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A Classification Method of Circular Objects Based on Gray Level Statistical Features

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***Abstract*—This paper presents a classification method of circular objects based on gray statistical features. Firstly,use circular object detection to extract the region where the circular object is located. Then, standardize the detected circular region to the circular region with the uniform radius. At the same time, normalize the gray level of the circular region; then, we divided the standard circular region into little regions according to the determined pattern, and extract the gray level statistical features of each sub-region , which are combined into feature vectors. In this paper, we use Support Vector Machine and K-Nearest Neighbor for classification experiments.Experiments show that the method has a good classification effect.**

Keywords—circular object image; image classification; feature extraction ; image region division

I. INTRODUCTION

Image classification is a problem of describing the content classification of an input image. It is the core of computer vision and is widely used in practice.

The most commonly used method of image classification[1,2] is to distinguish images by their features. Therefore, image feature extraction[3] is the basis of image classification. Image features include texture features[4], color features, shape features and so on. Texture, as a basic property of object surface, is widely used in image analysis because it can well represent images.

Texture analysis is a technology that uses image processing technology to extract important surface gray information from images and to analyze texture features[5]. Four commonly used methods for texture analysis are statistical method, spectral method, model method and structural method. The main purpose of this paper is to classify circular objects. Because of the particularity of the shape of the object, we mainly use statistical method to analyze the texture of the image. As the gray level statistical feature, it usually has rotation invariance and strong resistance to noise. Therefore, for the classification of circular object images, this paper uses the method based on gray statistical features to achieve image classification. At the same time, in order to improve the robustness of the feature, we first divide the image into several small areas according to a certain pattern, and then extract the gray statistics of each small area as the feature of the image.

II. IMAGE PRE - PROCESSING

A. Detect the circular target

In this paper, the method proposed in reference [6] is used to detect circular targets. The author uses LSD algorithm to detect arc-support Line Segments, and then constructs a screening mechanism for ellipse detection based on arc-support Line Segments from coarse to fine.Key steps of algorithm are as following：

a) Connect and group the detected "arc-support Line Segments"

b) Generate the initial elliptical candidate set; Highlight author and affiliation lines of affiliation 1 and copy this selection.

c) Merge the candidates who may come from the same ellipse .

d) Verify the candidate ellipse and Delete the ellipse with low quality.

After determining the circular outline of the image, we calculate the center and radius of the circular target by taking three points on the circle.In order to avoid the influence of image background region and image translation on the experimental result, we extract the circular target region of the image and translate the circular target region to the same position.

B. Image normalization.

The image of circular targets will be affected by the intensity of light. In order to eliminate the influence of light change, the image of circular target will be normalized.If the circular target region is set to be R_c, the mean value of pixels and the variance of pixels in the region are set to be μ_b, σ_b, then the normalization formula is formula(1) as follows.

$$I_a(x,y) = (I_b(x,y) - \mu_b)\frac{\sigma_a}{\sigma_b} + \mu_a \ , \ (x,y) \in R_c \tag{1}$$

Where,

$I_b(x,y)$ =the pixel value of the image at (x,y) after normalization.

$I_a(x,y)$ =the pixel value of the image at (x,y) after normalization.

μ_a =the normalized mean.

σ_a =the normalized difference.

C. Image region normalization

In order to make the dimension of the extracted image feature consistent, it is necessary to normalize the image region, that is, to transform the circular target region into the standard size.

The standard circular target area is R_{cn} ,its center is (x_{no}, y_{no}) and its radius is r_n ;The standard circular target area is R_{cd} , its center is (x_{do}, y_{do}) and its radius is r_d ;then a point $(x_{ni}, y_{ni}) \in R_{cn}$ in the standard circular target area corresponds to the sub-pixel $(x_{si}, y_{si}) \in R_{cd}$ in the detected circular target area,which can be calculated by the following formula (2):

$$\begin{cases} x_{si} = (x_{ni} - x_{no})\dfrac{r_d}{r_n} + x_{do} \\ y_{si} = (y_{ni} - y_{no})\dfrac{r_d}{r_n} + y_{do} \end{cases} \quad (2)$$

Accordingly, the gray value of the normalized image at point $(x_{ni}, y_{ni}) \in R_{cn}$ can be calculated by the following formula(3):

$$I_n(x_{ni}, y_{ni}) = F(\underset{(x_{dj}, y_{dj}) \in N(x_{si}, y_{si})}{I_a}(x_{dj}, y_{dj})) \quad (3)$$

Where,

$N(x_{si}, y_{si})$ = the neighborhood of sub-pixel (x_{si}, y_{si})

$F(\cdot)$ =the difference function.

we choose Bilinear Interpolation[7] in this paper.

III. FEATURE EXTRACTION OF CIRCULAR OBJECTS IMAGES

The circular object in the image has translation change, scale change and rotation change.In addition to considering the influence of the optical axis and the imaging plane may not be vertical, there are still radiation changes (not considered in this paper).For translation changes, the detection of circular targets can be solved. For the scale change, the region normalization of the detected circular target region is carried out in the previous section, which can also be solved.For the rotation change, it is difficult to calculate the accurate rotation angle between the two circular objects. It is ideal to make the extracted features invariant to rotation.

Consider an annular region centered on the center of the circular object. When the circular target rotates, each annular region rotates accordingly, but the image content of the circular region does not change.In order to further improve the identification ability of image features, it is necessary to include structural information in the feature extraction region .The circular area is divided into several small sector regions along the radius direction with the center of the circular coin as the center of the circle. The gray statistical features of each sector region can be extracted as rotation invariant features of the image.The ith ring region R_i is described as formula(4):

$$R_i = \left\{(x, y) \mid r_{i-1} \le \sqrt{(x - x_o)^2 + (y - y_o)^2} \le r_i\right\} \quad (4)$$

Where,

r_i = Outer ring radius,

r_{i-1} =Inner ring radius.

After dividing the circular coin region into several annular region, in order to extract enough features and ensure that the extracted information contains more complete structural information. We divide the annular region into several small sector coin image regions.A sector area S_n in R_i can be described as formula(5):

$$S_n = \left\{(x, y) \middle| l_{n1}: a_{n1}x + b_{n1}y + c_{n1} < R_i < l_{n2}: a_{n2}x + b_{n2}y + c_{n2}\right\} \quad (5)$$

where,

l_{n1}, l_{n2} = Two straight lines in S_n .

In each sector region, gray statistical features of each order are extracted and cascaded together to form feature vectors.

The normalized central moment is defined as formula(6):

$$\eta_{ipq} = \mu_{ipq} / (\mu_{i00})^{\rho}, \rho = (p + q)/2 + 1 \quad (6)$$

Where ,

$$\mu_{ipq} = \sum_{(x,y)\in R_i} (x - \bar{x})^p (y - \bar{y})^q I(x, y), p, q = 0,1,2\cdots$$

$$\bar{y} = m_{01} / m_{00}$$

$$\bar{x} = m_{10} / m_{00}$$

$$m_{ipq} = \sum_{(x,y)\in R_i} x^p y^q I(x, y), p, q = 0,1,2\cdots$$

Construction of 7 Invariant moments- by using second-order and third -order Normalized Central moments

IV. FEATURE EXTRACTION OF COINS IMAGES

In this paper, the One yuan coin image is taken as the experimental object.The new and old One yuan coin image is shown in *Fig.1*. All the test sample images and training sample images are taken by the same industrial camera and light source, and the collected images are gray images. Keep the shooting distance fixed. Although the conditions of image acquisition are artificially controlled, the gray level of the image can not be strictly guaranteed, and the radius of the coin is the same.

The feature extraction of coin image adopts the method of circular image feature extraction.Firstly, pre-process the coin image. Detect the target of the circular coin image, and determine the center and radius of the coin image. According to the center and radius of the coin image, the sample image of all coins is translated to the same position and transform the circular target region to the standard size. Then, according to the partition template of circular image feature extraction according to the above, divide the feature region of circular coin. According to the radius of the collected coin image, divide the coin image into suitable circular areas. At the same time, on the basis of dividing the circular coin image into annular region, divided the circular region into several small sector regions along the radius direction with the center of the circular coin as the center of the circle. Finally, extract the statistical features of each small sector region to form a feature vectors.

Fig.1. The new and old One yuan coin image

A. *Dividing the circular coin image into annular regions*

In this paper, in order to further improve the identification ability of coin features and ensure the complete structural information, the circular coin image is divided into overlapping annular regions. Taking the image of the new One yuan coin shown in *Fig. 1* as an example, the center coordinate of the coin image is (702,466), and the standardized radius R= 444. In this paper, four annular regions contain all the information of the coin, and The area difference of each annular region should not be too much. *Fig. 2* is an image obtained by dividing a new coin into four overlapping annular regions:

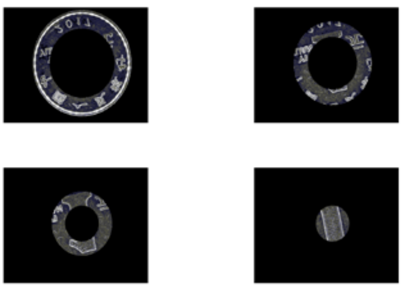

Fig. 2 . The image obtained by dividing the image into four annular regions

B. *Dividing annular region into Sector Coin Image Regions*

After dividing the circular coin region into several annular region, in order to extract enough features and ensure that the extracted information contains more complete structural information. We divide the annular region into several small sector coin image regions, and make each small sector coin image region overlap with each other.This paper divides the coin image into 20 overlapping small sectors. *Fig. 3* shows a circular image with the largest radius divided into seven small sector

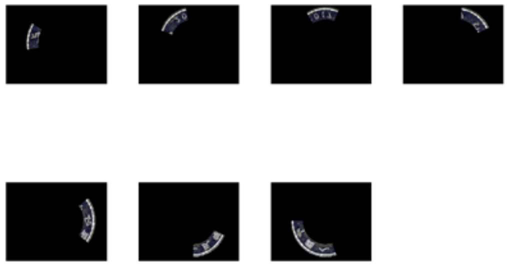

Fig .3. The image obtained by dividing a circular image with the largest radius into seven small sector

V. IMAGE CLASSIFICATION USING SUPPORT VECTOR MACHINE AND K-NEAREST NEIGHBOR

Image classification using Support Vector Machine and K-Nearest Neighbor algorithm includes three steps: building image feature vectors, training classifier and classification decision.

A. *Image Classification using Support Vector Machine*

The basic principle of Support Vector Machine[8,9] is to determine a regression hyperplane to divide different data. The circular image classification based on Support Vector Machine is a nonlinear separable case. Through the kernel function, transform the learning samples are into high-dimensional space so that different types of data can be linearly separable in high-dimensional space.

In this paper, LibSVM software package is used as classifier training platform. The process of training classifier mainly calls two functions. Svmtrain is modeled according to input vectors and specified classifier training. Svmpredict uses existing models to predict and classify.

B. *Image Classification using K-Nearest Neighbor algorithm*

Image classification based on K-Nearest Neighbor algorithm[10,11] is done by measuring the distance between different characteristic value. The main flow of the algorithm is as follows:

a) Calculate the distance between test data and training data;

b) Ranking according to the incremental relation of distance;

c) Selecting K points with the smallest distance;

d) Determine the occurrence frequency of the category of the first K points;

e) The category with the highest frequency in K points before returning is used as the predictive classification of test data.

VI. EXPERIMENTS AND RESULTS DISCUSSION

This experiment uses Support Vector Machine and K-Nearest Neighbor algorithm to classify old and new coins. In the experiment, training samples containing 20, 60, 80 and 100 coins were used to train the classifier, and then the test samples containing 334 coin images were tested with the trained classifier. For circular object detection, the performance of Support Vector Machine and K-Nearest

Neighbor algorithm are compared under the different training samples.

A. Image Classification using Support Vector Machine

*1) Selection of Parameters.*In the experiment of this paper, we choose Linear Kernel Function as the kernel function of Support Vector Machine.

In addition to the selection of kernel function, there are also the setting of parameter C and parameter g, C represents penalty coefficient, g represents polynomial kernel function parameters, and their selection directly affects the performance of classifier. The system searches for each parameter (C, g) in grid, and finally uses cross-validation accuracy (C, g) as the parameter of Support Vector Machine.

2) Experimental results TableIshows the classification accuracy obtained and time of decision by using Support Vector Machine under the condition that the test sample contains 334 coin images and the training samples contain 20, 60, 80, and 100 coin images respectively.

TABLEI . Accuracy and time of image classification using Support Vector Machine

training sample (number)	**20**	**60**	**80**	**100**
Accuracy(%)	94.9102	94.91 02	95.2096	95.8084
Time(s)	0.0047	0.0048	0.0051	0.0055

B. Image Classification using K-Nearest Neighbor algorithm

*1) Selection of Parameters.*The K value with the highest correct rate is selected by cross validation.

2) Experimental results TableII shows the classification accuracy obtained by using the K-Nearest Neighbor algorithm under the condition that the test sample contains 334 coin images and the training samples contain 20, 60, 80, and 100 coin images respectively.

TABLE II. Accuracy and time of image classification using K-Nearest Neighbor algorithm

training sample (number)	**20**	**60**	**80**	**100**
Accuracy(%)	95.8083	96.4067	97.9041	97.9041
Time(s)	0.1079	0.1080	0.1092	0.1081

VII. CONCLUSION

Table.Iand IIare experimented with Support Vector Machine and K-Nearest Neighbor algorithm respectively under the same basic conditions.It can be found that under the same sample conditions, for the classification of one-dollar coins, the K-Nearest Neighbor algorithm can get more correct classification labels than the Support Vector Machine.But Support Vector Machine is faster. It can be verified that extracting the gray statistical features of each small sector region in the circular object image as feature vectors can express the image well.Put the feature vectors into the model (Support Vector Machine,K-Nearest Neighbor algorithm).The trained classification model can classify circular images well.

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