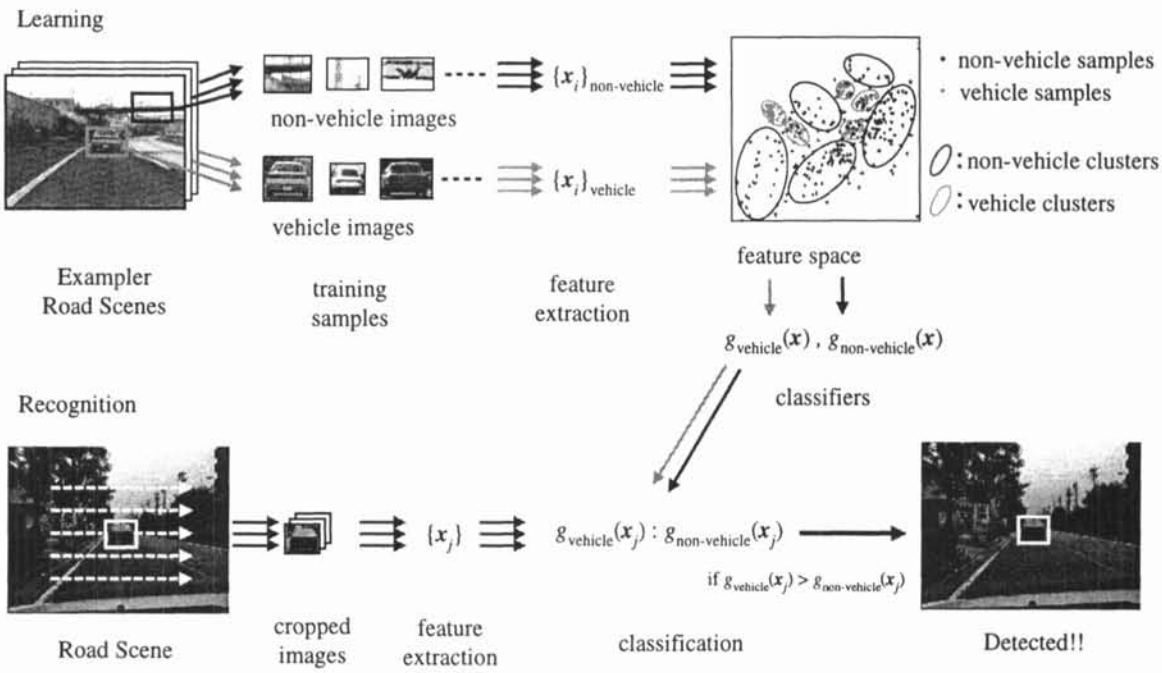

Fig. 1 Outline of proposed preceding vehicle recognition method

3. In order to suit complexly of the distributions, due to the variations of appearances and other reasons, the distribution is modeled as multiple multidimensional normal distributions in feature space for each class.

The outline is described in the following (Fig. 1).

Learning

1. The vehicle samples and the non-vehicle samples are prepared as training samples.
2. All training samples are projected into the feature space after normalization of the size(resolution) of the images (because an image cropped from a road scene does not have fixed size).
3. The training samples are divided into the clusters, which are considered as normal distributions.
4. The classifier is estimated from each cluster. We use improved MQDF for the classifier.

Recognition

1. An image is cropped from a window in a road scene.
2. The cropped image is projected into the feature space same as learning process.
3. It is classified either a vehicle or a non-vehicle by the classifiers which are estimated by learning.
4. If an image is classified as a vehicle, the vehicle should exist in the corresponding window of the road scene.

A vehicle could be recognized if the images cropped with the combination of all locations, heights and widths are classified exhaustively. The amount of calculation becomes enormous when classifications are done with the combination of all locations and sizes. However, it is possible to reduce combination substantially by the constraints such as the relation with road.

3 Improvement of MQDF

Modified Quadratic Discriminant Function (MQDF) is known that it has a good classification performance with a small set of training samples and low calculation cost, in the case of character recognition[6]. The MQDF of an n-dimensional feature vector x is given as

$$g(x)=\frac{1}{h^2}\left\{\|x-\hat{\mu}\|^2-\sum_{i=1}^{k}\left(1-\frac{h^2}{\lambda_i}\right)\left[\varphi_i^T(x-\hat{\mu})\right]^2\right\} + \ln\left(h^{2(n-k)}\prod_{i=1}^{k}\lambda_i\right) \quad (1)$$

Here, $\hat{\mu}_l$ denotes the mean, which is estimated from training samples. φ_i denotes the eigenvector of the covariance matrix $\hat{\Sigma}$ and λ_i ($\lambda_i \geq \lambda_{i+1}$) denotes the corresponding eigenvalue. h is an appropriate constant. For simplicity, the team of prior probability is omitted. The value of h^2 is determined to be the average of λ_{k+1} over all classes generally.

Eq.(1) shows that the calculation time of MQDF is almost in proportion to k. Therefore, the order parameter k had better be low in order to reduce calculation cost. But the performance of MQDF is usually deteriorated when k is low.

The deterioration of performance for MQDF when k is low is occurred due to the determination criterion of h^2. The value of h^2 is larger than proper with the ordinary determination criterion of h^2 when k is low. Thus, we modify the determination criterion of h^2 from the average of λ_{k+1} to the average of

$$\left(\sum_{i=1}^{k} \lambda_i \Big/ \sum_{i=1}^{n} \lambda_i\right) \lambda_{k+1} . \qquad (2)$$

A smaller value than λ_{k+1} is obtained when k is low and it coincides with λ_{k+1} when k is high.

4 Experiments

In order to reduce the calculation time, the evaluation was done with the finite test samples consisting of vehicle samples and non-vehicle samples, instead of classifying with the combination of all locations and sizes.

We evaluated our proposed method, the ordinary MQDF and the nearest neighbor method (NN) which is a popular non-parametric method, for comparison. The quantitative evaluation with large number of images for passenger vehicles was done. The reason why passenger vehicles are chosen, is easy to collect many samples.

1034 vehicle samples are collected for the evaluation. These samples are cropped by hand from still images of road scenes, which are recorded on a highway at daytime (Fig. 2).

The training samples for the vehicle class are drawn at random from the collected samples. And the test samples for the vehicle class are drawn form the remaining samples. The training and test samples for the non-vehicle class are cropped at random from corresponding road scenes, from which the training and test samples for the vehicle class are cropped, respectively.

The number of the training samples is 500, and the number of the test samples is 500, respectively for each class. The normalization size of image is 16x16. The classification rates are calculated 50 times with the different sets of training and test samples, and averaged.

5 Results

Fig.3 shows the classification rates for the proposed method, the MQDF and the NN. It is

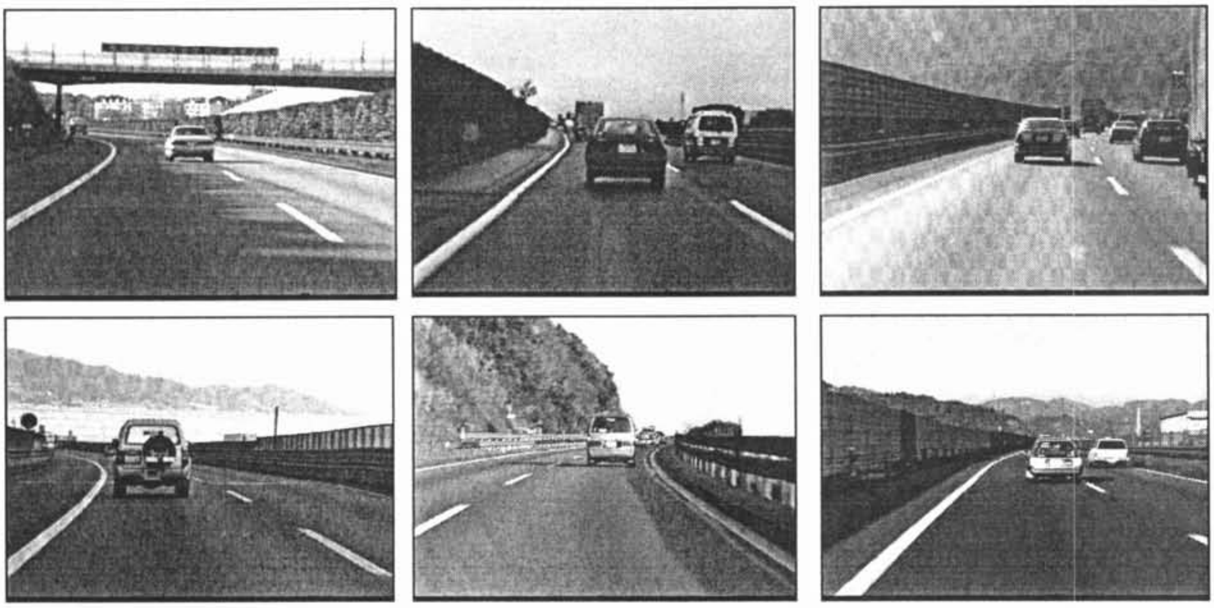

Fig. 2 Examples of the road scenes

indicated that our proposed method has better performance than the ordinary MQDF and the NN. And the performance in a low order is improved greatly from the ordinary MQDF.

The best classification rate of the proposed method is $98.3 \pm 0.4\%$ at k = 75.

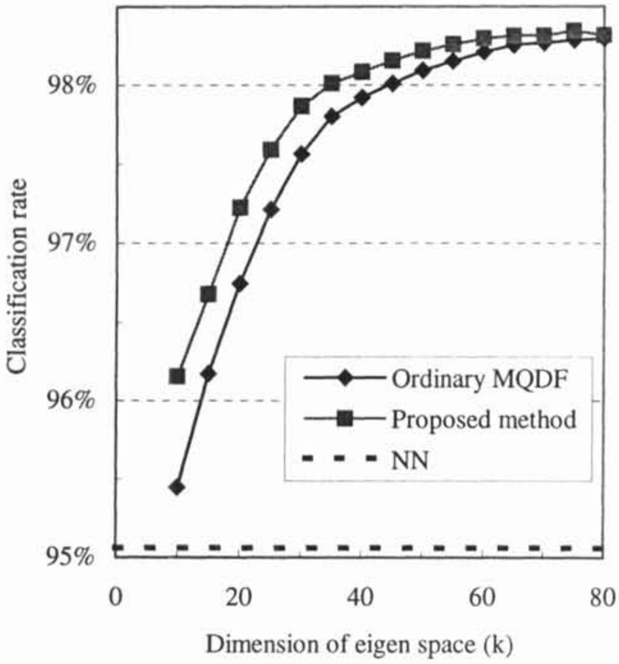

Fig. 3 Classification rate

6 Conclusion

Preceding vehicle recognition is important to develop a driver assistance system and an autonomous vehicle system. We have already proposed the preceding recognition method using supervised learning, and proved the feasibility of the proposed method with small number of images for passenger vehicles and motorcycles.

In this paper, the quantitative evaluation for the proposed method is done with large number of images for passenger vehicles. The purposes of the evaluation are to reconfirm the feasibility of the proposed method, and to show the efficiency of our improvement for MQDF.

The evaluation result shows that the performance in a low order case is improved from the ordinary MQDF. And we have reconfirmed the feasibility of the proposed preceding vehicle recognition method, based on the fact that the proposed method indicates $98.3 \pm 0.4\%$ as classification rate, in the experiment with the 1034 sample images.

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