

A Novel Classification Algorithm for New and Used Banknotes

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Abstract With the development of global economy, the amount of banknotes is rapidly increasing. However, in the circulation process of banknotes, banknotes are readily torn or contaminated. The broken or contaminated banknotes should be retrieved by banks to keep the steady development of the economy. The banknotes sorting machine is a high-technology product with optical-mechanical-electrical integration, which utilize classification algorithms of new and used banknotes as their key algorithm. However, current existing banknotes classification methods suffer from time consuming and low accuracy. In this paper, through analyzing the feature of defects and contaminations in a gray-scale image, we propose an algorithm to classify new and old banknotes into five levels based on the statistical parameters of the feature points in a gray-scale image, gray level-gradient co-occurrence matrices and a multi-DAG-SVM classifier, which can be easily adopted by banknotes sorting applications. Experimental results show that the proposed method is a promising potential application with superior calculating speed and classification efficiency.

Keywords Feature points extraction · Gray level gradient co-occurrence matrix · DAG-SVM · Image classification · Banknote

1 Introduction

Banknotes play a significant role in modern economics [1]. The circulation of banknotes inevitably leads to contamination and depreciation of banknotes in different degrees [2]. Since old and contaminated banknotes can easily result in a shortage of currency supply which will affect the steady development of the economy, central banks retrieve these banknotes periodically. How financial institutions sort collected currency so as to distinguish whether the banknotes are available or not is emerging as a pressing problem needs to be solved.

For a long time, banknotes have been sorted artificially, which not only consumes plenty of manpower and material resources but also suffers from ambiguous standard. This promotes the development of the banknotes sorting machine. Utilizing automatic machines to replace manual sorting not only improves the efficiency, lowers the cost, but also improves the accuracy. In recent years, with the development of computer technologies especially artificial intelligence and image processing, researches of banknotes classification are rapidly increasing.

As we have mentioned before, banknotes recognition and classification have received a lot attention in recent years. Most researchers in this field focus on banknotes recognition. The classification of old and contaminated banknotes is becoming a central issue in currency sorting systems. Since, in 1998, Kang et al. presented a method to classify the sound data of banknotes, which is filtered by using

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BP neural network [3, 4], various other banknotes classification methods were proposed successively. Generally speaking, studies in this field can be divided into two categories: image-based and acoustic-based method. In 2008, Jiang et al. proposed an algorithm based on image recognition for old and new banknotes classification reserved in the fifth edition of RMB [5]. In 2009, J. W. Dong et al. put forward an algorithm based on color image processing [6]. In 2010, Hong Wang et al. proposed an approach based on BP-LVQ neural network [7]. Besides, Shan Gai et al. used quaternion wavelet transform and contourlet transform for banknotes classification [8, 9]. Seyed Aliakbar Mousavi et al. adopted MLP neural networks, LVQ and SOM in classification [10].

Though these studies have achieved remarkable progress in the aspect of both accuracy and time consuming, there still exist some problems in this field. The algorithm proposed by Kang utilizes the sound data of paper currency, which leads to low accuracy and weak robustness. Because, acoustic signals are not stable and they could be easily affected by noise and environment. The algorithm proposed by Jiang et al. only focuses on the reserved region while ignoring other regions which may be stained. The algorithm proposed by Dong et al. based on HSI color model demands large calculation which requires much time. In practical banknotes classification applications, time consuming is a significant factor, because most of these applications should process dozens of banknotes per second. However, neural network-based methods suffer from time consuming. Statistical analysis-based methods suffer from low accuracy and false detection.

Considering the above problems, first of all, we define five grades according to the degree of banknotes' contamination and breakage. Based on the five grades that we have defined, we present a method which makes statistics of the selected feature points as well as the gray level-gradient co-occurrence matrix, then sort the banknotes by a DAG-SVM classifier. Considering the high real-time requirement, we use the gray scale image in BMP format. Besides, we conducted serial experiments to test the accuracy and efficiency of the proposed method. According to our experiments, the features adopted in the proposed method can retrieve the characteristics of the five grades of banknotes respectively. Besides, the experiments have also proven that the proposed method can classify banknotes into five grades with more than 98 % accuracy.

The paper is organized as follows. Related work especially on gray level-gradient co-occurrence matrix and DAG-SVM classifier is given in Section 2. The classification algorithm including feature extraction and algorithm flow is introduced in Section 3. Section 4 discusses the experimental results and correlated analysis. Conclusion and relevant discussions are in Section 5.

2 Related work

This section introduces the related work in brief to help understand the development of banknotes classification and algorithms adopted by the proposed method. Briefly, first of all, we will demonstrate the development of banknotes classification especially old and new classification. Then we will illustrate feature extraction methods that we adopted in this paper. Finally, we will introduce some basic ideas and developments of SVM.

2.1 Banknotes classification

In recent years, most researchers focused on banknotes recognition of different kinds [11], classification of banknotes into categories of different value [12] and recognition of forgery [13]. Little work focused on the classification of old and contaminated banknotes.

The problem of old and worn banknotes classification was firstly proposed in 1996 [3, 4]. In serial researches of Kang et al., they defined the basic guideline of this problem, and adopted some machine learning algorithms such as neural networks to solve this problem. The most challenging work in this field is how to acquire high classification while guarantee time efficiency. Generally speaking, classification of old and worn banknotes can be divided into two kinds of methods: acoustic-based methods and image-based methods.

Image-based methods consist two subprocess: feature extraction and classification. Most of these approaches transform this problem into a classification problem in machine learning such as [3, 4]. In [14] Sun et al. proposed a method based on SVM to recognize the banknotes levels of new and old. However, in their work, they only considered the degree of old and new. Contamination and breakage were not taken into consideration. Artificial Neural Networks were also adopted in denomination recognition [15]. In [16], Liu et al adopted LVQ network in damaged RMB recognition. They classified banknotes into two categories: new and old banknotes. This is not sufficient enough for modern applications. Besides, though their method seems achieved high accuracy, train a neural network spends a lot of time.

Acoustic-based methods classify banknotes by utilizing acoustic signals. In [17], a dynamic spectrum classification method was proposed. In this paper, the authors also investigated the influence of kernel functions on banknotes classification.

2.2 Feature extraction

The quality of features in machine learning algorithms directly result in the efficiency of the algorithm. In [18],

Wang et al. studied how to effectively extract invariant features to enhance banknotes classification. In the following, we briefly introduce some state-of-the-art features which have achieved great success in other fields of image processing.

2.2.1 GLGCM

Texture feature extraction technique is an important step for image recognition, there are histogram properties [19], local binary pattern [20], autocorrelation [21], gray level co-occurrence matrices [22], and so on. Gray level co-occurrence matrix (GLCM) were presented by Haralick in 1973, and have been employed in extracting texture features for a long time.

Gray level gradient co-occurrence matrix (GLGCM) was developed to capture the second order statistics of gray level gradients by Wang-Cheung Lam S. in 1996. Gray level gradient co-occurrence matrix reflects the relationship between the gray level and gradient in the image.

The way to analyze texture with gray level gradient co-occurrence matrix is to extract texture feature in an image by using comprehensive information of gray level and gradient [4]. The element of GLGCM $H(x, y)$ is denoted as the number of the pixel, which gray value is x in the normalized gray image and the gradient is y in the normalized gradient image, that is the number of elements contained in the collection $\{(i, j) \mid F(i, j) = x \cap G(i, j) = y, i, j = 0, 1, \dots, N - 1\}$, where $F(i, j) \in [0, L - 1], G(i, j) \in [0, L_g - 1]$.

We normalize the gray level-gradient co-occurrence matrix to make the sum of every element to be 1, as shown in Eq. 1.

$$\hat{H}(x, y) = \frac{H(x, y)}{\sum_{x=0}^{L-1} \sum_{y=0}^{L_g-1} H(x, y)} \tag{1}$$

Due to , the equation above can be also presented as Eq. 2.

$$\hat{H}(x, y) = \frac{H(x, y)}{N^2} \tag{2}$$

The origin of the matrix is in the top left corner, where gradient value increases toward right and gray level increases toward down. For images with coarse texture, there is concentrated distribution of around gray level axis, while only a few boundary points stay away from the gray level axis. However, for fine texture, is distributed along gradient axis instead of gray level one [5]. The followings are the numerical characteristics in gray level gradient co-occurrence matrix used in this paper. 1) Inhomogeneity of Grayscale

Distribution: $T_1 = \sum_{x=0}^{L-1} [\sum_{y=0}^{L_g-1} H(x, y)^2]$ 2) Inhomogeneity of Gradient Distribution: $T_2 = \sum_{y=0}^{L_g-1} y [\sum_{x=0}^{L-1} H(x, y)^2]$ 3) Average Grayscale: $T_3 = \sum_{x=0}^{L-1} x [\sum_{y=0}^{L_g-1} H(x, y)^2]$ 4) Average Gradient: $T_2 = \sum_{y=0}^{L_g-1} y [\sum_{x=0}^{L-1} H(x, y)^2]$.

2.3 DAG-SVM [23, 24]

The support vector machine (SVM) is presented by Corinna Cortes [25] in the 1995, SVM is a learning machine to solve two-group classification problems. For a multi-classification problem, John C. Platt [23] proposed a new algorithm called DA-GSVM. The Decision Directed Acyclic Graph (DDAG) is employed in the algorithm, which combines many two-class classifiers into a multi-class classifier.

DAG-SVM is an algorithm which combines the results of 1-v-1 SVMs. From Fig. 1 we can see that it is safe to discard the losing class, because all of the losing classes are far away from the decision surface, that is to say, the DAG-SVM separates the individual classes with a large margin. The DAGSVM algorithm is superior to many other multi-class SVM algorithms, especially in the evaluation time, because it can reach the result only after 4 decisions.

3 Classification algorithm for old and contaminated banknotes

The classification algorithm proposed by this paper is introduced as follows. First of all, sort the banknotes in data set artificially. Then, extract some features from the feature points and the GLGCM. Finally, train a SVM model by using a labeled training data set. Then we test the trained model in a test set.

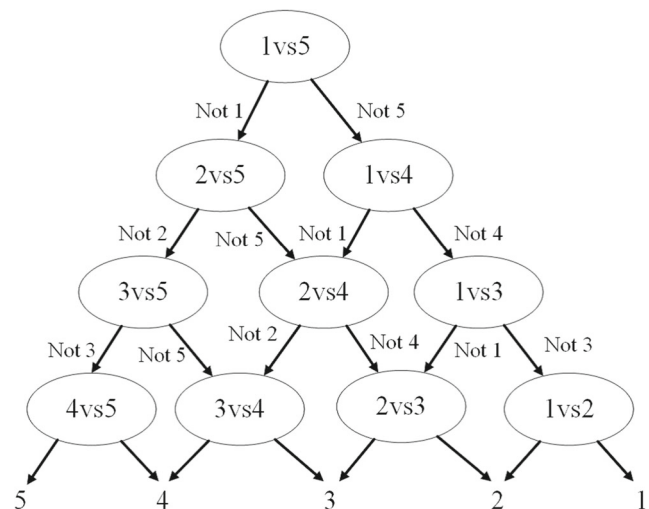


Fig. 1 The decision DAG for finding the best class out of five classes

3.1 Search of feature points

First of all, the proposed algorithm needs to search some feature points to represent the lighter points. The main ideas in feature points search includes:

- 1) Highlights with high gray level;
- 2) edge around this point in a certain range;
- 3) N points selected in total with uniform distribution in the whole image.

There are several reasons why we choose these points as feature points. First, the points with low gray level are not suitable to be feature points for they are less obvious after banknotes depreciation than those with high gray level. Then due to no accurate matching before classification, no edge around this point in a certain range is needed so that even if there are some deviations, the change of gray value will be acceptable. Finally, it is more representative for the information of feature points we selected when these points have comparatively uniform distribution.

The concrete steps for extraction of feature points are as follows.

- 1) Calculate the gradient in four directions for each point, and save the maximum gradient of each point to the corresponding Buffer;
- 2) Traverse from the point (d, d) ;
- 3) Traverse the next point (x, y) one by one from left top to the right down. If the point (x, y) chosen now does not meet the condition $d \leq x < width - d, d \leq y < height - d$, go to 8);
- 4) Judge if the gray value of the chosen point (x, y) is less than the average gray value of the whole image. If so, turn to step 3);
- 5) Check the gradient values within d range from this point. If there is a gradient value larger than α in this region, go to 3);
- 6) Check if there has already been a feature point in d range from this point. If there is one, turn to step 3), and start the traverse for next point;
- 7) Save the coordinate of the point in our feature point set and add one to register count, then turn to step 3);
- 8) After the end of traverse, judge if the value of count equals N . If so, the algorithm ends. Otherwise, if it is larger than N , increase the value of d . Start traverse and judge it again until they are the same. If it is smaller, choose the result which is the last time in condition of count bigger than N and reject count- N feature points by programs randomly. If count is smaller than N at the very first time, decrease the value of d , which is similar to the situation of count bigger than N .

In the algorithm above, N is the total number of the feature points, d is the radius adjusted by the algorithm itself,

Table 1 Selection of parameters

	Linear	Polynomial	RBF	Sigmoid
C-SVC	98.5	81.5	28	27.5
V-SVC	95	96	28.5	15

α is the threshold of gradient to distinguish whether a point is in the edge or not, width is the width of the image, and height is the height of the image.

As we can see in the algorithm, the complexity to calculate every point's gradient is $O(n^2)$. The complexity to select feature points is $O(n \cdot d \cdot d)$. Thus, the total complexity of feature extraction is $\max(n^2, n \cdot d \cdot d)$.

After searching the feature points, we can calculate the average of the grey scale simply without solving the troublesome image registration. The process is shown in Algorithm 1.

3.2 Extraction of the digital feature in the GLGCM

The depreciation of banknotes mainly reflects in several respects: abrasion, stain, hole and fold. Abrasion leads to fade, means that the average of grey scale will be increased and the grey scale will become symmetrical. Stain, hole and fold will cause the grey scale in the region to decrease, while the grey scale will also become symmetrical. So the features will be affected by the depreciation are the average of grey scale, the average of gradient, the inhomogeneity distribution of grey scale, and the inhomogeneity distribution of gradient.

3.3 Train the SVM with the features

After the extraction above, the level of the picture, the average of the grey scale between the feature points, the average of grey scale, the average of gradient, the inhomogeneity distribution of grey scale, and the inhomogeneity distribution of gradient in the GLGCM combine a vector which can be used to train the SVM.



Fig. 2 A 100-yuan banknote of the fifth edition with face up

Algorithm 1 Feature

Require: $image_i$ is the i th input banknote image; N denotes the number of feature points that we require

1: $n = 0$; $feature_set = \emptyset$; $isLoop = True$; $count = 0$

Ensure: Arr_N the N feature points

2: **for** $i = 1$ to n **do**

3: **for** $j = 1$ to n **do**

4: $buffer[i][j] = \max\{gra(n_{i-1,j}, n_{i,j}), gra(n_{i+1,j}, n_{i,j}), gra(n_{i,j-1}, n_{i,j}), gra(n_{i,j+1}, n_{i,j})\}$

5: **end for**

6: **end for**

7: **while** $isLoop == True$ **do**

8: Traverse from the point $(x, y) = (d, d)$

9: **while** $count \neq N$ **do**

10: **if** not $\{d \leq x < width - d$ and $d \leq y < height - d\}$ **then**

11: break

12: **end if**

13: **if** $grey_{x,y} > avg_grey$ **then**

14: $(x, y) = \text{next point}$

15: Continue

16: **end if**

17: **for** $i = x - d$ to $x + d$ **do**

18: **for** $j = y - d$ to $j = y + d$ **do**

19: **if** $grey_{x,y} > \alpha$ **then**

20: $(x, y) = \text{next point}$

21: Continue

22: **end if**

23: **end for**

24: **end for**

25: **for** $i = x - d$ to $x + d$ **do**

26: **for** $j = y - d$ to $j = y + d$ **do**

27: **if** x, y is a feature point **then**

28: $(x, y) = \text{next point}$

29: Continue

30: **end if**

31: **end for**

32: **end for**

33: Add x, y to $feature_set$

34: $count++$

35: $(x, y) = \text{next point}$

36: **end while**

37: **if** $count == N$ **then**

38: $isLoop = False$

39: **end if**

40: **if** $count > N$ **then**

41: $d++$

42: $last_feature_set = feature_set$

43: **end if**

44: **if** $count < N$ **then**

45: randomly select n points from $last_feature_set$

46: return

47: **end if**

48: **end while**

Choose half of the pictures in each level of the data set classified artificially, extraction the features in these pictures to train the SVM. Then extract the features in the rest of pictures in the set, and check them by the SVM trained above. In this paper, we adopted the method similar to [26] to train a SVM classifier.

As is shown in Table 1, as the proposed method is a multi classification problem, we only consider SVC as kernel function. Through Table 1 we can easily find that linear C-SVC performs best. There are many researches focus on the complexity of SVM [27, 28].

4 The result and analysis of the experiment

In this section, we will illustrate serial experiments that we have conducted to test the proposed method. Besides, evaluations of the experimental results are also given in the following section.

4.1 Dataset

In this paper, we used 1000 pieces of RMB (hundred-yuan) bills of the fifth edition which is shown in Fig. 2. 800 of

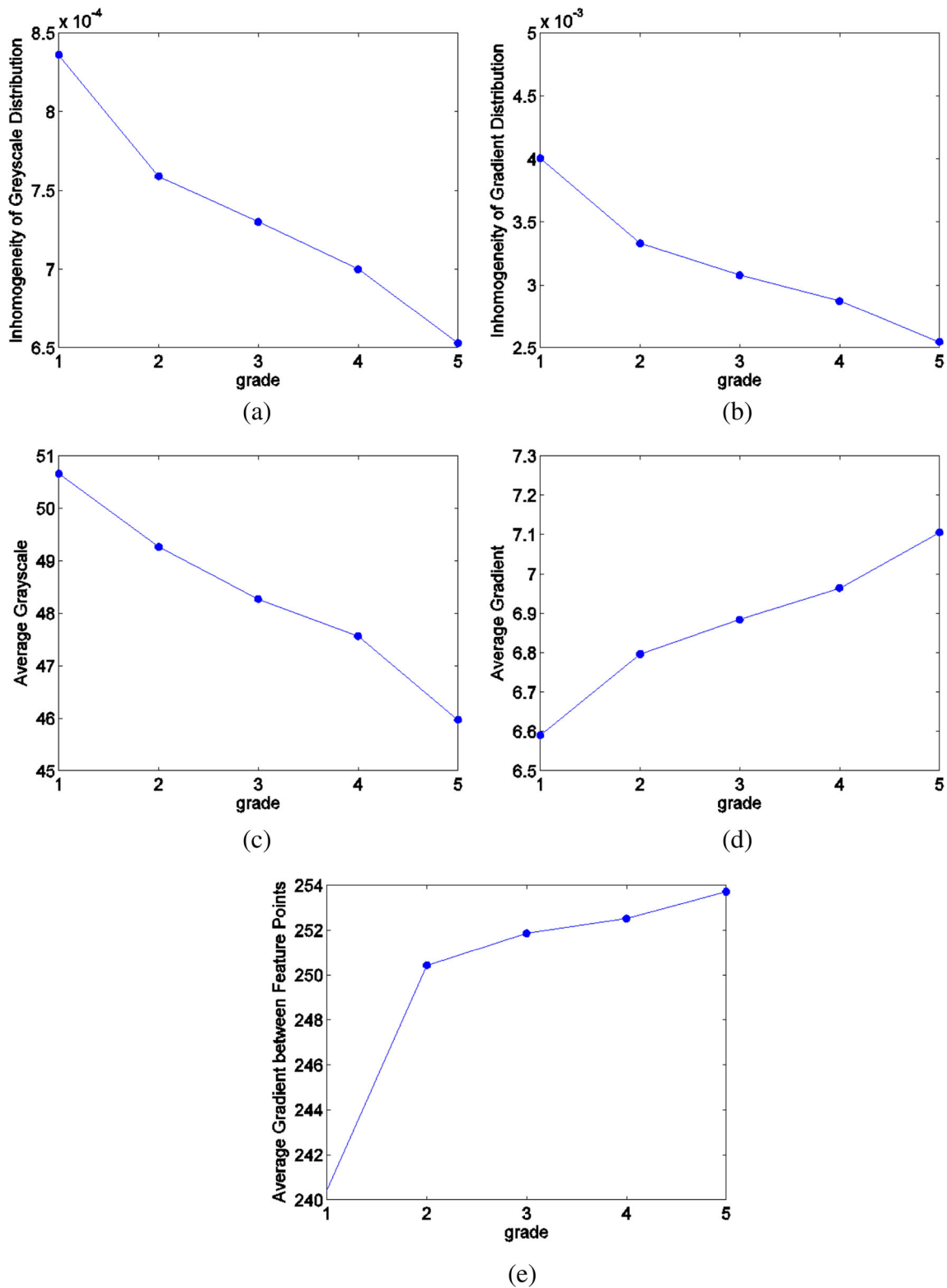
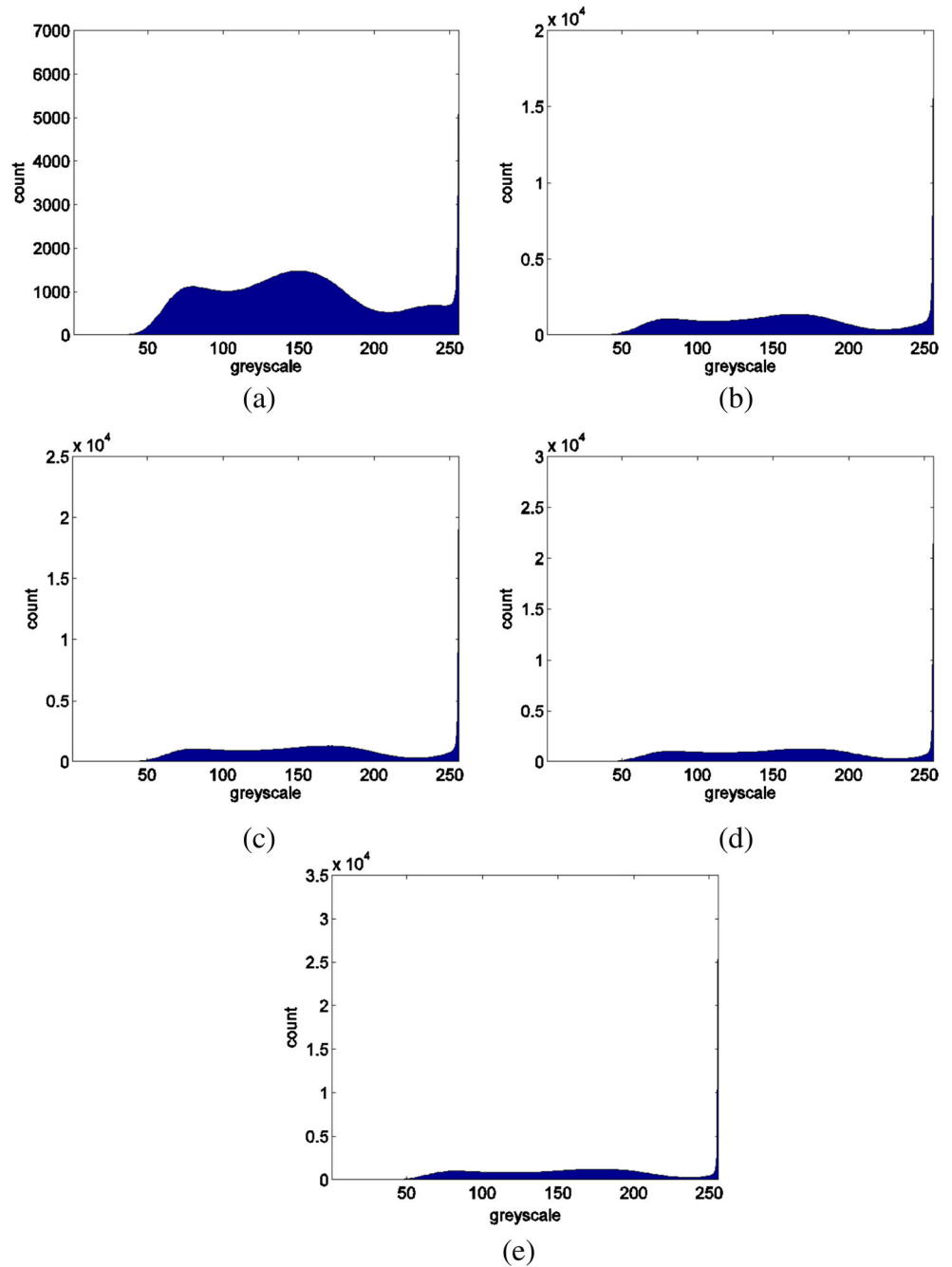


Fig. 3 The average value of the features in the grade is calculated to observe the change from level 1 to level 5. **a, b:** The inhomogeneity distribution of grey scale and gradient decline from old to new mean that as the depreciation of the banknote, the grey scale and gradient have a less uniform distribution. **c:** The average of grey scale falls from

old to new reveal that the abrasion plays an important role to increase the grey scale of the banknote. **d:** The average of gradient rises due to blur of edge contour in the picture. **e** shows an opposite phenomenon to that in (c) because that the feature points affected by the stain, hole and fold mostly)

Fig. 4 From (a–e), they are the grey scale distribution for grade 1 to 5



these bills are used as training set, while the other 200 bills are used as test set.

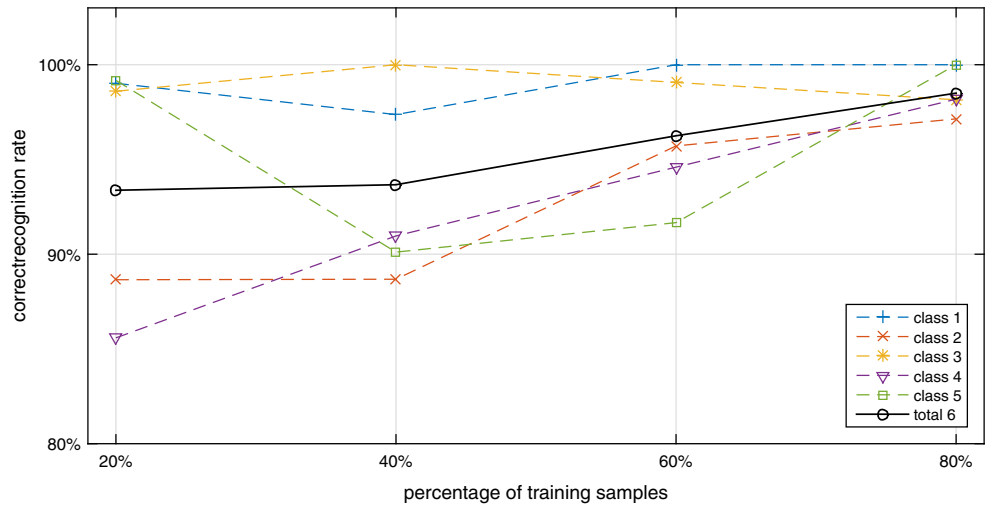
4.2 Efficiency of the selected features

Figure 3 shows the variation trend of the features extracted. However, it just tells us how much the inhomogeneity distribution is. Furthermore, we want to observe how the distribution of the grey scale is.

Table 2 Five levels classified by our algorithm

	Sample size	Correct quantity	Recognition rate
Level 1	202	201	99.51 %
Level 2	200	199	99.5 %
Level 3	208	208	100 %
Level 4	194	193	99.48 %
Level 5	195	195	100 %
Total	1000	997	99.7 %

Fig. 5 The change rule of accuracy varies on the size of training set



As is shown in Fig. 4, with the depreciation, the distribution becomes disperse clearly. Although the picture (c), (d), (e) look alike, it is noting that the y axis can find out the trend of dispersion is still existing.

4.3 Efficiency of the proposed method

The images are classified manually based on the “Circulated” Grades [25] of Banknotes Certification Service Company. Half of them which have been sorted by us are used as the training set and the rest are used as the test set.

The result after applying our algorithm is displayed in Table 1. (Level 1 represents the oldest, while level 5 the newest).

As is shown in Table 2, almost all the samples are in the correct classification. Furthermore, there is one for each level in level 1, 2 and 4 that are mistaken into level 3. Chances are that banknotes in level 3 are most common,

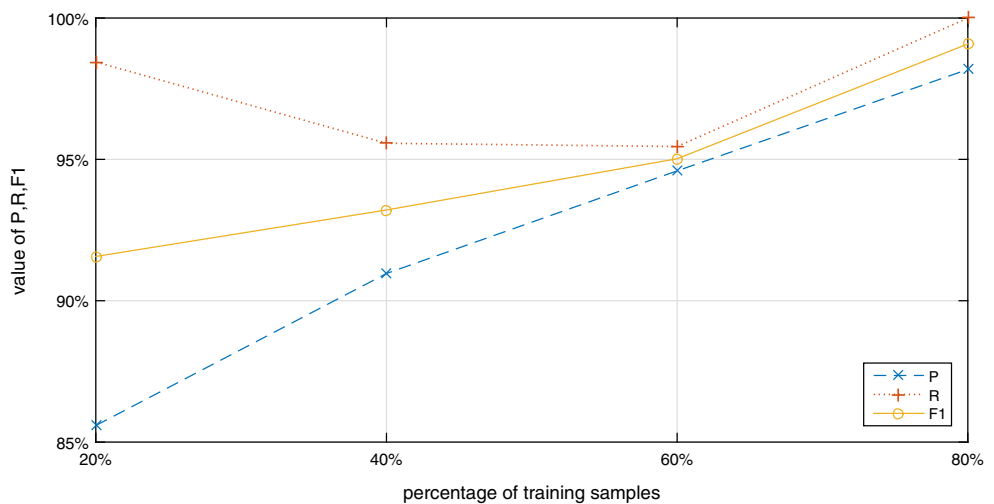
so that it is comparatively easy for other levels to be misjudged into level 3. The deeper observation on how every eigenvalue affects the situation is shown in Fig. 3.

As is shown in Fig. 5, the classification accuracy of the five levels of the proposed method increasingly improves with the increase of training set’s size. As we can see in Fig. 5, when we only adopt 20 % of all the data set as training set, the accuracy of the proposed method is 93.375 %. When we adopt 80 % of all the data set as training set, the accuracy of the proposed method is about 98.5 %. That is to say, the accuracy of the proposed method can increase stably with the increase of training set. In other word, our method is robust and practical.

To further elaborate the efficiency of the proposed method, we test every level of the proposed method. We adopt three criteria to test our method.

$$Sensitivity = \frac{TP}{TP + FN} \tag{3}$$

Fig. 6 The change rules of P, R and F varies on the size of training set



$$\text{Specificity} = \frac{TN}{TN + FP} \quad (4)$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FN + FP} \quad (5)$$

Take level 4 as example, TP means we can correctly classify a level 4 banknote; FP denotes we classify banknotes belong to other levels as level 4; TN denotes we classify other levels as other levels; FN means that we classify a banknote belongs to level 4 as other levels.

As is shown in Fig. 6, we can clearly see that P , R and F all increase with the increase of training set. When the size of training set reach 80 %, the values of P , R and F are larger than 98 %. This is also consistent with our previous experimental results.

5 Conclusion

With the rapid development of global economy, classification of old and contaminated banknotes is emerging as a pressing problem needs to be solved. In this paper, we present an algorithm to classify new and used banknotes into five levels. Firstly, we extract several features from grey-level banknotes images. Then we train a DAG-SVM classifier to classify banknotes. The benefit of our algorithm is that it gives consideration to the global characteristics and describes the changes of a certain area with light color by using its feature points. It has a better global superiority and higher accuracy and does not have the problem of failing to discover some fouling or wear outside the selected region compared with other method such as [5] which only use feature extraction from a certain feature region. Besides, real-time ability can be guaranteed as it takes the algorithm only 8–9 s to process 1000 banknotes, while the speed of currency-counting machine on the markets is around 1000 pieces per minute. Series of experiments are conducted to test the efficiency and accuracy of the proposed approach. The experimental results show that the proposed method can efficiently classify over 99 % banknotes into five grades.

Recently, deep learning algorithms have achieved great successes in image processing. In the future, we will utilize some state-of-the-art deep learning approaches in classification of new and old banknotes.

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