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Vision-based Vehicle Type Classification Using Partial Gabor Filter Bank*

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Abstract - A vision-based vehicle type classification method using partial Gabor filter bank is present in this paper for five vehicles categorization: sedan, van, hatchback sedan, bus and van truck. To reduce the influence caused by the hues of vehicles, we extract the Gabor features from the edge image of vehicle, instead of from the grey image. Partial Gabor filter bank approach, which can save memory and computation cost significantly, is introduced and a new partial sampling method is proposed. The experimental results show that the recognition rate reaches 95.17% using partial Gabor features, illustrating the effectiveness of the proposed approach.

Index Terms - Vehicle classification, Gabor filter, ITS.

I. INTRODUCTION

Recently, the Intelligent Transportation System (ITS) has been developed to make the existing traffic infrastructure more efficient. As an important issue with applications to ITS, robust vehicle classification has been an active research area [1] [2]. The traditional approach is embedding the electronic sensors in road and detects the wheelbase. However, these sensors are not removed easily and not robust for heavy traffic day and night. Consequently, the main drawback of such system is its poor maintainability and higher maintenance cost. To overcome such shortages, more and more researchers turn to vision-based classification, which employs digital camera as detector.

Generally, there are three stages in a vision-based vehicle classification system: vehicle segmentation, feature extraction and vehicle classification. In this paper, our emphasis is focused on feature extraction. Considering the application, the robust and real-time attributes are of most importance. What features should be employed and how to extract them become crucial in vision-based vehicle classification. Some of the existing works are purely based on structural features (such as height and length of a vehicle, etc). In S. Gupte et al. [2], vehicles are modelled as rectangular patches with certain dynamic behaviour and Kalman filtering is used to estimate the vehicle structural features. A. Lai, et al. [3] suggests a method to extract moving vehicles from image sequences and fits them with a simple deformable model. Moreover, using known camera parameters, vehicle's structural features are estimated. In such methods, a suitable vehicle model is required to extract the structural features. And there are heavy computation burden in modeling, which can hardly be practical for real-time application. Therefore, we need to develop convenient approach that can detect the invariable features for each vehicle category respectively. Two classification algorithms – "Eigen-Vehicle" and PCA-SVM (Principal Component Analysis - Support Vector Machine), are proposed and implemented to classify vehicles into trucks, sedan, van, and pick-up in [4]. But the performance of such algorithms depended on the accuracy of vehicle normalization. As shown in their paper, such methods can not classify the vehicle robustly. For three vehicle types, (such as sedan, van and pickup), T. R. Lim et al. [5] achieved a recognition rate of 93.88% using Gabor features. Y. N. Zhao et al. [6] proposed a non-even sampling of Gabor features for classification on the basis of the edge distribution in vehicles, and four vehicle types were recognized. However, they all extract the features from the grey image, which would be influenced by the hues of the vehicles generally. And it is found that to extract features from the edge image of the vehicles will produce much better performance than from grey vehicle image. A problem when using Gabor features is the high dimension of Gabor feature vectors, which will cause heavy computation burden and large memory requirement. To solve this problem, we introduce the partial Gabor filter bank, which is original proposed in [7] for facial expressional recognition, to reduce the computation and memory requirement. Moreover, we propose a partial sampling technique for feature extraction. It is based on the fact that the differences of various vehicles are mostly at the upper part. Consequently, instead of extracting features at the whole vehicle image, we just need to extract features from the upside partial sampling points. The experimental results show that the method proposed is effective for both dimension and computation reduction.

This paper is organized as follow. In section II, we discuss the Gabor feature extraction. The partial Gabor filter bank is represented in Section III. The detail of the partial sampling method is described in Section IV. Section V briefly introduces the feature compression using PCA and classifier design. Experimental results and discussion are given in section VI.

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II. GABOR FEATURE EXTRACTION

Gabor filter have been widely applied in the area of pattern recognition due to its optimal localization properties in both spatial analysis and frequency domain. The Gabor filters, whose kernels are similar to the 2D receptive field profiles of the mammalian cortical simple cells, exhibit desirable characteristics of spatial locality and orientation selectivity [8]. The 1D Gabor function was first defined by Gabor, and later extended to 2D by Daugman [8]. In the spatial domain, a 2D Gabor filter is a complex exponential modulated by a Gaussian function, which is defined by,

$$G(x,y;\omega,\theta) = (1/(2\pi\sigma^2)) \times \exp((x'^2 + y'^2)/(2\sigma^2)) \times [\exp(i\omega x') \quad \exp(\omega^2\sigma^2/2)] \tag{1}$$

$$x' = x\cos\theta + y\sin\theta, y' = \quad x\sin\theta + y\cos\theta$$

where (x, y) is the pixel position in the spatial domain, ω is the radial frequency, θ is the orientation of Gabor filter, and σ is the standard deviation of the Gaussian envelope along the x and y-dimensions. In addition, the second term of the Gabor filter, $\exp(-\omega^2\sigma^2/2)$ compensates for the DC value because the cosine component has nonzero mean while the sine component has zero mean. In practical application, it is usually set $\sigma \approx \pi/\omega$ to define the relationship between σ and ω [9].

Generally, a Gabor filter bank with four frequencies and eight orientations is used to extract the feature [6] [7]. When selecting the maximum frequency $\omega_{\max} = \pi/2$, $\omega_m = \omega_{\max}/\lambda^{m-1}$, $(m = 1,2,3,4)$, $\lambda = \sqrt{2}$, $\theta_n = (n-1)\pi/8$, $(n = 1,2,\cdots 8)$, the real part of the Gabor filters with four frequencies and eight orientations is illustrated in Fig. 1. We can see that the Gabor filters exhibit strong characteristics of spatial locality and orientation selectivity.

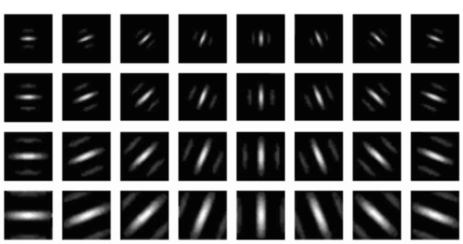

Fig. 1 The global Gabor filter bank

The representation of an image $I(x, y)$ by means of Gabor feature is the convolution of the image with the Gabor filter $G(x,y;\omega,\theta)$ as given by:

$$O_{m,n}(x,y) = I(x,y) * G(x,y;\omega,\theta) \tag{2}$$

where * denotes the convolution operator. However, if extraction features simply by (2), the dimension of Gabor feature vector is excessively high. For example, if the size of normalized image is 64×128, with 32 filters, the dimension will be 262144(64×128×32). Partial Gabor filter and sampling technology are two good ways to solve this problem, which will be present in section III and IV respectively.

III. PARTIAL GABOR FILTER BANK

Since the Gabor feature representations of an image are very similar using the filters with the same orientation, especially using the filters with the neighboring frequencies, the Gabor feature vector with all the 32 filters shown in Fig. 1 becomes quite redundant and correlative. According to [7], a partial Gabor filter bank with part of frequencies and orientations is proposed for redundant information reduction.

We denote the normal Gabor filter bank with all the m frequencies and n orientations as G(m×n), while a partial filter bank with part of m frequencies and n orientations as PG(m×n). In order to select few Gabor filters to reduce the dimension and computation without degrading the recognition performance, it should cover all the frequencies and orientations. Several global and partial Gabor filter banks are shown in Fig. 2. The black blocks shown in Fig. 2 are the selected filter for PG(m×n). The method of selecting the PG1(m×n) is that the parameter m of frequency increases repeatedly from min to max, and the parameter n of orientation increases one for each time. The difference of PG2(m×n) is that the parameter m of frequency decreases from max to min. For PG3(m×n), it is selected every two filters.

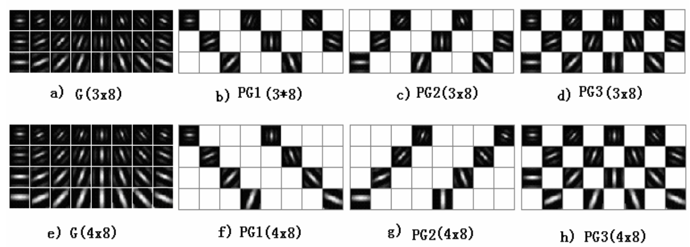

Fig. 2 Examples of global and Partial Gabor filter bank

The computation and memory required by different global and partial Gabor filter bank are given in Table 1. It can be seen that PG(m×n) has the advantages of reducing the dimension and memory requirement significantly. The recognition performance will be presented in Section V.

TABLE 1
COMPUTATION AND MEMORY REQUIRED BY DIFFERENT GABOR FILTER BANK SCHEME

Gabor Filter Bank	Original Dimension	Feature dimension	
		Global Sampling	Partial Sampling
G(4x8)	262144	4096	3072
G(3x8)	196608	3072	2304
PG1(4x8)	65536	1024	**768**
PG2(4x8)	65536	1024	**768**
PG3(4x8)	131072	2048	1536
PG1(3x8)	65536	1024	**768**
PG2(3x8)	65536	1024	**768**
PG3(3x8)	98304	1536	1152

IV. SAMPLING METHOD

Due to the high dimension and redundancy, sampling method is usually employed before feature extraction. The typical sampling method is even sampling. Y. N Zhao [6] introduces a non-even sampling according to the edge distribution in vehicles.

It is known that the differences among various types of vehicle, (such as the shapes at the front and the rear, the existence and the location of the windows) are mainly at upside of the vehicles. And the undersides of some different vehicles are often quite similar (see Fig. 4(a)-(c)). Furthermore, there are more noises at the underside. Such as noise caused by printed advertisement on the vehicle. That would add the difficulties for vehicle categorization. Thus we propose a partial sampling technique. Instead of sampling at the whole image, we adopt sampling only for upside at certain percentage. In the experiment, we take the percentage of 68.0%, from the top of the image. Some examples of partial sampling are shown in Fig.3.

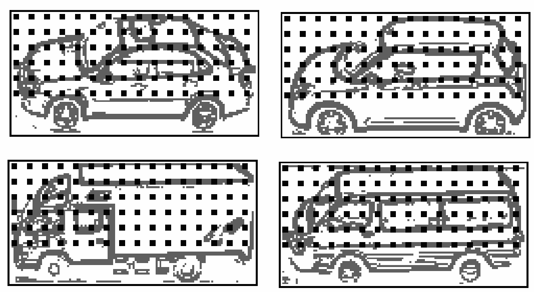

Fig.3 Partial sampling

A comparison of these three sampling methods used in our experiments is depicted in Table 2.

TABLE 2
THE DESCRIPTION OF THREE SAMPLING METHODS

Sampling Method	Description
Global sampling	Sample the vehicle image with regular interval (8 pixels in our experiment)
Zhao's method	The image is divided into 32(4×8) sampling windows. Then 19(32×60 %) of them are defined as Key Sampling Windows, which adopt 9(3×3) sampling points. The rest are called Assistant Sampling Windows, adopting 4(2×2) sampling points
Partial sampling	Even sampling is adopted at the upside of the image (68.0% from the top). The interval is also 8 pixels

V. FEATURE COMPRESSION & CLASSIFER DESIGN

Another approach to coping with the problem of dimension reduction is by Principal Component Analysis (PCA) [10]. PCA seeks a projection that best represents the data in a least-squares manner. In our experiment, we adopt PCA to further compress the feature dimension to 256.

The classifier employed in our experiment is minimum distance classifier, which is derived from the Bayes' decision theory [10]. To classify an unknown feature vector $\mathbf{x}$, the Euclidean distance $\|\mathbf{x}-\boldsymbol{\mu}_i\|$ from $\mathbf{x}$ to mean vector $\boldsymbol{\mu}_i$ of every class is firstly computed, and then $\mathbf{x}$ is assigned to the class with the minimum distance.

VI. EXPERIMENTS AND RESULTS

Five types of vehicles are classified in our experiment, which are sedan, van, hatchback sedan, bus and van truck, as shown in Fig. 4. More samples are illustrated in Fig.5. Vehicles in same row belong to the same category. It can be seen that even within the same category, the variation of shapes, hues and sizes is great. This makes the classification of multiple categories vehicles even more difficult.

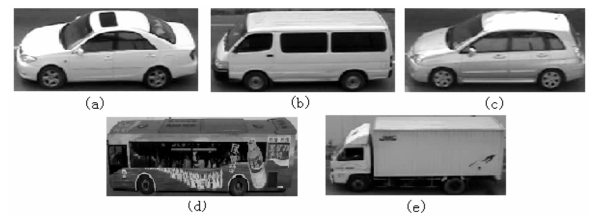

Fig. 4 The five types of vehicles for classification

Fig. 5 Some samples in our experiment

Total 1196 vehicle samples are used in our experiments. The number of each vehicle class is shown in table 3. We perform three cycles of test. In each cycle of test, 50 samples from each category are randomly selected as training data (total 250 training samples), and the remaining 946 samples are used as testing data. The average recognition rate of these three cycles of test is computed as the final recognition results.

TABLE 3
NUMBER OF SAMPLES FOR EACH VEHICLE CATEGORY

Vehicle class	Number
Sedan	553
Van	197
Hatchback sedan	108
Bus	214
Van truck	124

In the following experiments, we extract the features from edge image and grey image of vehicle respectively. The performances between these two approaches are compared in terms of the recognition rate. Simultaneity, the performance of different sampling methods is also compared.

A. *Extracting the Gabor features from edge image of vehicle*

The Sobel operator is first used to detect the edges of the vehicle in the image, and then a threshold algorithm based on the statistics of the histogram distribution is applied. We extract the Gabor features using different sampling methods described in section IV. The performances among different types of Gabor filter bank and different sampling methods are compared. The recognition results are given in Table 4.

TABLE 4
RECOGNITION RATE USING DIFFERENT SAMPLING METHODS (EDGE IMAGE)

	Global sampling	Zhao's method	Partial sampling
G(4×8)	95.00%	81.92%	94.68%
G(3×8)	94.64%	81.54%	94.12%
PG1(4×8)	93.76%	82.52%	93.87%
PG2(4×8)	94.82%	81.61%	93.83%
PG3(4×8)	**95.17%**	**82.06%**	**94.79%**
PG1(3×8)	93.83%	80.80%	93.55%
PG2(3×8)	93.94%	81.85%	94.15 %
PG3(3×8)	94.57%	81.47%	94.19 %

From Table 4, it can be seen that partial Gabor feature outperform global Gabor feature, and our method is much better than Zhao's method. Table 4 shows that the partial Gabor feature is effective. PG3(4×8) produces the best recognition rate of 95.17%. In comparison with the performance of G(m×n), although in some situation PG1(m×n) and PG2(m×n) decrease a little, much fewer Gabor features is used as shown in Table 1, that means a lot of memory and computation will be saved. This experiment also shows that global sampling performs the best. However, partial sampling achieves similar performance with the global sampling (with less than 1% decrease), but the dimension of the feature vector reduces greatly.

B. *Extracting the Gabor features from Grey image of vehicle*

In this experiment, we extract the Gabor features from the origin grey image of vehicle directly. We also use different sampling methods and different filter banks respectively. The recognition results are shown in Table 5.

TABLE 5
RECOGNITION RATE USING DIFFERENT SAMPLING METHODS (GREY IMAGE)

	Global sampling	Zhao's method	Partial sampling
G(4×8)	86.12%	79.39%	83.57%
G(3×8)	86.86%	**81.18%**	83.12%
PG1(4×8)	**89.57%**	80.66%	**86.36%**
PG2(4×8)	81.47%	74.67%	76.85%
PG3(4×8)	85.76%	79.25%	82.56%
PG1(3×8)	86.89%	76.22%	82.91%
PG2(3×8)	86.93%	77.41%	83.19%
PG3(3×8)	85.91%	80.55%	81.85%

From Table 5, it can also been seen that the partial Gabor features with global sampling produce the best results. Comparing with the results shown in table 4, it can be seen that the approach based on edge vehicle image achieve significantly higher recognition accuracy than that based on grey vehicle image.

VII. CONCLUSIONS

In this paper, we present a vision-based vehicle recognition approach based on Gabor filter banks. Partial Gabor filter bank and partial sampling method were introduced to reduce the dimension and computation. The partial Gabor feature based method can reduce the dimension and redundancy of the features and therefore much fewer memory and computation were involved. Although partial sampling method is not as good as the global sampling (with only less than 1% decrease), but the dimension of the feature can also be reduced greatly by this way. Experimental results showed that partial Gabor filter bank outperforms the global Gabor filter bank in some situation. The best recognition rate we got is 95.17% using partial Gabor features and global sampling method on the edge vehicle image. That shows the effectiveness of the proposed approach.

REFERENCES

[1] C. L. Huang, W. C. Liao, "A vision-based vehicle identification system", Proceedings of the 17th International Conference on Pattern Recognition, ICPR 2004, Vol. 4, 23-26 Aug. 2004, pp.364 – 367.

[2] S. Gupte, O. Masoud, R. F. K. Martin, and N. P. Papanikolopoulos, "Detection and classification of vehicles", IEEE Transactions on Intelligent Transportation Systems, Vol.3, Issue 1, March 2002, pp.37-47.

[3] A. H. S. Lai, G. S. K. Fung and N. H. C. Yung, "Vehicle Type Classification from Visual-Based Dimension Estimation", 2001 IEEE Intelligent Transportation Systems Conference Proceedings, (Oakland, CA,USA), 2001, pp.201-206.

[4] C. C. Zhang, X. Chen, W. B. Stork, "A PCA-based Vehicle Classification Framework", Proceeding of the 22nd International Conference on Data Engineering Workshops, 2006.

[5] T. R. Lim, A.T. Guntoro, "Car recognition using Gabor filter feature extraction", Circuits and Systems, APCCAS'02, Vol. 2, 2002, pp.451-455.

[6] Y. N. Zhao, Z. D. Liu, J. Y. Yang, "Research on Gabor Filters with Applications to Vehicle Detection and Vehicle Classification", Ph. D. Dissertation of Nanjing University of Science & Technology, 2004.

[7] H. B. Deng, L. W. Jin, L. X. Zhen, J. C. Huang, "A New Facial Expression Recognition Method Based on Local Gabor Filter Bank and PCA plus LDA", International Journal of Information Technology, Vol. 11,No. 11, 2005, pp.86-96.

[8] J. G. Daugman, "Complete Discrete 2-D Gabor Transforms by Neural Networks for Image Analysis and Compression", IEEE Trans. Acoustic, speech and signal processing, Vol. 36, 1988, pp.1169-1179.

[9] T. S. Lee, "Image Representation Using 2D Gabor Wavelets", IEEE Transaction on Pattern Analysis and Machine Intelligence, Vol. 18,NO.10, October 1996, pp.959-971.

[10] R. O. Duda, P. E. Hart, D. G. Stork, Pattern Classification. Wiley, New York, 2001.