A ROTATION INVARIANT HOG DESCRIPTOR FOR TIRE PATTERN IMAGE CLASSIFICATION

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ABSTRACT

Texture feature is important in describing tire pattern image which provides useful clue in solving crime cases and traffic accidents. In this paper, we propose a novel texture feature extraction method based on HOG (Histogram of Oriented Gradient) and dominant gradient (DG) in tire pattern images, named HOG-DG. The proposed HOG-DG is not only robust to illumination and scale changes but also is rotation-invariant. In the proposed HOG-DG, HOG features are first computed from circular local cells, and HOG features from an image are concatenated and normalized using the DG to construct the HOG-DG feature. HOG-DG is used to train a support-vector-machine (SVM) classifier for tire pattern classification. Experimental results demonstrate its outstanding performance for tire pattern description.

Index Terms— Tire pattern classification, texture feature, rotation-invariant, histogram of gradient, dominant gradient

1. INTRODUCTION

Tire pattern of suspected vehicle provides useful clues in traffic accident control and crime case solving [1]. Texture feature is most commonly used for tire pattern representation [1, 2]. Due to the lack of standard test bed in this special field, not much work has been done in texture feature extraction from tire pattern images and existing algorithms mostly are designed based on classical texture features with little modifications [1-4]. For instance, in [1], Curvelet transform is first applied onto tire pattern image, then mean and variance are calculated from each subband in Curvelet domain to form the texture feature vector, which is cyclically shifted till the statistics of the subband with most energy comes to the first position. The texture feature obtained is rotation-invariant. In [2], the algorithm combines Tamura feature with statistics such as mean, standard deviation and smoothness obtained from the histogram of intensity to describe tire pattern images.

These algorithms, though have brought improvement in tire pattern description to certain extend, are not designed based on the inherent characteristics of tire patterns. Natural texture images such as grass, pebble, generally display similarity in local structure but the internal texture directions are chaotic. Differently, tire pattern image demonstrates obvious texture direction, which is robust to scaling, rotation, illumination changes and noise [1].

Histogram of oriented gradient (HOG) feature [5] describes the distribution of local intensity change in terms of gradient direction and is suitable for texture structure representation. It is robust to illumination and scale changes but is sensitive to the rotation which is common in tire pattern image. In this paper, we make use of the inherent dominant gradient in tire pattern image and propose a novel HOG-based texture feature descriptor named HOG-DG, which not only inherits the illumination and scale invariant property of HOG, but also overcomes the HOGs rotation variance issue with the following two techniques (1) Circular neighborhood of different radius are defined as cells. In this way, the same group of pixels is contained in a cell no matter how the image rotates. (2) Dominant gradient of the tire pattern image is detected and all the cell feature vectors are aligned to it. The cell feature vector are normalized and concatenated to construct the HOG-DG feature.Experimental results show that the HOG-DG attains competitive performance with CNN method and outperforms other traditional methods.

2. DESCRIPTION OF HOG-DG

2.1. HOG descriptor

HOG feature extraction mainly includes two stages:

(1) Histogram extraction of oriented gradient

In this stage, the magnitude and direction of gradient are extracted from each pixel in the image, and these are used to generate an angular histogram of gradients which is used as a feature vector of image texture. For image*I*(*i,j*) ,the horizontal and vertical derivatives at pixel (*i,j*) are respectively calculated as follows:

$$G_i(i,j) = I(i+1,j) - I(i-1,j) \tag{1}$$

$$G_j(i,j) = I(i,j+1) - I(i,j-1) \tag{2}$$

$$G(i,j) = \sqrt{G_i(i,j)^2 + G_j(i,j)^2} \tag{3}$$

$$\alpha_0(i,j) = tan^{-1}\left[\frac{G_j(i,j)}{G_i(i,j)}\right], \alpha_0 \in [-\frac{\pi}{2}, \frac{\pi}{2}] \tag{4}$$

where $G_i(i, j)$, $G_j(i, j)$are the derivative along horizontal and vertical direction at pixel (i, j), respectively.

(2) Construction of HOG descriptor

Then, HOG descriptor is constructed based on the image gradient. Firstly, the whole image is divided into blocks of size 8*8. The gradient direction range [-π/2, π/2] is uniformly quantized into 9 direction intervals (bins). In each cell, the gradient histogram of all the pixels in the cell is calculated in terms of direction bin to obtain a feature vector of length 9. Then, 4 adjacent blocks are merged into a super block and the feature vectors of the 4 adjacent blocks are concatenated to form a vector of length 36. Finally, by scanning the image block-by-block, the HOG feature of image is constructed by concatenating the 36-D vectors of all super blocks. To make it robust to illumination changes, the resulted HOG feature is further normalized by dividing each bin with the total of the histogram.

2.2. HOG-DG

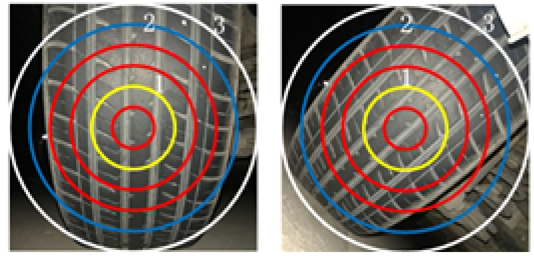
The HOG-DG consists mainly of three steps: (1) Defining circular cells and calculating cell feature vectors (CFV). (2) Detecting the dominant gradient and aligning all CFVs. (3) Normalizing CFVs and concatenating them to construct the HOG-DG feature.

2.2.1. Defining circular cell and calculating cell feature vector

In order to preserve the content in every cell, we design circular cells instead of squares as in conventional HOG descriptor. After tire pattern detection, it make the object image only contain the tire pattern.Taking the center of the object image as the center,*R* circular cells are defined with radius as *r*=1,2,3,...,*R*, while *R* is the radius of the maximum inscribed circle. It can be seen that points 1,2,3 on the tire tread in Figure 1(a), remain in same cell as in Figure 1(b).

Then, the gradient magnitude and direction of each pixel in a cell are obtained using Equations (1)-(4).

Different from conventional HOG that defines the gradient direction interval to be [-π/2, π/2], in HOG-DG, the gradient direction is mapped from [-π/2, π/2] to [0, 2π], for easier orientation normalisation.



(a) Original (b) 45 degree

Fig. 1: Circular cells for two tyres with different orientations.

$$\alpha(i,j) = \begin{cases} \alpha_0 \; G_i \geq 0, G_j \geq 0 \\ \alpha_0 + \pi \; G_i < 0, where \; \alpha_0 \in [-\frac{\pi}{2}, \frac{\pi}{2}] \\ \alpha_0 + 2\pi \; G_i \geq 0, G_j < 0 \end{cases} \tag{5}$$

In the above equation, $\alpha(i,j)$ and α_0 are the gradient direction at location (i,j) for interval [0, 2π] and [-π/2, π/2] respectively. G_i and G_j are the derivatives at location (i,j) along horizontal and vertical direction, respectively.

Then, the gradient direction range [0, 2π] is uniformly quantized into 30 direction intervals (bins), that is, *bin_k*=1,2,...,30. The number 30 is set based on experimental statistics (given in Section 3.1). Thus, we can obtain a 30-D cell feature vector (CFV) for each of the *R* cells, expressed as,

$$\begin{aligned} C_r = \{c_r(1), c_r(2), ..., c_r(k), ..., c_r(30)\} \\ r = 1,2,3,...,R \end{aligned} \tag{6}$$

where C_r is the component in C_r with directional interval *bin_k*=*k*.

2.2.2. Detecting dominant gradient and aligning cell feature vectors

By summing all the R CFVs and calculating the average value, a 30-D global feature vector (GFV) is obtained as following,

$$\begin{aligned} G = \{g_1, g_2, ..., g_k, ..., g_{30}\}, \; k = 1,2,...,30 \\ g_k = \frac{1}{R}\sum_{r=1}^{R} c_r(k) \end{aligned} \tag{7}$$

Table 1 gives the GFV of the image in Figure 2 with different shooting conditions. In the GFV, the number marked in red is the dominant component with maximum gradient magnitude, the number marked in blue is the 2nd dominant component. It can be seen that the position (k_m) of the dominant component shifts with the change in the shooting angle, and the relationship between the shifting amount Δk and the change in the shooting angle $\Delta\alpha$ is,

$$\Delta k = \left[\Delta\alpha * \frac{bin\_k}{2\pi} + 0.5 \right] \tag{8}$$

$$k_m = \arg\max_k \{g(k), k = 1, 2, ..., 30\} \tag{9}$$

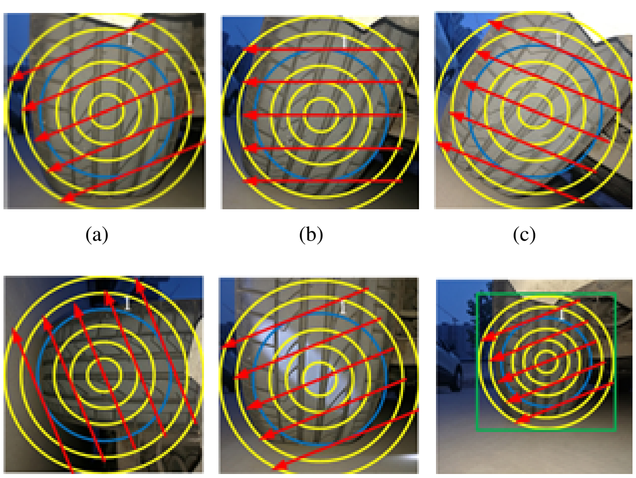
$k_m$is the directional bin of the dominant component in G.

The 'position' k_m (directional interval) of the dominant component in the GFV determines the dominant direction in the tire pattern image. In this paper, the left side of the directional interval k_m is defined as the dominant direction . The red arrows in Figure 2 demonstrate the dominant gradient of the sample tires. Under illumination and scale changes, the dominant gradient remains unchanged. It can be observed that the dominant gradient of tire patterns is robust to rotation, illumination and scale changes.

Based on the relationship between the dominant gradient and the dominant direction of the tire, we propose to align all the CFVs to the dominant gradient by cyclically shifting each CFV by k_m-1 to the left.

2.2.3. *Normalization and Concatenation*

Each of the aligned cell feature vector C'_r is then normalized into [0, 1]. Finally, all the R normalized cell feature vectors $C_r^N(r = 1, 2, ..., R)$ are concatenated to construct the final HOG-DG feature vector of R*30 dimensions.



(a) (b) (c)

(d) (e) (f)

Fig. 2: Tire pattern images under different shooting conditions for one pattern image, where the yellow rings are the cells and the red arrows are the dominant gradient. (a) original, (b) 22.5° rotation, (c) 45° rotation, (d) 90° rotation, (e) illumination change, (f) scale change (the green box is the external least square of the tire region).

TABLE I: Global feature vectors of the images in Figure2

Shoot Condition		(a)	(b)	(c)	(d)	(e)	(f)
Directional interval	1	2.58	2.56	2.03	2.85	2.00	2.52
	2	3.08	3.03	2.20	2.91	2.98	3.45
	3	3.16	1.51	2.06	2.77	2.45	2.70
	4	3.42	1.78	2.23	2.83	3.56	3.70
	5	3.65	4.10	1.66	3.20	4.05	3.49
	6	3.94	4.85	1.79	3.26	6.04	4.78
	7	4.61	4.36	3.51	3.09	5.24	3.96
	8	4.98	5.15	3.79	3.15	7.81	5.42
	9	2.84	4.65	4.39	2.21	2.11	2.60
	10	3.07	5.49	4.47	2.25	3.14	3.56
	11	2.96	2.56	5.28	3.12	1.85	2.36
	12	3.20	3.03	6.08	3.19	2.75	3.23
	13	2.74	2.50	3.46	3.85	1.52	2.39
	14	2.96	2.95	3.74	3.93	2.27	3.28
	15	2.72	2.15	2.43	5.03	1.79	2.37
	16	2.93	2.55	2.62	5.19	2.67	3.25
	17	2.51	3.01	2.61	2.82	1.46	2.22
	18	2.71	3.55	2.82	2.88	2.18	3.04
	19	4.85	2.16	2.73	3.07	5.60	4.11
	20	5.24	2.55	2.95	3.13	8.34	5.64
	21	3.59	4.74	1.53	2.64	3.63	3.36
	22	3.88	5.60	1.65	2.70	5.41	4.61
	23	3.03	3.87	5.70	2.79	2.41	2.63
	24	3.27	4.57	6.57	2.85	3.60	3.61
	25	2.89	2.38	4.85	2.39	2.24	2.41
	26	3.12	2.81	5.24	2.43	3.34	3.30
	27	2.86	2.77	3.29	5.13	2.12	2.43
	28	3.09	3.27	3.56	5.29	3.16	3.33
	29	2.81	2.54	2.16	4.47	1.68	2.63
	30	3.04	3.00	2.33	4.56	2.50	3.60

3. EXPERIMENTAL RESULTS

3.1. Database and performance measures

In our experiments, the dataset CIIP-Tread Data is used, which contains 5100 tire pattern images in 102 classes. This is a self-built dataset by Center for Image and Information Processing (CIIP), Xian University of Posts and Telecommunication collaborating with public security of China[6]. Each class contains 50 tire pattern images obtained under different shooting conditions (with changes in illumination, scale and shooting angles). Examples can be seen in Figure 1 and Figure 2.

To test the performance of HOG-DG, the LIBSVM classifier (with RBF: radical basis function) [7] is trained for tire pattern classification, with 4/5 of the images used for training and 1/5 for testing. The program is run under MATLAB2014, with PC setting as Windows 7 Ultimate, Core i5-4258U @ 2.40GHz and NVIDIA GeForce GT 820M.

The performance evaluation parameters used include: classification accuracy (CA), feature dimension (Dime) ?and algorithm running time (ART). CA is the ratio of the number of correct classifications to the total number of samples. Dime is the number of components in eigenvectors. ART is the total amount of time used for feature extraction and for training SVM classifier.

3.2. Experimental results

(1)Determining the value of directional interval bin_k

In HOG-DG, the larger the value of bin_k, the higher the feature dimension is. Figure 3 explains how CA changes with the value of bin_k. It is found that the the value of CA increases with the increase of bin_k at first, and flatens when bin_k reaches 30. In other words, afterwards, further increase in the value of bin_k only results in higher feature dimension but no further improvement in classification performance. Hence, bin_k=30 is the optimal bin interval. That is, the gradient direction range [0, 2π] is uniformly quantized into 30 direction intervals (bins).

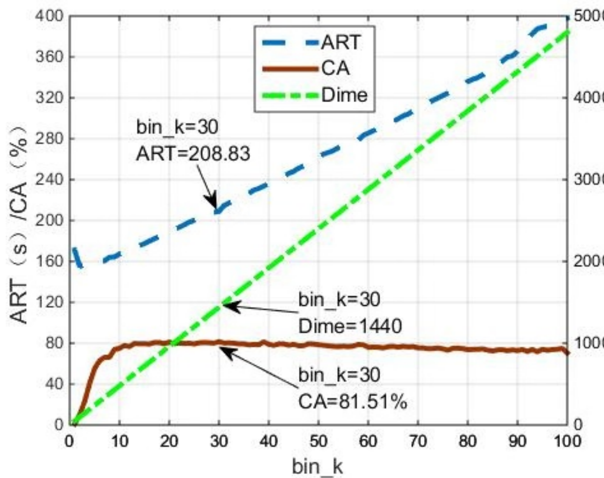


Fig. 3: Classification performance $\sim$ value of bin_k

(2)Performance evaluation

In this experiment, different texture features are used to train LIBSVM classifier for the tire pattern classification, including the proposed HOG-DG, conventional HOG by Dalal [5], DWT-based texture feature [8], Curvelet Domain Energy Distribution Algorithm (CEDA) [1], Compressed Histogram of Oriented Gradients (CHoG) [9]. In addition, the CNN based method (Convolutional neural networks) [10] trained by Alexnet is also compared.

Figure 4 compares CA of different algorithms tested on different subsets of the CIIP-Treat Data. It can be seen that HOG-DG provides the best performance among all, with its performance close to that of CNNs and CHoG, but clearly better than HOG. For example, for the 5000 dataset, the CA value of HOG-DG is 81.51%, moderately higher than that of CNNs (80.36%) and CHoG (78.93%), but is much higher than that of HOG (68.30%).

Table 2 compares the feature dimension (DIME), ART of different features tested. Obviously HOG-DG takes less running time than HOG, CHoG and CNNs. DWT and CEDA though have less complexity in computation but their classification performance ranks far behind others.

From the above experimental results, it can be concluded that HOG-DG is effective in describing texture feature of tire pattern image and it is robust under different conditions such as illumination, scale and shooting angle changes. In the experiments, CNN does not demonstrate any advantage over HOG-DG. A possible reason is that the size of the test dataset is not large enough to demonstrate the advantage of CNN. As there is yet no standard large size tire pattern image test dataset available, an initial testing based on a combined feature using HOG-DG and CNN feature (Alexnet) with weight ratio as 4:6, gives a classification accuracy of 97.57% on the 5000 tire pattern image dataset used above. This will be further explored in our future work with larger scale database.

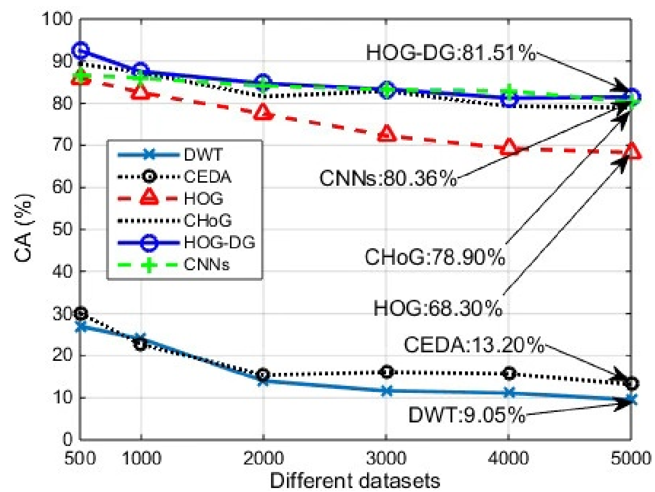


Fig. 4: Classification performance comparison

TABLE II: Computational load of different texture features

Features	HOG-DG	CHoG	HOG	CNNs	CEDA	DWT
DIME	1440	1800	4356	4096	54	14
ART	208.83	463.96	402.65	899.22	79.74	29.65

4. CONCLUSIONS

In this paper, we have proposed a novel HOG-based texture feature using dominant gradient. The new HOG feature is robust not only to illumination and scale changes, but also to rotation transformation. The HOG-DG makes two major changes to the conventional HOG descriptor in order to overcome its drawback of not being rotation-invariant. (1) Defining circular cells instead of square cells so that the pixels in each cell remain the same under different rotation angles; (2) Each cell feature vector is aligned to the dominant direction detected in the image. The HOG-DG feature was used to train SVM classifier for tire pattern classification and experimental results show the superiority of HOG-DG over other related methods in describing tire pattern images.

5. ACKNOWLEDGEMENT

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6. REFERENCES

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