A Coin Recognition System with Rotation Invariance

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Abstract—**This paper introduces a coin recognition method with rotation invariance. The rotation invariance feature is represented by the absolute value of Fourier coefficients of polar image of the coin on circles with different radii. Moreover, the Fourier approximation of the coin image is used to reduce the variations on surface of coin such as light reflection effect. Then coins can be distinguished by feeding those features into a multi-layered BP neural network. Finally the coin recognition experiments are given to show the effectiveness of the proposed method.**

Keywords-coin recognition; Fourier transform; coordinate transform; BP neural network

I. INTRODUCTION

The coin recognition systems on the market can be divided into two categories: mechanical method and electromagnetic method. The mechanical method uses three important parameters: diameter, thickness, weight and one minor important parameter magnetism to detect different coins. But the method can not detect different materials. This means that the coins with same diameters, thickness, weight and similar magnetism but with different materials can be recognized as the same target coin. The electromagnetic method can detect different materials as well as the other parameters mentioned above by letting a coin pass through an oscillating coil at a certain frequency. Different materials can bring different changes on the amplitude and direction of the frequency. The changes can be the main parameter to detect coins as well as the other parameters. But this improvement can not still distinguish the target coins from some game coins. In recent years, the recognition technologies based on images are used in the coin recognition system. The main principle is that a camera is installed in a coin operated system. Then the extracted features are used to assist the system to detect different coins or act as the main recognition method.

The coin recognition systems based on image can also be divided into two categories: method based on image registration[1][2] and method based on feature vectors with rotation variance[3][4][5][6]. The image registration is the process of overlaying two or more images of the same scene taken at different times, from different viewpoints, or by different sensors. In coin recognition system it extracts feature points from the reference image and the second image and then uses similarity measurement to find the matched pairs by which the second image is spatially transferred. The spatial transform parameters are used for image registration. The method based on feature vectors has to find the vectors with rotation invariance, translation invariance and scaling invariance. The translation invariance and the scaling invariance can be realized by segmenting and interpolating the coin image. There are many methods to get the feature vectors with rotation invariance. In [3] the coins which are rotated at various degrees are generalized and binarized. The binarized coin image is compressed to 100×100 pixels image which is further reduced to a 20×20 bitmap by segmenting the image using segments of size 5×5 pixels and then taking the average pixel value within the segment. Finally the 20×20 bitmap provides the input data for the neural network training and testing. In [4] the RGB model is transferred to the HSI model where canny edge detection is performed by using adaptive threshold. Then the numbers which denote the value of the coin can be extracted from the edges. At last Gabor transform is used on the numbers to get the vectors with rotation invariance which will be the input vectors of the neural network. In [5] the statistics of Gabor features have been extracted from a coin image and Euclidean distance measure is used to measure the similarity between two coin images. In [6] the absolute value of Fourier coefficients are extracted as the feature vectors which are then used to recognize different coins according to the Euclidean distance between the tested coin and the reference coin. In [7] the edges which are derived from the coin image by using canny operator are divided into many concentric circles. The number of edge points in each circular strip is chosen to represent the image. Apparently this feature is scale and rotation invariant. In this paper, the coin image is converted from Cartesian coordinates to logarithmic polar coordinates. The rotation problem under the Cartesian coordinates becomes the translation problem under the logarithmic polar coordinates. The absolute values of the Fourier coefficients of the coin image under the polar coordinates are the feature vectors which will be the input vectors of the neural network. In section 2 coordinates spatial transform and feature vectors extraction are introduced. In section 3 the BP neural network is configured. In section 4 the conclusion and future development are drawn.

II. COORDINATES TRANSFORM AND FEATURE VECTORS EXTRACTION

Before coordinate transform and feature vectors extraction, the coin image must be segmented from the background. Three steps are adopted to realize this task: step 1: The RGB image is converted into the gray image; step 2: the sobel operator is used to detect the edges of the

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gray image; step 3: Hough transform is used to detect the coin. In computer vision and pattern recognition, we always wish the target objects only translate without rotation, because this assumption is helpful for recognition and tracing of the target objects. In [8] the image transform from Cartesian to logarithmic polar coordinates is introduced. Suppose the coin image can be denoted as f(x,y) under the Cartesian coordinates and as $f(r,\theta)$ under the logarithmic coordinates. The coordinates transform from f(x,y) to $f(r,\theta)$ can be defined as:

$$r = \log_a \sqrt{(x-x_c)^2 + (y-y_c)^2} \quad (1)$$

$$\theta = \arctan(\frac{y-y_c}{x-x_c}) \quad (2)$$

where $0 \le \theta \le 2\pi$, (x_c, y_c) is the coordinates of center of the coin under the Cartesian coordinates. The center coordinates can be acquired after the segmentation of the coin. Fig. 1 shows the images of the coin after being rotated at 60 degree and 120 degree and corresponding images under the logarithmic polar coordinates. From fig. 1, we can see that the rotation problem under the Cartesian coordinates becomes the translation problem under the logarithmic polar coordinates.

Figure 1 A coin rotated by different degrees

If $f(r,\theta)$ is periodically expanded on the θ direction, then $\hat{f}(r,\theta)$ can be gotten as the follow:

$$\hat{f}(r,\theta) = f(r,\theta + 2m\pi) \quad (3)$$

Where m is any integer and $\hat{f}(r,\theta)$ is expanded into Fourier series by letting $r = r_k$ (constant) as

$$\hat{f}(r_k,\theta) = \sum_{m=-\infty}^{+\infty} a_m^{(k)} e^{jm\theta} \quad (4)$$

Where $a_m^{(k)} = \frac{1}{2\pi}\int_0^{2\pi} \hat{f}(r_k,\theta) e^{-jm\theta} d\theta$ and r_k denotes a certain value along the r axis under the polar coordinates. After the coin is rotated by angle α about its origin and periodically expanded, we can get $\hat{g}(r_k,\theta) = \hat{f}(r_k,\theta+\alpha)$, so its Fourier coefficients is

$$b_m^{(k)} = a_m^{(k)} e^{jm\alpha} \quad (5)$$

It can be seen from (5) that the absolute value of Fourier coefficients will not change after the image is rotated. i.e. $u_m^k = |b_m^{(k)}| = |a_m^{(k)}|$. So if the absolute values of Fourier coefficients are used as feature vectors, then the feature vectors are rotation invariant. Fig. 2 shows $|a_m^{(k)}|$, obtained from the same coin which were rotated by different degrees. i.e. u_m^{30} . u_1^{30} is the DC components which is supposed to be much bigger than other coefficients and shortened by 20 times.

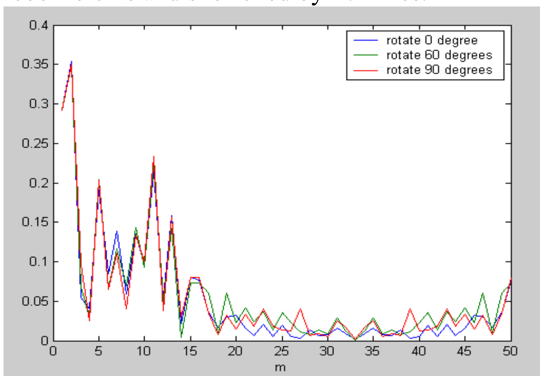

Figure 2 Fourier coefficients of the coin after rotated by different degrees

Fig. 2 shows that the Fourier coefficients are quite close after the coin is rotated by different degrees, especially for low frequency coefficients. But in a coin recognition system, due to different light condition, different effect of light reflection or different abrasion, the same type coins maybe have very different Fourier coefficients. In order to reduce the difference significantly, this paper adopts the following measures: 1. improve the image contrast. 2. ignore the first Fourier coefficient because it only represents the average intensity of the image. 3. generalize the coefficients for each radius. 4. use neural network to recognize different coin. The Fourier coefficients can be used to reconstruct the image under the logarithmic polar coordinates. The number of Fourier coefficients maybe be infinite, but with increasing frequency, the amplitude of the coefficients will be reduced significantly. So the Fourier coefficients above a certain frequency can be ignored. Fig. 3 shows the reconstructed image using 50 coefficients, 30 coefficients and 15 coefficients respectively. We also can see that the detail part becomes vague when we use less coefficients to reconstruct the coin image.

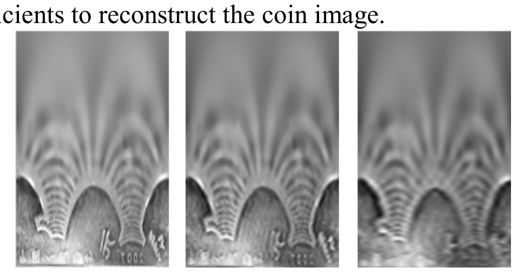

Figure 3 the reconstructed coin images under polar coordinates

III. BP NEURAL NETWORK

As stated above, because of different light condition and different reflection effect, etc. the Fourier coefficients of the same type of coin may have very different values.

It is hard to use linear classifier to distinguish different coins. The neural network is a good way to solve this kind of nonlinear problem. The neural network usually has three layers, i.e. input layer, middle layer (hidden layer) and output layer. Every layer has different neurons. The number of neurons on the input layer is equivalent to the dimensions of the feature vector. The number of neurons on the hidden lays is not easy to decide. It is directly related to the requirement of the problem and the number of neuron on the input layer and output layer. It can be decided after trial and error. This algorithm uses the formula $n_1 = \log_2 n$ to decide the number of neurons on the hidden layer, where n is the number of neurons on the input layer. Too many neurons maybe result into too long learning time and fail to converge. Too few neurons maybe fail to distinguish from different coins.

Figure 4 different coins from China

The algorithm is used to recognize coins from China, but it also works for other coins. Fig. 4 shows the total types of coins in China. There are 10 different images. Usually we should choose 10 different values represent different image, but we find if the system outputs 12 values, then the algorithm can not converge. Rather if we just choose 3 values to represent 3 different nominal values, then the algorithm can converge. So in this system the number of neurons on the input layer are 64×50， 12 neurons on the hidden layer and 1 neuron on the output layer.

IV. CONCLUSION

In order to evaluate the performance of the proposed method, 900 coin images are captured under controlled conditions, 300 coin images for each type. Each image shows exactly one coin and the images are all 1000×800 in size. 200 images of each type serve as a training set and 100 images of each type serve as a test set. The experiments show 252 coin images are correctly recognized. The accuracy rate is 83.3%.

To further improve higher accuracy, we can consider the following two aspects: first, using scanner instead of digital camera can reduce the effect of different light condition. Second, ignoring some high frequency part of the Fourier coefficients can decrease the difference between new coins and old coins which belong to the same type. The genetic algorithm can also be adopted to optimize the input feature vectors.

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