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Coin Recognition Based on Multi-Layer Matching of Geometric Texture Features

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Abstract In order to recognize coins in a complex background and improve the accuracy and efficiency of coin recognition, a comprehensive recognition method based on multi-layer matching of geometric texture features is proposed. Firstly, a coin image is preprocessed through grayscale and threshold transformation; secondly, the image is segmented through the canny operator. And then the gray level co-occurrence matrix is constructed to obtain the texture features and geometric features of the coin image. Finally, the types of coins are determined through the multi-layer template matching. The test results show that the proposed algorithm can improve the recognition accuracy of different coins in the case of coin rotation and translation.

Keywords Coin recognition; Regional segmentation; Texture features; Geometric features; Multi-layer matching

1. Introduction

At present, coin recognition is widely used in the fields of true and false currency recognition, vending machines, etc. Computer vision is a typical method for coin recognition. How to quickly and accurately identify coins is the difficulty of image processing. In order to achieve more effective and accurate recognition effect, Bi *et al*. [1] put forward a new coin identification method based on an ant colony algorithm with clustering characteristics. Six preferably effective feature functions are confirmed according to the characteristics of a coin image. The identification of various coin images is achieved by ant clustering of the feature function values. Liu *et al*. [2] presented a coin identification method based on BP network. According to the research to several familiar coin images, six feature functions which describe many kinds of coins roundly were proposed. Experimental results show that the BP network method can recognition different kinds of coins and the recognition process is fast, simple and convenient. The above two algorithms do not preprocess the image, and the extraction of image features is limited to the gray histogram, which can not fully reflect the comprehensive features of the coin image. There is a certain error rate on the true or false coin recognition; especially the recognition rate will be significantly reduced in complex backgrounds. In view of the shortcomings of the existing algorithms in the identification process, based on the image preprocessing [3], a multi-layer matching model is built to recognize the coins in this paper. The experimental results show that the proposed coin recognition method not only ensures the accuracy of coin recognition, but also has a higher recognition rate compared with a traditional method in rotation and translation.

2. Image Features

For digital images, the geometric shapes, surface texture and color distribution are the easiest to perceive. The geometry shape features focus on the description of the appearance of images and their outline edges, such as the area, circumference and roundness of images. For the human eye, the most intuitive and easily identifiable features can be used as one of the characteristics of coin images. The color distribution is mainly for the expression of the RGB arrangement value of the pixel, but it can not make an effective judgment for the distribution of the whole space. The most commonly used method is the grayscale histogram. Although this method can give the gray distribution of an image concisely and clearly, it is very difficult to carry out further analysis. Texture features are one of the important factors that reflect the image surface features. Compared with the geometric features, texture is one of the important means to judge the image. It is one of the basic attributes of things. The spatial features focus on the description of the position relationship among the internal various parts of the segmented image. However, since the spatial relationship is susceptible to rotation and translation, this feature is generally not used. The most important feature for coin recognition is texture features. Through the identification of the texture, the type and authenticity of coins can be accurately distinguished. In addition, some geometric features and shape features of coin images can also be used as a secondary standard of judgment.

3. Image Preprocessing

3.1. Gaussian Filtering

Gaussian filtering is a kind of linear filtering. Its purpose is to eliminate the Gaussian noise. First, a template for scanning image pixels is needed, such as a 3×3 or 9×9 template. And then the entire image is scanned, and the original gray value of each point is replaced by the weighted average gray value of the adjacent points of the corresponding points in the template, which can achieve overall blur effects of images. In this paper, the commonly used two-dimensional Gaussian function is selected to achieve the weight of each pixel in the template block, as shown in Eq. (1).

$$G(x,y)=\frac{1}{2\pi\sigma^2}e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{1}$$

where, $G(x, y)$ represents the weight of the gray value of the (x, y) point in the template. x and y are the horizontal and vertical coordinate of the point in the template. σ is the standard deviation of the normal distribution of noise points. Generally, the higher the value of σ, the more blurred the image.

3.2. Edge Detection

Edge detection [4] is to find the point where the grayscale in the image changes significantly, which usually reflects the important information in the image and these changed points are generally called boundary points. Point of change is generally referred to as the boundary point. In general, after the edge detection, the border of the image will become clearer. In this paper, the canny algorithm with better processing effect is adopted. First, the Canny algorithm uses the two Sobel convolution cores (see Fig. 1) to convolve all the pixels in the image, and two gradient values in horizontal and vertical directions are obtained. Then, Eq. (2) and (3) are used to achieve the gradient value and gradient direction of the point.

-1	0	+1
-2	0	+2
-1	0	+1

(a) G_x

+1	+2	+1
0	0	0
-1	-2	-1

(b) G_y

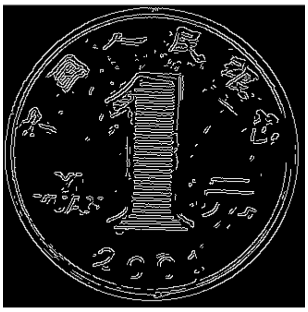
Figure 1: Convolution kernel of Sobel algorithm

$$G=\sqrt{G_x^2+G_y^2} \tag{2}$$

$$\theta=\arctan(\frac{y}{x}) \tag{3}$$

However, the boundary detected by the Gaussian filter and the gradient searching is relatively vague and the lines are coarse and inconspicuous. Then, the boundary needs to be further selected with non-maximal suppression. Based on the gradient direction and intensity of each pixel, the gradient direction is simplified to eight directions, i.e., up, down, left, right and four diagonals. By comparing each point's own gradient strength with the gradient strength of each point in the gradient direction, and removing the maximum of them, the boundary can be refined to make it more obvious. In addition, according to the definition of the boundary point, the edge part of the image can not be the boundary point, and the point whose gradient value is 0 can not be the boundary point. If the gradient of the current pixel is a local maximum, the point may be a boundary point, otherwise it is impossible. Then the noise is further reduced by double threshold segmentation. That is, an upper threshold and a lower threshold are set. If the gradient value of the pixel in the image is greater than the upper threshold, it is called an edge and is called a strong edge. If the gradient value is smaller than the lower threshold, it is inevitable that edge. If the gradient value is between two thresholds, it is not processed and is called weak edge. Finally, the hysteresis technique is used to track the boundaries: First, find the first boundary point from left to right and from bottom to top. The top left is used as the initial search direction. If the top left point is not a boundary, the 45 ° clockwise direction is redefined as the new search direction. So cycle until you find a new border. Then the newly found boundary point is used as a starting point, and the search is continued in a counterclockwise direction of 90 ° until the initial boundary point is returned.
The specific border search results are shown in Fig. 2.

(a) Original image



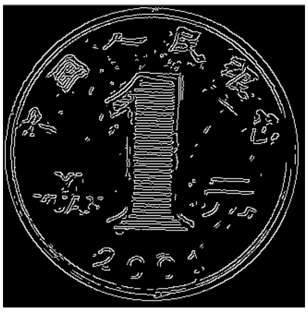
(b) Search results

Figure 2: Border search results

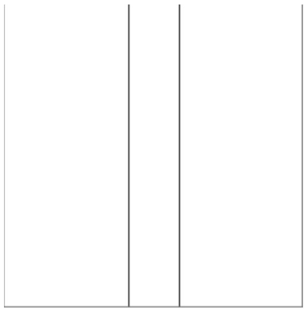
4. Feature Extraction

4.1. Geometric Feature Extraction

General geometric features include: Area, perimeter, radius, rectangular degree and so on. Although these geometric properties are easy to extract and use, the accuracy of the image can not be guaranteed if the image is scaled and rotated. So, a new concept, namely word to word ratio, is proposed for coins in this paper. That is, find straight lines that are parallel to each other in an image through Hough parallel line detection, and compare the distance between the two straight lines that are farthest away from the diameter of the image. Figure 3 shows the line detection results.



(a) Segmentation results based on Canny



(b) Line based on Hough straight line detection

Figure 3: Line detection results

In this paper, the area and perimeter are selected as auxiliary judgment features. The area feature extraction method is mainly finished by counting all the pixels of the image which is segmented by canny operator. The extraction of perimeter features [5] requires the creation of a chain code to calculate. First, a 3x3 template is constructed. For each pixel (x, y), there are 8 neighborhoods, and they can be written in an aggregate form, that is, the neighborhood $F(x, y)$ can be described:

$$F(x,y)=\{f(x-1, y-1), f(x-1, y), f(x-1, y+1), f(x+1, y-1), f(x+1, y), f(x+1, y+1), f(x, y-1), f(x, y+1)\} \quad (4)$$

First, mark the pixel (x-1, y) as the initial orientation code: 0, and then increase it in clockwise direction to obtain the direction code value corresponding to the 8 pixels as shown in Table 1.

Starting from the left adjacent pixel point (x-1, y), the direction code is 0, and the clockwise direction is incremented, and the direction code value corresponding to the pixel point in the following table can be obtained.

Table 1: Code values of eight points

$f(x-1, y)$	$f(x-1, y-1)$	$f(x, y-1)$	$f(x+1, y-1)$	$f(x+1, y)$	$f(x+1, y+1)$	$f(x, y+1)$	$f(x-1, y-1)$
0	1	2	3	4	5	6	7

Accordingly, the edge of the image can be obtained according to the two parameters, namely, the starting point coordinate (x0, y0), and the direction code set $\{a_0, a_1, a_2, \ldots, a_n\}$ of all pixels, where $a_i \in \{0, 1, \ldots, 7\}$. It is easy to find that when the search of next pixel is performed after completing a pixel scan, the scanning step will be 1 if the pixel is located in the upper, lower, left or right of the previous pixel, that is, the direction code is even. If the next pixel is located in the upper left, upper right, lower left, lower right direction of the previous pixel, that is, the direction code is odd, the scanning step will be $\sqrt{2}$. Let p_1 be the number of all even direction codes after traversing the edge, and p_2 be the number of all odd direction codes, the circumference of the image can be described:

$$c = p_1 + \sqrt{2} \cdot p_2 \quad (5)$$

4.2. Extraction of Texture Feature

Texture feature [6] is a description of the whole image, which mainly shows the properties of the image surface. It is characterized by good rotation invariance, and the good performance also exists in noise situation. In this paper, the gray-level co-occurrence matrix with relatively good effect is used for the extraction and analysis of texture feature. First of all, for an image, choose a pair of points (namely, point (x, y) and point ($x + a$, $y + b$)) arbitrarily, and let the gray level of the pair points be (m, n). If the image has k-level grayscale, then there will be k^2 kinds of permutations and combinations. The k^2 permutations are arranged in a matrix according to the number of occurrences. Since there are only 0 and 255 gray levels in the image after edge segmentation, the pair points have a total of 4 cases (0, 0), (0, 1), (1, 0), (1, 1). In general, we choose a = 1, b = 0 level scan or a = 0, b = 1 vertical scan. If the sample grayscale matrix is shown on the left in Figure 4, and 0 and 1 represent the two grayscales respectively, the sample grayscale co-occurrence matrix is shown on the right of Fig. 5.

0	1	1	1
0	0	0	1
0	0	1	1
1	1	1	1

Figure 4: Sample grayscale

	0	1
0	3	3
1	2	4

Figure 5: Gray covariance matrix

After getting the gray level co-occurrence matrix of the coin surface texture, we can then characterize the matrix with some scalars, as shown in Eq.(6).

(1) Energy

$$E = \sum_{i=1}^{k} \sum_{j=1}^{k} (G(i, j))^2 \quad (6)$$

where G(i, j) denotes the element value of the i^{th} row j^{th} column in the gray matrix.

The energy is the sum of the squares of each matrix element. Its value can reflect the uniformity of the gray-level distribution of an image. A larger value indicates that the image changes more evenly. If the image changes sharply somewhere, the value is smaller. For a pre-processed coin image, this value is larger due to the larger diagonal elements.

(2) Entropy

$$S = \sum_{i=1}^{k}\sum_{j=1}^{k} G(i,j)\log G(i,j) \tag{7}$$

The entropy characterizes the level of information in the image, ie, the non-uniformity and complexity of the texture. It can be seen from Eq.(7) that the entropy value is larger when the gray matrix is evenly distributed. For coin images, the entropy value is smaller.

(3) Contrast

$$Con = \sum_{\mathrm{n}=0}^{k-1} n^2 \{\sum\nolimits_{|i-j|=n} G(i,j)\} \tag{8}$$

The contrast reflects the gray value comparison of a point and its neighborhood point. If the value of the non-diagonal elements in the gray matrix is larger, the value is larger, that is, the gray value of the image changes rapidly. By definition, the larger the value, the more noticeable the texture of the image, that is, the clearer it looks. For a coin image, the elements of the gray matrix are mainly concentrated on the diagonal, so the value is smaller.

(4) Consistency

$$Cor = \sum_{i=1}^{k}\sum_{j=1}^{k} \frac{(ij)G(i,j) - u_i u_j}{s_i s_j} \tag{9}$$

$$u_i = \sum_{i=1}^{k}\sum_{j=1}^{k} i \cdot G(i,j) \tag{10}$$

$$u_j = \sum_{i=1}^{k}\sum_{j=1}^{k} j \cdot G(i,j) \tag{11}$$

$$s_i^2 = \sum_{i=1}^{k}\sum_{j=1}^{k} G(i,j)(i-u_i)^2 \tag{12}$$

$$s_j^2 = \sum_{i=1}^{k}\sum_{j=1}^{k} G(i,j)(j-u_j)^2 \tag{13}$$

The consistency is the similarity of the gray level co-occurrence matrix in the row and column direction, which reflects the gray correlation of local pixels in an image. When the gray matrix elements are evenly distributed, the value is larger; otherwise, it is smaller. For a coin image, the value is very small.

If each set of a, b values is selected, four texture-related eigenvalues can be obtained. For coin images, the scanning can be carried out in three directions of horizontal, vertical and diagonal because the rotation of a coin image will not cause deformation. That is, (a, b) can be (1, 0), (0, 1) and (1, 1) three groups. Because their rotation will not cause deformation, the three directions of horizontal, vertical, diagonal scanning in three directions, that is, (a, b) can be (1, 0), (0, 1), (1, 1) three groups. Finally, a feature vector $f=\{E_1, S_1, Con_1, Cor_1, ..., E_3, S_3, Con_3, Cor_3\}$ is integrated.

5. Multi-layer Template Matching

Template matching [7] is the basic method of human judgment and cognitive things. By comparing and matching the characteristics of the captured things with their own known, similar characteristics, then the properties of things are determined.

For the characteristics of an image, we can determine the importance of different features on the image according to the overall impact of these features on the image. Each feature is compared with the standard value set by each template separately, and the error is recorded. The allowable error range is divided according to the importance of the feature. If all feature errors are within the allowable error, you can be sure that the image and the template image belong to the same class. If some of the errors are outside the allowable range, the images are hierarchically matched. The previous feature that exceeds the error range is judged by multiplying it by the coefficient of different degrees.

First layer match:

Feature 1-----------> Threshold 1-----------> Error 1

Feature 2-----------> Threshold 2-----------> Error 2

Second layer match:

$$\text{Error 1} \xrightarrow{*k_1} \text{Error range 1}$$

$$\text{Error 2} \xrightarrow{*k_2} \text{Error range 2}$$

Figure 6: Multi-layer matching diagram

If all the errors in the second layer of judgment are multiplied by the degree coefficient and meet the requirements of the template, it can be considered that the sample belongs to the template type, and if not, the third layer matching is required. The identification method of the third layer of is different from the previous two layers, and is to judge all the features of the image again. The recognition is more global and holistic, so the credibility is higher than the second-level identification method. If there is a conflict between the second and third level identified categories, the third level identification category is preferentially selected as the matching result.

6. Experimental Results and Analysis

In order to verify the validity of the proposed coin recognition method, some experiments are carried out. The overall process of coin recognition is as follows: Sample Image -> Gaussian Filtering -> Calculate Gradient -> Edge Tracking -> Feature Extraction -> Template Match. The size of the sample image is 276 × 276 pixels. The recognition results are compared with those of basic template matching as shown in Table 2.

Table 2: Comparison of four algorithms

Methods	Basic Template matching	Multilayer template matching
Accuracy	92%	96%
Execution time/ms	342	381
Accuracy(Complex background)	90%	94%

The experimental results show that the recognition rate of the proposed method is about 96%, the program running time is short, and the calculation is small. In addition, the method has low environmental requirements and can be used in most of the coin detection occasions.

7. Conclusion

The coin recognition based on vision is widely used. How to improve the recognition accuracy and efficiency is the difficulty of coin recognition. In this paper, a recognition method based on multi-layer matching of geometric texture features is put forward. During the coin image preprocessing, the grayscale and threshold transformation is used. And the coin image is segmented based on the canny operator. The texture features and geometric features of the coin image is got based on the gray level co-occurrence matrix. Finally, the coin is recognized through multi-layer matching. The experimental results also verify the validity of the proposed method.

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