AN IMPROVED VEHICLE CLASSIFICATION METHOD BASED ON GABOR FEATURES

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Abstract: Vehicle classification is an important issue in the domain of ITS (Intelligent Transportation Systems). In this paper we presents an improved one based on Gabor features, which contains three consecutive stages: vehicle segmentation, Gabor features extraction and template matching. A novel non-even sampling of Gabor features is proposed. The experimental data show that this method can heavily reduce the computation and memory requirements, and illustrate good performance both in discrimination ability and robustness.

Key words: ITS, Gabor features, Template matching, Vehicle classification

1. INTRODUCTION

Vehicle classification is an important issue in the domain of ITS. The conventional methods are mostly focused on the uncertainties associated with ground vehicle classification, for example vehicle orientation. Deformable template [1] is applied in this field. However, the uncertainties are comparatively minor in the application of park area, toll station, etc. In this context Gabor filtrer [2] is one good solution. To reduce heavy computation and memory requirements caused by Gabor features, we put forward a novel non-even sampling method on the basis of the edge features in vehicles as an improvement for vehicle classification.

The organization of this paper is as follows. Section 2 presents vehicle classification. Section 3 shows the performances of this method, and conclusions are drawn in Section 4.

2. VEHICLE CLASSIFICATION

There are three stages in vehicle classification, i.e. vehicle segmentation, Gabor features extraction and template matching.

First, vehicle segmentation using background subtraction is applied in predefined area of the image. Logarithmic intensities are selected here to weaken the affection caused by illumination factor, as described in Ref. [3]. Then we do opening operation to smooth the vehicle edges. Next the vehicle at the optimal area will be clipped by calculating the cumulative histogram value for each possible existence of vehicle.

Second, we do Gabor features extraction. The Gabor wavelets can be defined as follows [4]:

$$\psi(x,y,\omega_0,\theta)=\frac{1}{2\pi\sigma^2}e^{-((x\cos\theta+y\sin\theta)^2+(-x\sin\theta+yxos\theta)^2)/2\sigma^2} \times\left[e^{i(\omega_0 x\cos\theta+\omega_0 y\sin\theta}-e^{-\omega_0^2\sigma^2/2}\right] \quad (1)$$

where σ is the standard deviation of the Gaussian envelope along the x and y-dimensions (here $\sigma_x=\sigma_y$), ω_0 and θ are the radial center frequency, and orientation respectively. Let $I(x,y)$ denotes the image, then $C_{\psi I}(x,y,\omega_0,\theta)$, the convolution result corresponding to the Gabor wavelet at radial center frequency ω_0 and orientation θ, is defined as follows:

$$C_{\psi I}(x,y,\omega_0,\theta)=I(x,y)*\psi(x,y,\omega_0,\theta) \quad (2)$$

where $*$ denotes the convolution operator. We select experimentally three center frequencies $(\pi/2,\sqrt{2}\,\pi/4,\pi/4)$ with a scale factor of $1/\sqrt{2}$, and 8 orientations as suggest in Ref. [3]. As for a specific point (X,Y), we thus get a set of filter responses for that point. They are denoted as a Gabor jet. A jet J is defined as the set $\{J_j\}$ of complex coefficients obtained from that point, and can be written as

$$J=\{J_i\}=\{a_j\exp(i\phi_j)\} \quad j=1,2,\cdots,n \quad (3)$$

where a_j is magnitude, ϕ_j is phase of Gabor features, and n is the number of sampling points.

To reduce the heavy computation and memory requirement caused by Gabor feature vectors and to maintain the recognition performance as well, we propose a non-even sampling scheme, which is described as follows:

(1) Detect edges in a sample image by Sobel operator. Open operation is done to remove the effect caused by some minor edges and isolated noises.

(2) Sort sampling windows descending by the number of edge pixels contained in each one.

(3) A certain percentage of the sampling windows are then selected backward as Key Sampling Windows (KSW). The remaining sampling windows are called Assistant Sampling Windows (ASW). If the sampling windows with edge pixels are inadequate to the selected percentage, the remaining without edge pixels, which are nearest to the center of the image, will be chosen as KSW to reach this percentage.

(4) We adopt different sampling interval on the KSW and ASW, as the points in these two kinds of sampling windows have different levels of importance for vehicle classification.

(5) A Gabor feature vector of lower dimension can therefore be generated. It can be concluded that most of the points in KSW appear near the important features in the sample image.

Finally, we use Gabor jet matching method to recognize vehicle type by the following equation:

$$\max_{\forall J'} S_a(J, J') = \frac{\sum_j a_j \cdot a_j'}{\sqrt{\sum_j a_j^2 \cdot \sum_j a_j'^2}} \tag{4}$$

where J is Gabor jet of the image and J' is Gabor jet of template image.

3. EXPERIMENTAL RESULTS AND DISCUSSION

The proposed method is evaluated by recognition rate using 4 types of vehicles, i.e. sedan, truck, minibus and autobus. Table 1 shows the recognition rates with different sampling intervals in KSW and in ASW, and regular intervals in KSW only, where $n:m$ means that the sampling intervals for the points in KSW and in ASW are $n \times n$ and $m \times m$. The tested sample images are 30 unknown vehicles without disturbance. The results imply that the points in KSW contain the dominant discrimination information. Table 2 gives a comparison of classification rate using methods of Ref. [3] and the presented. 60 unknown vehicles are tested under four different circumstances, i.e. no disturbance, global blur, local glance and the highlighting, each of which is composed of 15 images. In the former, 4×4

sampling interval is selected, and in the latter, the portion of KSW is 2/3 and the different sampling interval is 4:6. The data show that the presented outperforms the conventional both in discrimination ability and robustness.

Table 1. The average recognition rates with two different sampling methods

Proportion	Sampling methods	Different sampling intervals			Sampling KSW only	
of KSW	Sampling interval	4:6	4:8	6:8	4×4	6×6
1/3	Recognition rate (%)	96.9	96.0	94.8	96.5	94.2
	Dimension (D)	4,352	3,456	2,176	2,304	1024
2/3	Recognition rate (%)	97.6	96.3	95.9	97.1	95.2
	Dimension (D)	5,632	5,184	2,624	4,608	2,048

Table 2. The comparison of average recognition rates (%) using different methods

Vehicle classification	Regular sampling			
methods	No disturbance	Global blur	Local glance	Highlighting
Ref. [3]	93.7	68.4	84.5	71.4
Presented	97.8	73.2	87.6	80.9

4. CONCLUSIONS

To lower the dimension of Gabor feature vector, we put forward a novel non-even sampling of Gabor features for an improved vehicle classification. The experimental results show that the presented method illustrates good performance both in discrimination ability and robustness. However, this method is only fit for the recognition of objects with apparent edge features. In fact, any features in an object do have different levels of importance for recognition. How to select key points and assistant points after the training of some samples for non-even sampling is our future work.

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