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Statictics of Gabor Features for Coin Recognition

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***Abstract*—We present an image based approach for coin classification. Gabor wavelets are used to extract features for local texture representation. To achieve rotation-invariance, concentric ring structure is used to divide the coin image into a number of small sections. Statistics of Gabor coefficients within each section is then concatenated into a feature vector for whole image representation. Matching between two coin images are done via Euclidean distance measurement and the nearest neighbor classifier. The public MUSCLE database consisting of over 10,000 images is used to test our algorithm, results show that significant improvements over edge distance based methods have been achieved.**

Keywords-Gabor wavelet; coin classification; edge distance

I. INTRODUCTION

An automatic coin classification system recognizes the value of a given coin based on certain measurement of the coin. Most of current systems in use adopt the measurement of physical properties like weight, radius and conductivity. However, real systems in use have found increasing number of fake coins accepted by the machine due to similar properties. As the most distinguishing property of a coin is the stamp, visual information would provide additional information for both coin recognition and fake/real discrimination.

One of the early works for image based coin recognition was developed by Fukumi et al. in 1992 [1]. In this paper, rotation invariant slabs were designed to extract features, which were then input to a trained neural network for classification. The system was able to recognize 500-yen and 500-won coins. A recently developed Dagobert system [2] from ARC Seibersdorf is capable of recognizing more than 600 coin types with more than 2000 coin face types. ARC Seibersdorf also created a benchmark dataset, which was used to evaluate coin recognition algorithms in MUSCLE competition workshop in 2006 [3]. Two systems were presented in the workshop, while Maaten et al.'s work [4] uses edge based features for classification, Reisert et al.'s system [5] is based on registration techniques. Using the rotation invariant pattern similar to that of [6], Maaten and Postma compared edge distance, wavelet features and Gabor histograms, and found that multi-scale edge distance method achieved the best performance. In Huber et al.'s work [7], thickness from thickness sensor measurement was first used to decide the candidate classes of input coin, rotation angle was then estimated based on the correlation between input and reference images. Matching was done in the Eigenspace trained for each coin class. The method required sophisticated training process and large number of training images.

In this paper, we propose to use statistics of Gabor feature for coin recognition. Compared to edge features, Gabor feature is more representative of the local textures and is also robust to illumination variance and noise. The successful application of Gabor wavelets for face recognition [8] clearly proves its discrimination power. Once the center of the coin is located, concentric rings is used to achieve rotation-invariance. To reduce feature dimension and give an overall representation, the first order statistics of Gabor coefficients within each ring is computed. Multi scale strategy is also applied to achieve better discrimination power and robustness. The method is tested using the publicly available MUSCLE dataset and compared with that of edge based methods, the results clearly show the advantages of our approach

II. SEGMENTATION

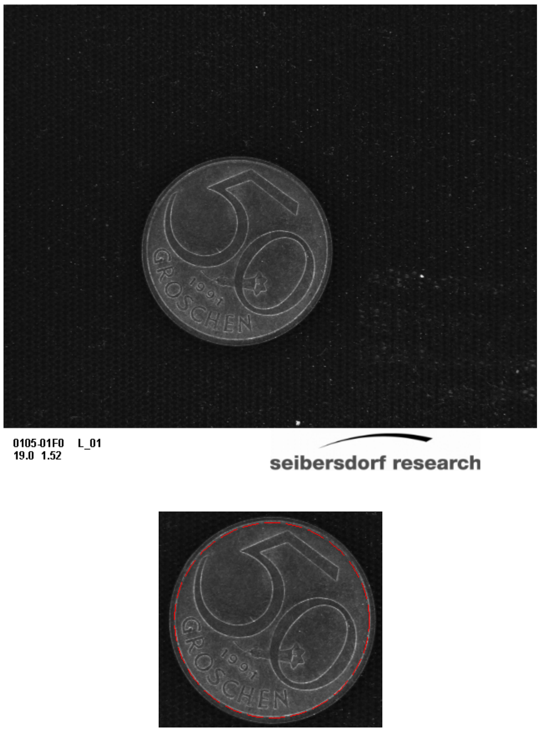

Figure 1. Coin segmentation results

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The fist step of coin recognition system would be segmentation, i.e. separate the coin image from the background. As the coin images used in this paper were captured on a conveyor belt, low contrast between the coin and belt, rich background texture and coins inhomogeneous are the main challenges to the segmentation algorithm. To utilize the knowledge that coins are round, a Hough transform based method proposed by Reisert [5] was implemented to segment coin from the background. The algorithm uses a generalized hough transform with a three dimensional voting space to search for the location of coin center and its radius. Figure 1 shows an example coin image and the segmentation result.

III. STATISTICS OF GABOR FEATURES

A. Gabor Wavelets and Feature Extraction

In the spatial domain, a 2D Gabor wavelet is a Gaussian kernel function modulated by a sinusoidal plane wave:

$$\varphi_{(f,\theta,\sigma)}(x,y)=\frac{1}{2\pi\sigma^2}\exp\left(-\frac{(x^2+y^2)}{\sigma^2}\right)\exp(j2\pi f(x\cos\theta+y\sin\theta)) \quad (1)$$

where f is the central frequency of the sinusoidal plane wave, θ is the anti-clockwise rotation of the Gaussian and the plane wave and σ is the scale of the Gaussian function. The Gabor wavelets are self-similar - all wavelets can be generated from one mother wavelet by dilation and rotation. To extract useful features from an image, e.g. coin, normally a set of Gabor wavelets $\{\varphi_{(f,\theta,\sigma)}\}$ with different frequencies, orientations and scales are required. In conventional setting, the parameters of frequencies, orientations and scales are usually set as $f_u=f_{\max}/\sqrt{2}^u, u=0,\cdots U-1$, $\sigma=\frac{2\pi}{f_u}$, and $\theta_v=\frac{v}{8}\pi, v=1,\cdots V-1$, where f_u and θ_v define the orientation and frequency of the Gabor wavelet, $f_{\max}$ is the maximum frequency and $\sqrt{2}$ (half octave) is the spacing factor between different central frequencies. A total number of $U\times V$ wavelets can be obtained. To extract Gabor features, the image is convolved with the set of wavelets and convolution result contains important information about the strength of signal changes in different frequencies and orientations. In this paper, 24 wavelets with 4 frequencies and 6 orientations are used to generate 24 convolution images, which are then used to extract features for coin recognition.

B. Statistics of Gabor Features

The convolution images could be simply concatenated to form a large feature vector for recognition [8]. However, the huge dimension could bring large computational cost the following classifier and make such system inapplicable. When translation invariance could be achieved by segmentation step, rotation variance could have significant effects on features extracted in this way. As a result, some rotation invariant features based on fusion of the convolution results shall be used.

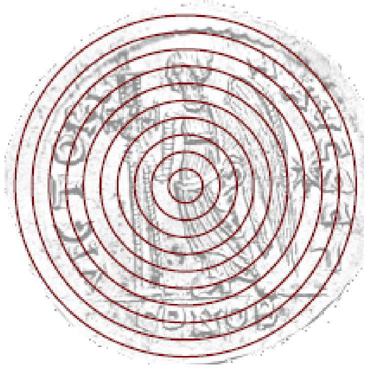

Figure 2. The rotation invariant ring structure

In this paper, we fist divide the coin image into a number of rings, for each convolution result of the image with certain Gabor wavelet, statistics of the coefficients within rings are concatenated to form a feature vector. Given a coin image I and a set of wavelets $G_j, j=1,2,\cdots J$, a number of convolution images $P_j=\|I*G_j\|, j=1,2,\cdots J$ could be obtained. The convolution image is then divided into a number of K ring areas: $A_k=\{(x,y)|r_{k-1}<x^2+y^2\le r_k\}$, where $r_k=\frac{k}{K}r$ and r is the radius of the coin. The mean and standard deviation of the Gabor coefficients within the ring is used to represent the texture features, and thus a feature vector with size $2\times K\times J$:

$$[\mu_1^1\ o_1^1\ \mu_1^2\ o_1^2 \cdots \mu_1^K\ o_1^K \cdots \mu_j^1\ o_j^1 \cdots \mu_j^K\ o_j^K \cdots \mu_J^K\ o_J^K]$$ c

ould thus be extracted to represent the coin, where

$$\mu_j^k=\sum_{(x,y)\in A_k}P_j(x,y) \quad (2)$$

$$\sigma_j^k=\sqrt{\sum_{(x,y)\in A_k}\frac{1}{N}\left(P_j(x,y)-\mu_j^k\right)^2} \quad (3)$$

C. Classification

Once the statistics of Gabor features x have been extracted from a given coin image, the feature would be compared with the feature of each coin image $\{q_j\}$ saved in database and the class label with the closest match will be assigned to the test image. In this paper, Euclidean distance measure is used to measure the similarity between two coin images

IV. EXPERIMENTAL RESULTS

A. Datasets

Coin data supplied by MUSCLE Benchmark site [] is used in this paper to evaluate the performance of the proposed method. The images in the dataset were captured under controlled conditions: each image shows exactly one coin on a conveyor belt. The images are all 640×575 in size and 8 bits grayscale in depth.

The dataset provides a training set with 8762 coin images and a test set with 2200 images for public use. The images in training set were captured from 109 coin types originating from different countries. For each coin type, coin images might look different for different versions. As a result, there are 389 coin image classes available in the training set. The test set consists of 2200 coin images captured from both sides of 1100 coins. Figure 3 shows two example coin images in the database, the text string holds meta information, e.g. filename, thickness and diameter etc. about the coin. However, thickness and diameter are not used in this paper.

Figure 3. Figure 1 Example coin images

B. *Recognition Results*

To test the performance of our method, we also implemented two edge based methods, i.e. Edge Distance Histogram Distribution (EDHD) and Edge Angle Histogram Distribution (EAHD) [4]. For EDHD, Sobel operator was first used to get the edge image of coin inner area, which is then thresholded to remove the effects of noises. To achieve rotation invariance, ring structure as shown in Figure 2 is used to divide the edge image into a number of small sections. Number of edge pixels in each ring is then counted and used as the feature to represent the coin image structure. While the same procedure is used to get the binary edge image, EAHD divide the coin image into pie-shaped sections (see Figure 4) with reference to the center. The process to calculate the distribution is the same as that of EDHD. While this feature is rotation variant, the modulus of FFT could be used to construct rotation invariant features.

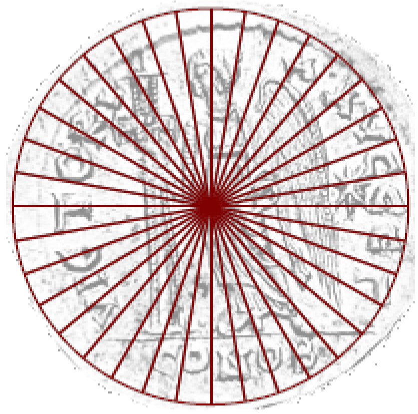

Figure 4. The pie-shpae structure

Table 1 shows the performance of the proposed method on the MUSCLE dataset, together with that of EDHD and EAHD. Due to the presence of rotation, EAHD only achieve 24.73% accuracy, which is increased to 30% when combined with EDHD. Due to the usage of ring structure, over 50% accuracy is achieved for EDHD. Since the representative Gabor feature is applied, the discrimination power of our system is significantly improved and as high as 74.27% accuracy has been achieved.

TABLE I. RECOGNITION PERFORMANCE

Methods	**Accuracy (%)**
EDHD	53.09
EAHD	24.73
EDHD + EAHD	30.68
Proposed Approach	**74.27**

V. CONCLUSIONS

Visual features are useful when the measurement of simple physical properties does not suffice for recognition. A Gabor feature based visual coin recognition approach has been developed in this paper. The method uses statistics of Gabor coefficients within different ring sections as feature and substantially outperformed previously proposed edge distance based approaches. However, the accuracy of the proposed method is still not satisfying and further research needs to be performed. While thickness, diameter and conductivity could be combined to achieve higher accuracy, we are also investigating other approaches and feature fusion methods to improve the performance of our system..

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