Coin Recognition Based on Physical Detection and Template Matching

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Abstract. At present, coin circulation automation technology has been widely used in many aspects, so it is necessary to install coin recognition and detection devices in related equipment to prevent coin confusion. However, many current coin detection methods have high requirements for hardware,which increases costs and makes it difficult to install and use equipment in narrow spaces. In this paper, we propose a coin recognition method with low hardware requirements and high accuracy. The design is to take a picture of the coin, detect the image and match the template to distinguish three different coins in the fourth edition of RMB. Compared with other detection methods using the eddy current method, it is lighter and easier to assemble, and can be easily embedded in narrow places.

Keywords: Coin recognition · Image processing · Template matching

1 Introduction

Facing the increasing coin circulation, the market needs a mature and reliable coin identification device. Therefore, the efficient detection of coins has become a very meaningful work, and a large number of coin detection methods have been proposed, some coin sorting devices also appeared.

The coin sorting machine [1] is a system that recognizes and counts coins passing at high speed, and at the same time eliminates counterfeit coins and residual coins. It is the basis of many coin processing tools such as sorting machines, counting machines, packaging machines, and destruction machines. Due to different national conditions and currency systems, it is unrealistic to develop a unified coin sorting system for all countries. Therefore, in this field, researchers have done a lot of work [1, 3, 16–23]. The developed products are roughly divided into three grades, low-end, mid-range and high-end. The low-end sorting speed [2] is below 1000 pieces/min, the mid-range is about 1000–1500 pieces/min, and the high-end is above 1500 pieces/min. There are

J. Wang and L. Bai—Contributed equally to the paper.

S. Shi et al. (Eds.): AICON 2020, LNICST 356, pp. 80–88, 2021.
https://doi.org/10.1007/978-3-030-69066-3_8

two main categories of sorting methods used, one is sorting based on physical technology, and the other is sorting based on performance indicators.

In the fourth set of coins currently used in China, the materials of one-yuan, five-dime and one-dime are nickel-plated steel core, copper-zinc alloy, and aluminum-magnesium alloy. They are special alloys specially used for coinage. There are three thresholds for the machine to distinguish coins: size, material, and weight. The inside of the machine generally has a limiting device composed of a high-frequency oscillation circuit [3], which can directly screen coins. The principle of screening is that when a coin enters the magnetic field generated by the high-frequency oscillation circuit through the coin slot, the difference between the metal material and the size of the coin affects the inductance, which leads to the change of the oscillation frequency, and then the detected frequency change, Compare with the set value, after confirming a certain coin type, the frequency signal is changed into a voltage signal and outputted to complete the identification of the metal coin. The weight recognition is carried out by the speed of the coin sliding to a certain set position in the machine.

At present, the commonly used coin denomination recognition methods include image methods and eddy current sensor methods. Modi S et al. [22] used Hough transform, pulsed averaging technology to extract the features of the coin image, and then sent it as input to a trained neural network for judgment. Gupta V et al. [23] established a coin recognition system based on image subtraction technology. By subtracting the input image and the database image, the value obtained was compared with the threshold value to complete the coin recognition. The School of Engineering of Soochow University [16] adopted a compensation measure to connect two identical eddy current sensors in series and install them on both sides of the coin rail to improve the detection accuracy. The University of Electronic Science and Technology of China [21] designed a dual-channel eddy current sensor composed of high-frequency reflection and low-frequency transmission to detect different parameters of coins, and realize high-speed and reliable detection of coins through FPGA. Shanghai Jiao Tong University [17], Beijing Architecture University [18], Hangzhou Institute of Electronic Technology [20], Tianjin University [19] and many other institutions have done in-depth research on how to correctly identify coins, and the eddy current method is generally used in the mechanism.

In this paper, we propose a coin recognition method based on digital image processing and machine learning technology, which can quickly and accurately verify coins, having broad application prospects.

In our work, we find that we can take advantage of the characteristic that five-dime coins are yellow to detect the number of five-dime coins in advance. In this way, the follow-up work will be greatly simplified, because then we only need to complete the two-classification problem of one-yuan and five-dime coins.

2 Approach

This device is mainly composed of two basic structures: imaging system and coin sorting system (image processing system). The imaging system is responsible for imaging the front and back sides of the coin, and the coin classification system is responsible for classifying various coins judged after imaging.

2.1 Equipment Selection in the Imaging System

In the imaging system, we need an industrial camera to shoot the target, and considering the lack of lighting, we need a light source for supplementary lighting.

For industrial cameras [5], we need to consider factors such as its resolution, frame rate, focal length, working distance, magnification and field of view. After the resolution and frame rate are determined, we need to combine specific application scenarios to determine the magnification and other factors, so we mainly consider the resolution and frame rate here. The first is the resolution. For the range of 30 mm diameter, the theoretical resolution calculation formula is:

Resolution (theoretical) = (high field of view/precision) * (width of field of view/precision) = (30/0.04) * (30/0.04) = 750 * 750

Taking into account the distortion of the camera's edge field of view and the stability requirements of the system, generally one-pixel unit is not used to correspond to a measurement accuracy value. Generally, a multiple of 2 or higher is selected, so that the single-directional resolution of the camera is 1500, so the camera resolution 1500 * 1500 = 2.25 million, so the camera pixel needs to be greater than 2.25 million. The second is the frame rate. The frame rate of a conventional industrial camera is basically greater than 30FPS, which means that it can take 1,800 photos per minute, which basically meets the needs.

In light source selection, we choose the LED light source [4]. It is the current mainstream machine vision light source, because it is powered by DC, has no stroboscopic, and has a very long life and high brightness. It can also be flexibly designed as a line light source with different structures, such as direct light, with condenser lens, backlight, coaxial and a diffuse reflection line light source similar to a bowl.

2.2 Coin Classification System (Image Processing System)

The flow of the whole system is shown in Fig. 1. For one-yuan and one-dime coins, the size of a one-yuan coin in the image is very different from that of a one-dime coin. The circle radius can be detected and compared in the process of coin recognition. The five-dime coin is very different from the one-yuan and one-dime coins in color. When detecting coins, the yellow component can be extracted and threshold segmentation can be performed to extract the number of five-dime coins.

First, we extract HSV color components [6] from the image. In the RGB model, the extraction of single-channel components is far from the effect that we need to extract the yellow component for threshold segmentation, so we use other color models to try. After many experiments, the extraction of the color component of the second channel in the HSV model is of high definition and can meet our requirements, so the HSV component is selected.

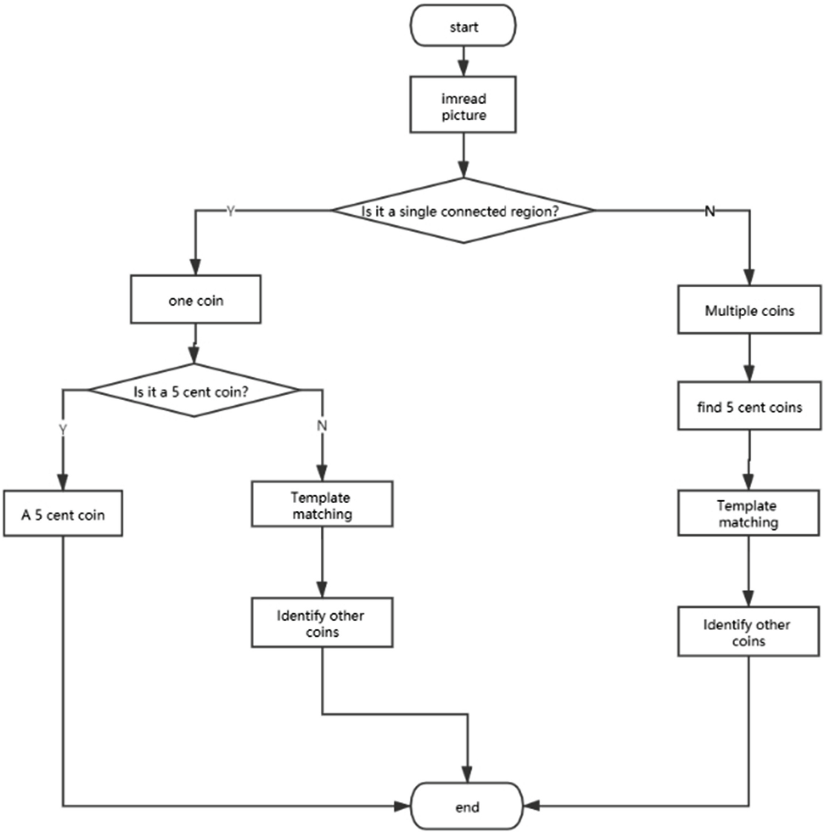

Fig. 1. Coin identification flow chart

Then, we perform image binarization on the image from which the yellow component has been extracted, and use image opening and closing operations, edge detection [8, 9, 13], inverted color changes to fill holes, and median filtering [7] in the preprocessing to make the image clear, Calculate the number of penny coins in the image to be tested by determining the number of connected regions.

Then, we change the gray scale and binarize the image again, and preprocess the image, use the above method to make the image clear and no noise, and then calculate the number of connected regions, that is, the total number of coins, and use the subfunction to find The center and radius of the function, using the value of the radius to extract the number of one yuan and the last of a corner, get the number of one corner based on the number of one yuan and five corners and the total number.

At the same time, if there are only multiple or one one-yuan or one-dime coin in the image, it cannot be recognized by the above method, so we select one of the connected regions of the image for template matching, and use Bayesian classifier to classify.

2.3 Template Matching

The basic process of template matching [10] consists of data acquisition, preprocessing, feature extraction, classification decision and classifier design.

First, in the image preprocessing of pattern recognition, a large number of details cannot be erased by using the structural elements of the image as the previous preprocessing. In pattern recognition [12], we need to extract their features, so we need to reduce the error caused by light intensity and reflection and at the same time preserve the details of the image as much as possible. Therefore, in the process of image preprocessing, we select small structural elements for edge detection [13]. However, if the edge detection is carried out directly on the total image, the error will be greater and the recognition rate will be reduced. Because light and other factors have little influence on the image in the small rectangular box, in the process of preprocessing, we first erase the details and extract the smallest rectangle in the simply connected region for segmentation, so as to make the image smaller and conduct boundary detection in the small image. This greatly improves our success rate of image detection.

Next, we used the selection of grid features to define a 10 * 10 template and extract feature values on each segmented coin graph. The length and width of each image were divided into 10 equal parts, so there were 100 equal parts. The size of the template can be changed, and the more equal it is, the more accurate the results will be in the process of comparison and classification, but the calculation will also become huge, which will lead to an increase in our running time, so we choose the ten decals that are more cost-effective. In feature extraction, binary images are selected, so the value of each pixel point is either 1 or 0, so we choose to compare the proportion of the number of 0 cells in each of the subgrids the number of black cells divided by the total number of cells. Then you get 100 decimals between 0 and 1. It is represented by a vector of 100 * 1, and this is the feature vector of the image, namely the image feature we want to extract.

The sample base is designed to be divided into six categories, representing one-yuan, five-dime, one-dime coins and their front and back respectively. We designed nine learning samples for each coin, each using a one-yuan, five-dime, one-dime coin and its front and back in different situations. When the features of each sample are extracted, all the sample data is stored in a template file, and each coin USES a structure to store the information.

Finally, we use Bayes formula to design the classifier. Bayes formula [11] is as follows:

$$P(A|B) = P(A)\frac{P(A|B)}{P(B)}$$

The so-called prior probability is the probability distribution based on the existing knowledge and experience, that is, the probability of the occurrence of this event, which is mostly uniform distribution. The posterior probability is the probability obtained after some actual observation statistics.

When the characteristic condition is the state of the object X to be tested, the posterior probability of ω is the largest among the different coin categories, that is, X belongs to the category ω.

Prior probability $P(\omega_i)$ is approximately calculated by the number of samples and the total number of those. N_i is the number of samples of coin i, and N is the total number of samples:

$$P(w_i) \approx \frac{N_i}{N}, i = 0, 1, 2, \ldots, 9$$

First, we compute the $P_j(\omega_i)$, and then we compute the conditional probability $P(X|\omega_i)$.

$$P_j(w_i) = \left(\sum_{k=0, X \in w_i}^{N_i} x_{ij} + 1 \right) / (N_i + 2)$$

Where i = 0, 1, 2 …, 9, j = 0, 1, 2 …, 99. The threshold value is set as 0.05. When the value of the 100 eigencomponents is greater than 0.05, the eigenvalue is considered to be 1; otherwise, it is 0. Pj(ωi) is an estimate of the probability that the j^{th} component of X under test is $1(x_j = 1)$ when sample $X(x_0, x_1, x_2, \ldots, x_{99})$ is in the ω_i category.. From this we can calculate:

$$P\left(x_j = 1 | X \in x_i\right) = P_j(w_i)$$
$$P\left(x_j = 0 | X \in x_i\right) = 1 - P_j(w_i)$$

Where i = 0,1,2…, 9, j = 0,1,2…, 99. It is assumed that X no matter what kind of coins, all of these classes sample characteristic, the first component is the first 1/100 grid probability value is 0, then we can assume that the eigenvalue of X must also be 0, and the probability of the inverse is 1.. Bayes emphasizes that the sample is fixed, the frequency is random, and the posterior probability is affected by the sample. Therefore, the conditional probability of the object X to be tested is:

$$P(X|w_i) = P[X = (x_0, x_1, x_2, \ldots, x_{99}) \Big| X \in w_i] = \prod_{j=0}^{99} P\left(x_j = a | X \in w_i\right)$$

Where i = 0,1,2… 9, a = 0 or 1.

Applying Bayes formula to calculate the posterior probability, namely the possibility that X to be tested belongs to i, we can get

$$P(w_i|X) = \frac{P(w_i)P(X|w_i)}{P(w_0)P(X|w_0) + P(w_1)P(X|w_1) + \ldots + P(w_9)P(X|w_9)}$$

Where i = 0,1,2… 9. The magnitude of P(X) is the sum of all the different categories of X in the denominator.

The category that computes the maximum value of the posterior probability is the category to which the coin belongs.

3 Results

Fig. 2. Part of test images [Fengxiaode1778 2020] (The images are 1, 2, 3, 4, 5, 6 from left to right and top to bottom)

We collected some pictures of one-yuan, five-dime and one-dime coins in the fourth edition of RMB from the Internet to test the software part of this method. At the same time, we collected some coins by ourselves and took pictures with the equipment meeting the imaging requirements of this paper. These photos were used to test the software part of this method.

The results show that our method has a good effect on the differentiation of one-yuan, five-dime and one-dime in the fourth edition of RMB. At the same time, when the coin is in a dark environment, LED lighting can also make the image become clear, to meet the needs of coin recognition.

The results can be seen in Fig. 2 and Table 1.

Table 1. Part of test result

	Test1	Test2	Test3	Test4	Test5	Test6
One-yuan coins	1	0	0	1	2	1
Five-dime coins	0	1	1	0	0	1
One-dime coins	0	0	1	1	0	1

4 Conclusion

Prior work concentrated only on physical methods by eddy current sensors or light detectors, having poor identification of counterfeit coins, either a high cost.

In this study, we propose a simple coin recognition method based on digital image processing and machine learning technology, which has a lower cost. At the same time, this method shows its extremely high precision in the pictures we choose or take. If we can have more data sets to train, we will get better results.

However, we still have some problems that need to be improved. First of all, for the detection of overlapping coins, we sometimes cannot realize the correct detection; Secondly, our program takes a long time to run and needs to be improved.

In the following work, we can use a token-based watershed segmentation [14] to split the overlapping coins. At the same time, if there are overlapping coins, we can extract a section of arc separately, and then use this section of arc to fit the circle equation, so as to calculate the number of coins.

Acknowledgement. This paper is sponsored by Beijing Natural Science Foundation (L191004).

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