Recognition Method of Banknote Dirty Degree Based on Regional Image Texture Features and Threshold Selection

Fu-Jun Guo, Cheng Xing*, Jie-Sheng Wang, and Wei-Zhong Sun

Abstract—**To a certain extent, whether a banknote can continue to circulate depends on how dirty it is. Therefor, a multi-layer support vector machines (MLSVMs) recognition method based on regional image texture features and threshold selection was proposed. Firstly, the contact image sensor (CIS) is used to collect the double-sided reflection gray-scale images of banknotes under blue light, green light, red light, infrared light and ultraviolet light, and the gray-scale images under green light transmission and infrared light transmission. Secondly, according to the pattern distribution of banknote images, the collected banknote image is divided into 8 areas with different sizes, and 22 texture feature parameters, such as entropy, dissimilarity and correlation of the banknote image, are extracted based on the gray-level co-occurrence matrix (GLCM) to describe the visual features of banknotes dirty degree. Then the 22 texture features by using GLCM under different light sources in different regions are selected through thresholds. Finally, MLSVMs are used to recognition the dirty degree of banknotes, and the simulation results show the effectiveness of the proposed method.**

Index Terms—**banknotes dirty degree, gray level co-occurrence matrix, texture feature, multi-layer support vector machines, threshold feature selection**

I. INTRODUCTION

In today's rapidly developing economy, the circulation of banknotes is getting faster and faster, and the number of banknotes circulation is also increasing. At the same time, as the circulation time increases, the proportion of defective and dirty notes also increases. Nowadays, there are a lot of banknotes circulating all over the country. After entering the market, many people touch them directly, and a large amount of stain will quickly accumulate on them. Therefore, banknotes have become one of the media that imperceptibly harms the human body, which makes the commodity transactions and convenience of people's lives be affected to some extent. In order to prevent these dirty banknotes from continuing to circulate in the market, when the banknotes dirtiness reach to a certain extent, banks often destroy them and recycle them centrally. However, sorting banknotes by banks and other financial departments is onerous and inefficient. Effective methods should be adopted to classify, recycle and destroy the dirty banknotes. Banks and other types of financial institutions usually use banknote sorting machines and other related financial equipment to identification the authenticity of banknotes [1].

Both foreign and domestic scholars have done some studies on the identification of banknote features. Banknotes usually have different designs depending on their denominations. Therefore, if the characteristics of each design can be identified, they can classify banknotes according to denomination. Portraits on banknotes are one such feature that can be used for classification [2]. Oyedotun et al. proposed a framework of three cognitive hypotheses based on competing neural networks for visual recognition of banknote denominations [3]. Choi et al. proposed a fast identification method of banknote serial numbers based on machine learning, using Bayesian optimization method and simplified deep learning model for classification. After a lot of experiments, the results show that the method can effectively improve the classification accuracy of banknotes [4]. Lee et al. carried out a series of experiments and studied a method for classifying banknotes from various countries based on visible light images. The method uses sensors to collect visible light images, and combines denomination size information to classify using convolutional neural networks (CNN) [5]. Fitness classification is a specialized technique that can be used to assess banknote quality, if fitness classification is performed by a human, it may cause problems of different fitness classification and waste time. To solve these problems, Kwon et al. carried out a series of experiments and proposed a fuzzy system method that can reduce the processing time needed for program [6]. Jin et al. carried out extensive experiments and developed a new banknote image processing system, which includes processes such as banknote identification and feature recognition [7]. Sun et al. believed that banknotes have different gray histograms. In order to distinguish between old and new banknotes, banknote image histogram features and histogram alignment dynamic time warping (DTW) are adopted, as well as support vector machines (SVM) for classifying old and new banknotes [8]. Han et al. conducted multiple experiments and developed a machine learning-based method

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for banknote type identification and counterfeit currency detection, and proposed a novel artificial intelligence approach to visualize relevant regions that aid in banknote identification and detection. Significant improvement in computation time [9]. Lin et al. conducted multiple experiments and designed an improved six-layer Convolutional Neural Network whose program extracts relevant features from image sequence numbers [10]. The Switzerland central bank has conducted a lot of experiments in the identification of dirtiness banknotes. It is proved that the dirtiness feature of banknotes is mainly generated by the contamination of banknotes in circulation in people's hands. The color of the stains is mainly brown and yellow. The different soiling grades of banknotes are most different in the dark blue and indigo spectrum. Dirty grade banknotes have the biggest difference [11-12]. Ji et al. realized the RMB similarity measure extraction based on Kirsch operator and improved the discrete moment invariant, which can quickly, effectively and accurately determine the dirty degree of banknotes [13]. However, both domestic and foreign scholars have seldom investigate the identification of banknote dirtiness [16]. There are several reasons as follows. Firstly, affected by subjective factors, there is no uniform standard for the banknotes dirty. Even if it is the same banknote, the degree of oldness and newness will vary from person to person [14]. Secondly, financial equipment has a speed advantage in calculating the banknotes, has a faster speed in data collection, and has higher requirements on image recognition speed. Finally, the process of banknotes image collection may be influenced by many factors, such as illumination, image resolution radio, banknote clarity and so on. How to solve these problems has become the key point of researchers in this field. The dirtiness of banknotes, which can be reflected in terms of integrity, roughness, optical properties, the only one that most directly reflects the dirty degree of banknotes is the optical property [15]. Ji et al. discussed 4 main research methods (counterfeit detection, banknote identification, fitness classification, and serial number recognition) of various sensors for accurate banknote identification, and discussed the advantages and drawbacks of these research methods [16]. Finding a method that can effectively detect counterfeit banknotes is an important task in socioeconomic transactions [17]. For some specific areas of banknotes, Pham et al. found that the type, direction and side of banknotes are easier to distinguish than other areas, and after experimental validation, it is presented a novel method for recognizing banknotes [18]. Therefore, in order to complete the task of banknote identification, financial equipment like banknote sorters are generally used to collect the optical properties of banknotes.

This paper proposes an MLSVMs recognition method on banknotes dirty degree based on regional image texture features and threshold selection. The grayscale images of banknotes with different dirty levels are collected under the illumination of various light sources. Then the extracted banknote images were segmented, and 22 texture features were extracted from the banknote images based on GLCM to describe the visual properties of banknote dirty degree, for example entropy, dissimilarity and correlation. Finally, the feature selection of the 22 texture feature parameters of the gray level co-occurrence matrix under different light sources in different regions are selected according to the threshold value. Using MLSVMs to classify and identify the dirtiness of banknotes, the simulation test results show that the investigated method is effective.

II. Dirty Degree Analysis of Banknote Image and Texture Feature Extraction

A. Dirty Degree Analysis of Banknote Images

The dirtiness of banknotes is sorted manually, and a total of 1,000 pieces 100 RMB are collected. According to the dirtiness of the banknotes, the banknotes are divided into New, Clean, Normal, Dirty, Very dirty, there are five types of 100 RMB, each with 272, 200, 220, 170 and 138 banknotes. Then, the double-sided reflection grayscale images of these five categories of banknotes under blue light, green light, infrared light, red light, and ultraviolet light, and the gray-scale images of the banknotes under green light and infrared light transmission were collected to distinguish the dirtiness of the banknotes. The collected images are separated from the background and revised to acquire the same size image, each of these images has a resolution of 600 x 288 pixels [11]. The gray-scale images are used as samples to provide basic data for subsequent research.

B. Texture Feature Extraction of Banknote Images Based on Gray-level Co-occurrence Matrix

Texture is an image feature with local irregularity and macroscopic regularity, which reflects the spatial distribution of pixels, that is, local texture information. Different degrees of repeatability of local texture information, namely global texture features, image texture can reflect the dirty characteristics of banknotes. The Gray Level Co-occurrence Matrix (GLCM) is defined on an image as the distribution of pixel values that co-occur at a given offset, and is also defined as a matrix that calculates the degree of co-occurrence of adjacent gray levels in an image. It is a texture analysis method. Fig. 1 is a schematic diagram of the GLCM, where i and j represent the gray value of the corresponding pixel [19].

Suppose that $f(x,y)$ is a two-dimensional digital image, and GLCM refers to the probability $P(i,j,\delta,\theta)$ that starts from the pixel with the gray level of i in the image $f(x,y)$, the pixel $(x+\Delta x, y+\Delta y)$ with the deflection angle θ, the distance of δ, and the value of j appear at the same time.

$$P(i,j,\delta,\theta)=\begin{cases}\left[(x,y),(x+\Delta x,y+\Delta y)\right]\\ \left|f(x,y)=i, f(x+\Delta x,y+\Delta y)=j;\right.\\ x=0,1,\cdots,N_x-1; y=0,1,\cdots,N_y-1 \end{cases} \quad (1)$$

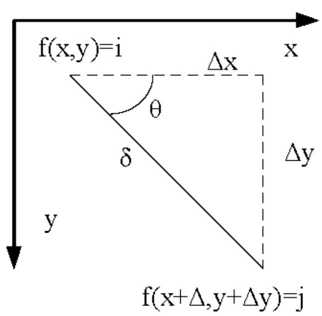


Fig. 1 Gray-level co-occurrence matrix.

where, $i, j = 0,1,\cdots,L-1$, x , y are the coordinates of the pixels in the image, L represents the number of gray levels, N_x and N_y represent the number of rows and columns of the image. In this paper, 22 texture feature parameters collected by GLCM are used to describe the contamination of banknotes [19].

III. Recognition of Banknote Dirty Degree Based on Regional Image Texture Features and Threshold Selection

A. Multi-layer Support Vector Machine

SVM is defined as a supervised learning method, which belongs to the generalized linear classifier, which can minimize the empirical error and maximize the geometric edge region, so the support vector machine is often also called the maximum edge region classifier [20]. When a sample set space $\Omega = \{(x_i, y_i) | i = 1, 2, \cdots, n\}$ is used to train the classification model $f(x)$, then use the model to classify the test sample set, compare the consistency between the predicted result category and the test data category, and calculate the coincidence rate to obtain the final result. It is known that the hyperplane expression in the sample space is:

$$w \cdot x + b = 0 \tag{2}$$

Eq. (2) satisfies:

$$\begin{aligned} x_i \cdot w + b \geq +1 \,,\; y_i = +1 \\ x_i \cdot w + b \leq -1 \,,\; y_i = -1 \end{aligned} \tag{3}$$

in the Eq. (3) , x is the feature vector, and b is a real offset, which determines the distance between the hyper-plane and the origin, w is the normal vector of hyperplane, which determines the direction of the hyperplane. From the Eq. (2)-(3) can obtain:

$$y_i(x_i \cdot w + b) - 1 \geq 0 \,,\; \forall i \tag{4}$$

According to Eq. (2) and Eq. (4), when w and b vary by the same ratio, hyperplane defined by them does note change. To solve this problem and enable hyperplane and $\{w, b\}$ to map to each other, impose stricter restrictions on w and b :

$$\min_i |x_i \cdot w + b| = 1 \,,\; i = 1,2,\cdots,l \tag{5}$$

At this time, the edge of hyperplane is defined by H_1: $w \cdot x + b = 1$ and H_2: $w \cdot x + b = -1$, and there is a parallel relationship between these two hyper-planes and H , it can be know from Eq. (4) that all training samples are not in H_1 and H_2 . Thus, SVM translates into the following expression for the optimization problem.

$$\min_{w,b} = \frac{1}{2}\|w\|^2 \tag{6}$$

Introduce the Lagrangian multiplier α_i and obtain:

$$\begin{aligned} &\min_{w,b} L_p = \frac{1}{2}\|w\|^2 - \sum_{i=1}^{l} \alpha_i y_i (x_i \cdot w + b) + \sum_{i=1}^{l} \alpha_i \\ &s.t. \begin{cases} \dfrac{\partial L_p}{\partial \alpha} = 0 \\ \alpha_i \geq 0 \,,\; \forall i \end{cases} \end{aligned} \tag{7}$$

$$\begin{aligned} &\max_{\alpha} L_D = \frac{1}{2}\|w\|^2 - \sum_{i=1}^{l} \alpha_i y_i (x_i \cdot w + b) + \sum_{i=1}^{l} \alpha_i \\ &s.t. \begin{cases} \dfrac{\partial L_D}{\partial w} = 0 \\ \dfrac{\partial L_D}{\partial b} = 0 \\ \partial_i \geq 0 \,,\; \forall i \end{cases} \end{aligned} \tag{8}$$

Further rewrite constraint conditions in Eq. (8) to obtain:

$$w = \sum_{i=1}^{l} \alpha_i y_i x_i \tag{9}$$

$$\sum_{i=1}^{l} \alpha_i y_i = 0 \tag{10}$$

Substitute Eq. (9) and (10) into Eq. (8) can obtain the final form of the SVM optimization problem.

$$\begin{aligned} &\max_{\alpha} L_D = \sum_{i=1}^{l} \alpha_i - \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l} \alpha_i \alpha_j y_i y_j (x_i \cdot x_j) \\ &s.t. \begin{cases} \sum_{i=1}^{l} \alpha_i y_i = 0 \\ \alpha_i \geq 0 \,,\; \forall i \end{cases} \end{aligned} \tag{11}$$

After solving Eq. (11), the α value can be obtained, and the w corresponding to hyperplane can be obtained according to Eq. (9). As everyone knows, support vector machine (SVM) is a typical binary classification algorithm in machine learning. However, the dirtiness recognition and classification of banknotes is a multi-classification problem, and there is no way to use a simple binary classifier to complete the classification. Therefore, the algorithm implementation in the multi-class case must be considered. After reconstruction, the SVM algorithm can be applied to multi-classification problems, mainly by combining multiple binary classifiers to realize the construction of multi-classifiers, there are two common methods: "one-to-one" (OVO) and "one-to-rest" (OVR). The OVR classification method used in this paper is used to classify the dirty degree of banknotes. Five types of banknotes need to be constructed with five 2-type SVM classifiers to enable the identification of dirty banknotes.

B. MLSVMs Recognition of Banknotes Dirty Degree Based on Regional Image Texture Features

Whether domestic or foreign, few scholars have segmented the banknote images and then investigate the identification of the banknotes dirty degree. Based on careful comparison and analysis on the real banknotes images, it was found that the dirtiness of banknotes in different areas is different. In areas with darker colors, the distinction between five types of banknotes is not very obvious, while in areas with light colors, the distinction between five types of banknotes is more obvious. This may be caused by people's usual holding habits of banknotes, so this paper divides the whole banknote into 8 areas with different sizes. The whiter area on the left is divided into 3 small areas and the whole whiter area on the left is one area. The remaining area is also divided into 3 small areas, and the whole banknote is one area.

Fig. 2 is an example diagram of 100 yuan RMB region segmentation. This article divides banknotes into full banknote area, left middle white area, left area, upper left white area, white area below the crown, middle 100 area, Mao head area and right area. The specific area descriptions are shown in Table 1. According to the different regions to be segmented, a total of 1000 banknote samples of 5 types of banknotes are processed in batches by region, and only the required regions are segmented to form a new image data set. Fig. 3 shows the multi-spectral segmentation images of white area in the left middle of the banknote.

For the formed 7 new banknote image data sets and the banknotes with different dirty levels of the full banknote area data set, there are 264 texture features of 12 images calculated by GLCM under the blue light double-sided reflection, the green light , the infrared light and the ultraviolet light double-sided reflection, also have the green light and the infrared light transmission. From the texture feature parameter data sets extracted from banknotes with different degrees of dirty, 20 data sets of each type banknotes are randomly selected as test samples, and the remaining data sets are used as training samples.

In the above 8 areas, the banknote dirty degree recognition model is trained and tested based on MLSVMs respectively. All the names of light sources are abbreviated, which are shown in Table 2. Fig. 4 shows the recognition accuracy of the banknotes dirtiness in each spectrum in the left middle white area. Statistics are performed on the average value of the recognition accuracy of banknote dirty degree randomly for 25 times simulation under different light sources and areas, and the experimental statistical results are showed in Table 3.

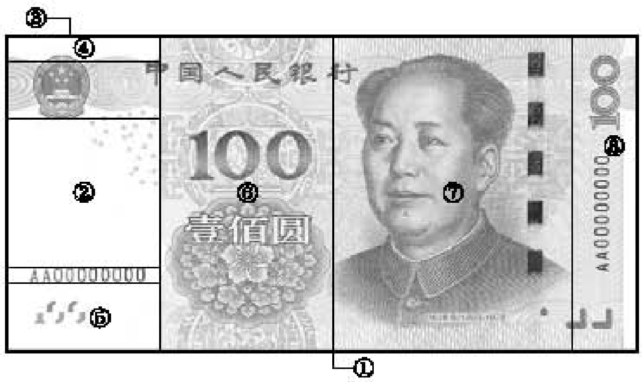


Fig. 2 Segmentation of banknote image area.

TABLE 1. DESCRIPTION OF BANKNOTE IMAGE AREA SEGMENTATION

Label	Illustrate
①	Full banknote area
②	Left middle white area
③	Left area
④	White area in the upper left corner
⑤	White area below the prefix
⑥	Middle 100 area
⑦	Hairy head area
⑧	Right area

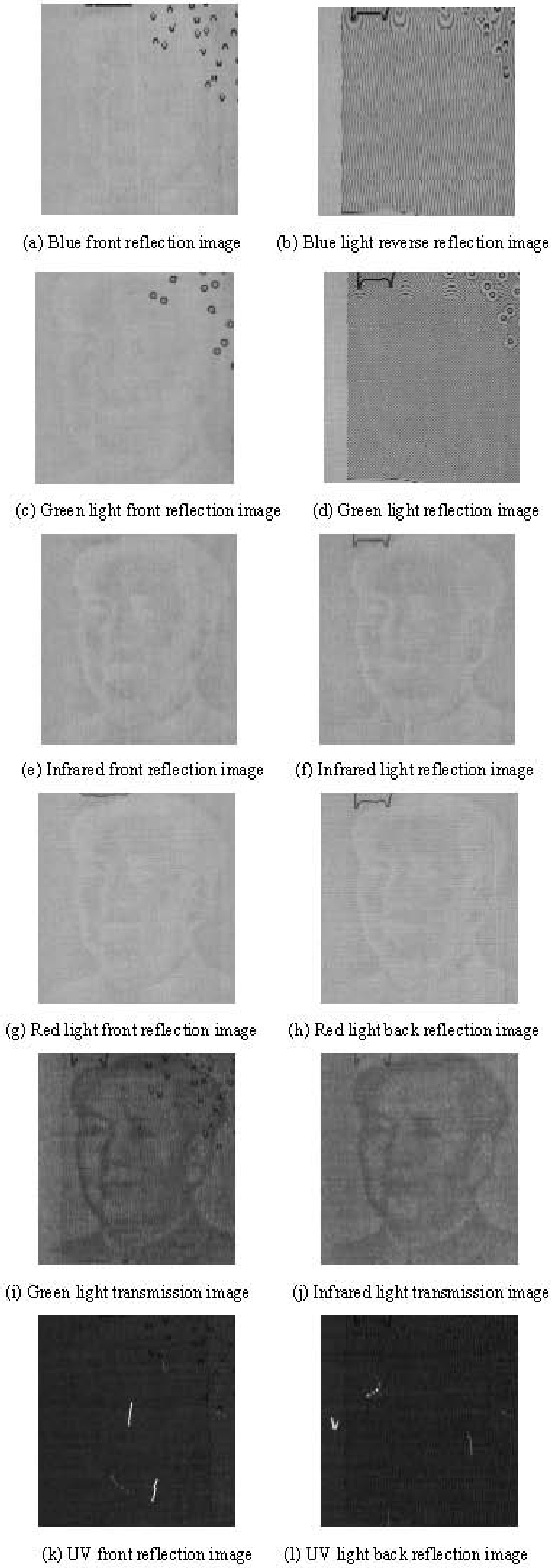
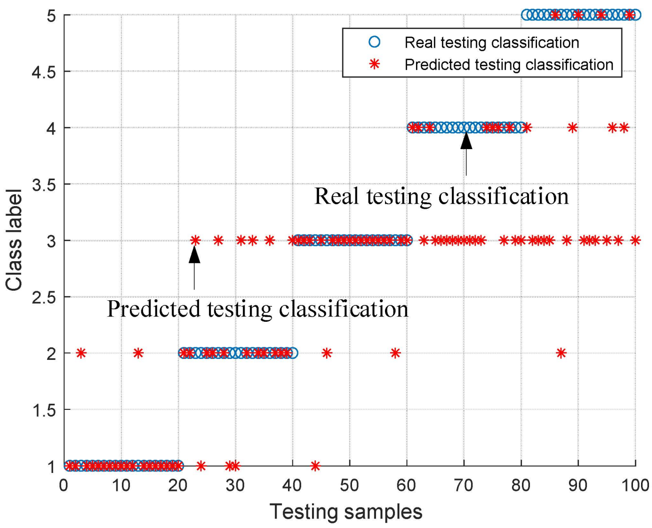


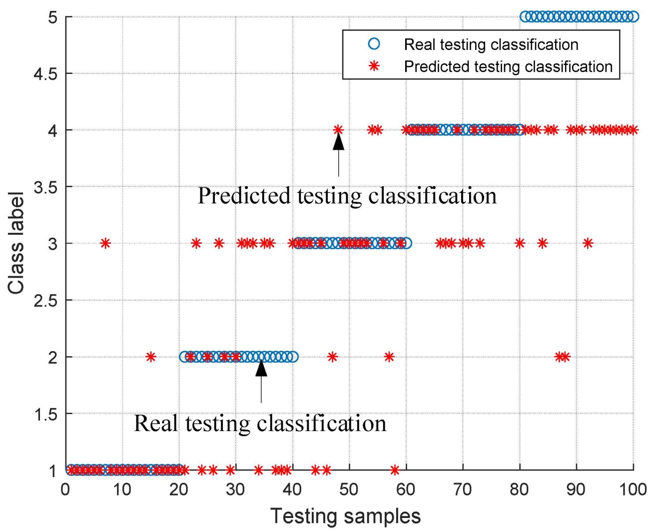
Fig. 3 Multi-spectral segmentation image of white area in the left middle of the banknote.

TABLE 2. ABBREVIATION DESCRIPTION OF LIGHT SOURCE

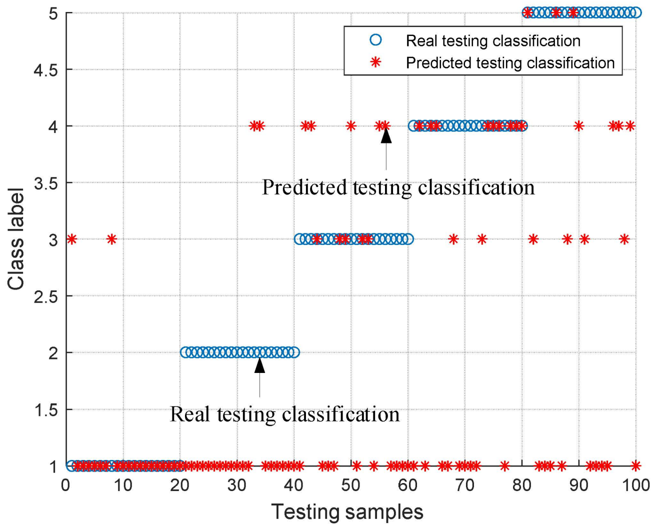
Label	Illustrate
ALL	Full spectrum image
BU	Blue reflection image
GN	Green light reflection image
IR	Infrared light reflection image
RD	Red light reflection image
TR	Transmitted light image
UV	UV light reflection image



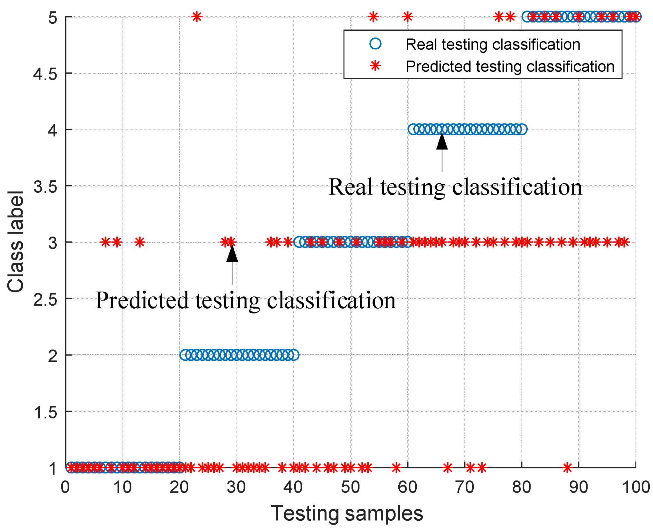
(a) Full spectrum image



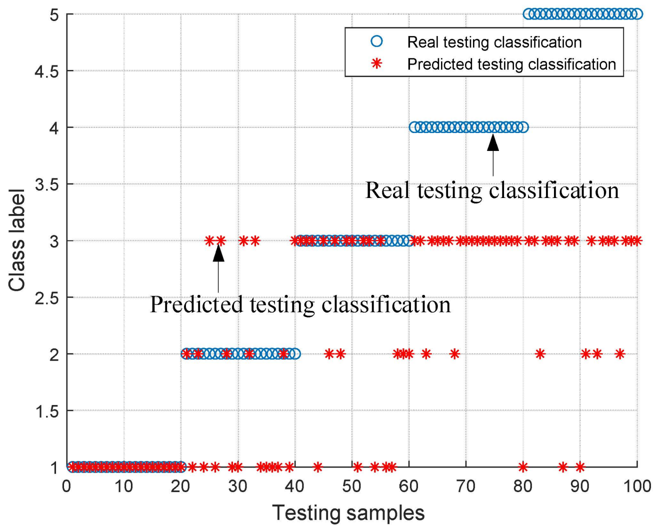
(b) Blue reflection image



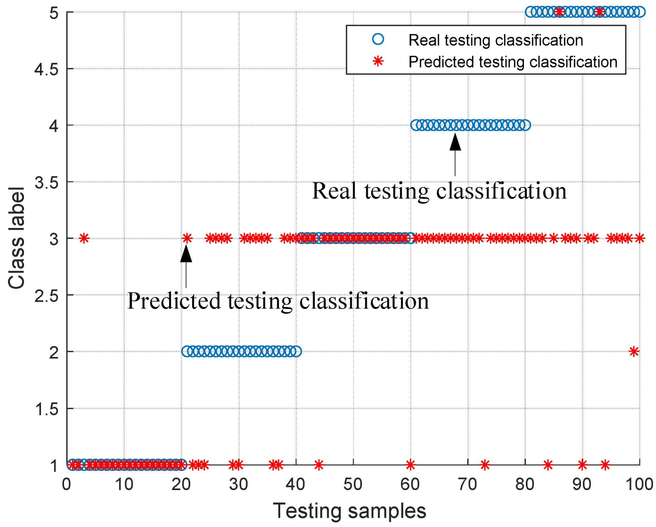
(c) Green light reflection image



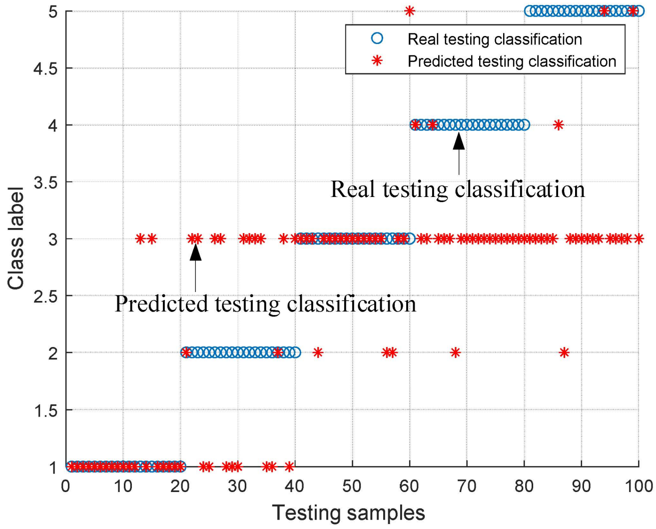
(d) Infrared light reflection image



(e) Red light reflection image



(f) Transmitted light image



(g) UV light reflection image

Fig. 4 Recognition of banknotes dirty degree based on MLSVMs.

TABLE 3. DIRTY DEGREE RECOGNITION RESULT OF BANKNOTES

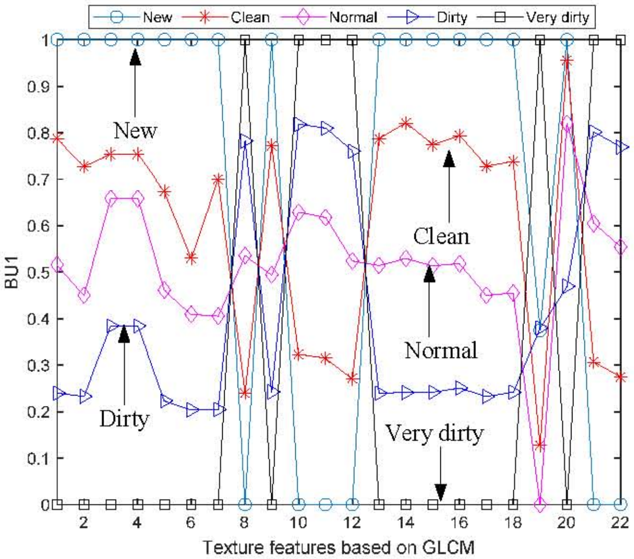
Area	Accuracy (MLSVMs with different illumination)						
	ALL	BU	GN	IR	RD	TR	UV
①	54.04%	48.44%	40.28%	35.04%	21.88%	46.60%	20.08%
②	52.72%	46.08%	27.32%	36.40%	36.92%	38.60%	42.84%
③	51.32%	48.52%	23.76%	39.80%	42.80%	34.68%	38.28%
④	47.40%	39.68%	25.92%	39.64%	41.08%	28.88%	36.92%
⑤	46.00%	46.56%	19.96%	37.00%	34.12%	30.36%	36.04%
⑥	48.88%	46.24%	20.56%	37.88%	42.60%	35.08%	47.32%
⑦	46.64%	43.04%	20.00%	30.56%	38.60%	33.44%	42.88%
⑧	45.64%	45.60%	22.56%	31.00%	35.48%	38.64%	38.88%

Through the comparison and analysis of Table 3, it can be concluded that the recognition accuracy of full spectrum banknotes is generally the highest, and the recognition accuracy of full banknotes area, the left middle white area, and the left area are relatively high and similar, both above 50%. The recognition accuracy of other areas is relatively lower. The left middle white area has a smaller area than the left area, and the average accuracy of full spectrum banknote discrimination is slightly higher than that of the left area, which shows that the left middle white area can replace the left area. The average accuracy difference between the rate of the full banknote area and the left middle white area is only 1.32%, which can be basically ignored. This shows that the left middle white area can completely replace the full banknote area to distinguish the old and new banknotes. Thus, the required recognition area is greatly reduced and the recognition speed is accelerated.

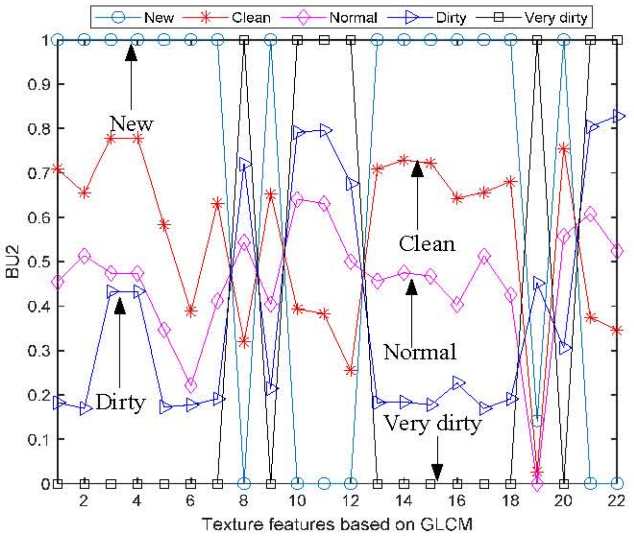
C. MLSVMs Banknotes Dirty Degree Recognition Based on Threshold Selection

(1) Analysis of Texture Features of Banknotes Images

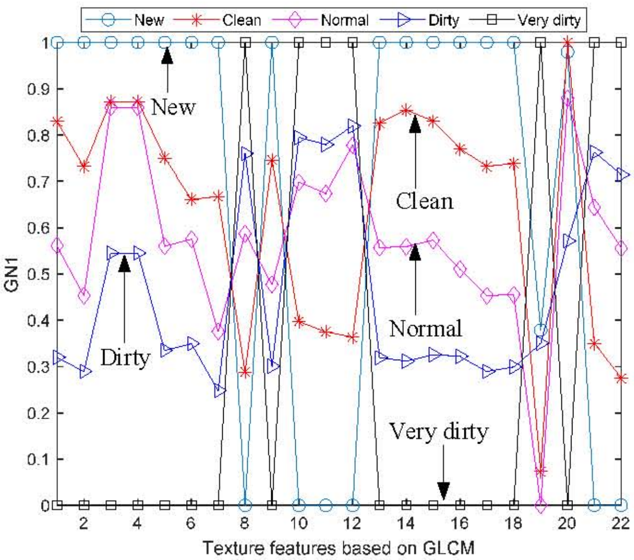
Although the banknote area segmentation method has reduced the required recognition area, it has not reduced the number of texture features. Every kind banknote has 22 texture feature parameters under each light source. Each banknote has blue light, green light, infrared light, red light, ultraviolet light front and back reflection grayscale images, and green light transmission grayscale images, infrared light transmission grayscale images, that is to say that there are a total of 12 images, which means that each banknote has a total of $12 \times 22 = 264$ texture features. But these 264 texture features may not be effective for distinguishing the dirty degree of banknotes. It is possible that a certain feature is effective under a certain light source, but is invalid under other light sources. Therefore, 264 texture feature parameters of five types of dirty degree banknotes are averaged for statistical analysis. The results ares shown in Fig. 5. The abscissa is 22 features, and the ordinate is the normalized average of 22 texture features of 5 types of banknotes. From Fig. 5 it can be concluded that the texture feature parameters of banknotes based on GLCM can reflect banknotes contamination, but the same kind of feature does not have the same influence on the recognition of banknotes dirtiness under different light sources, so a threshold feature selection strategy was proposed.



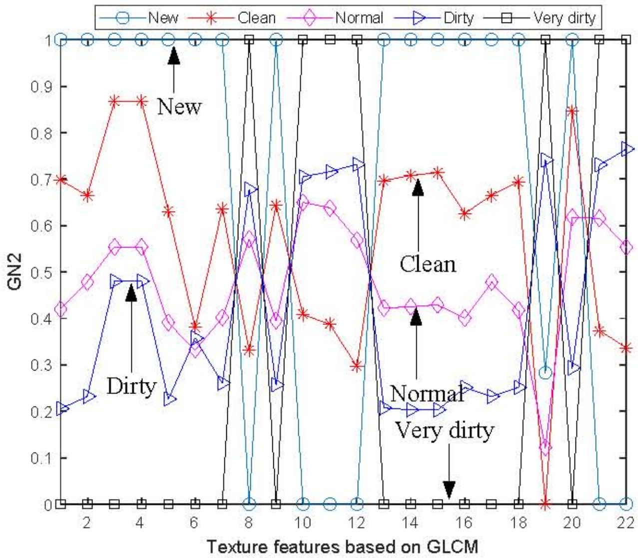
(a) Blue front reflection image



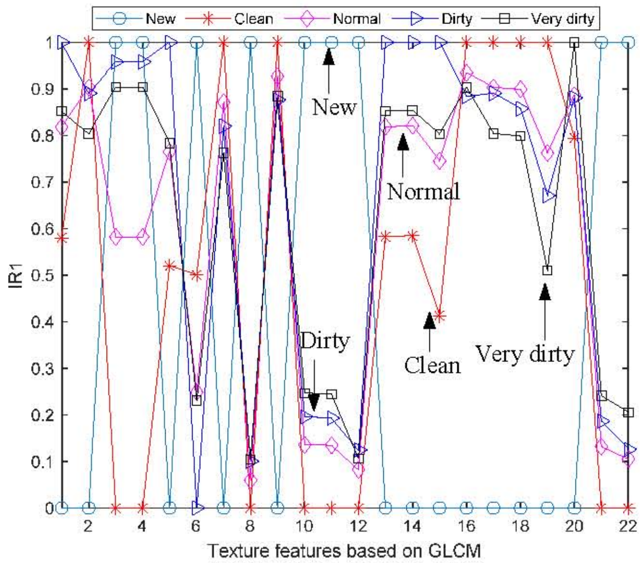
(b) Blue light reverse reflection image



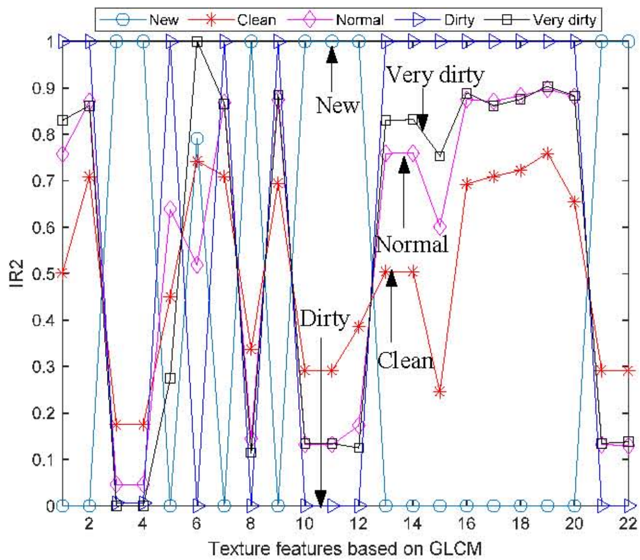
(c) Green light front reflection image



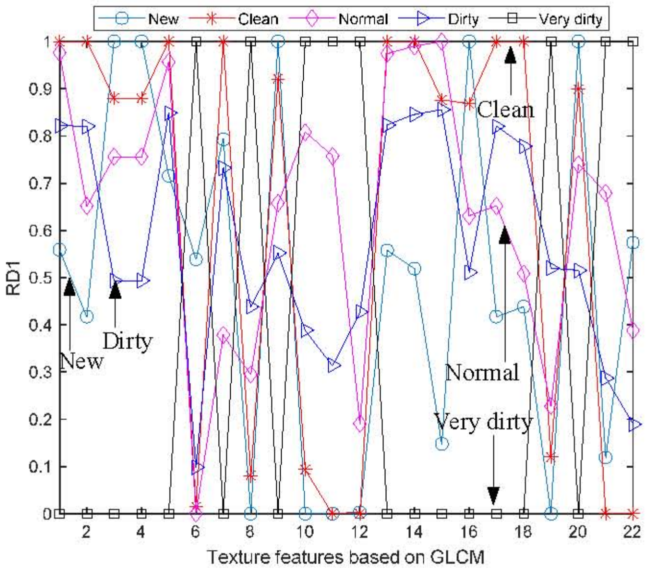
(d) Green light reflection image



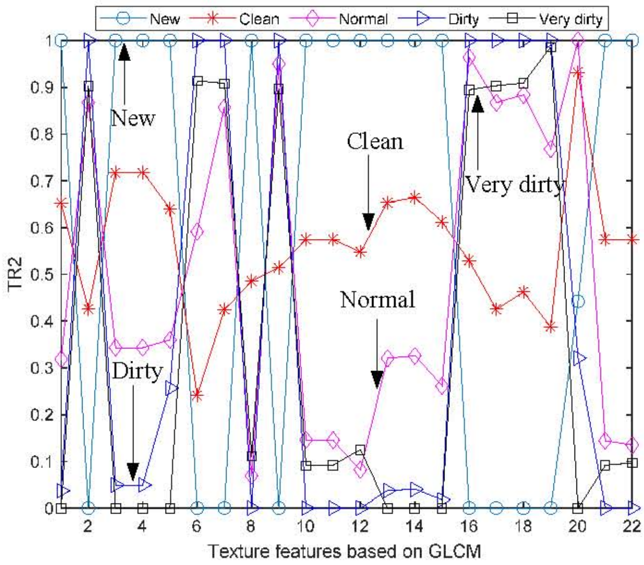
(e) Infrared front reflection image



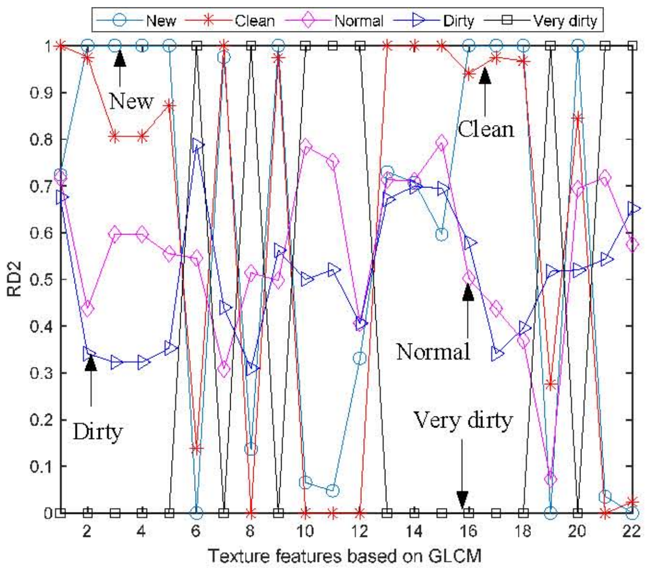
(f) Infrared light reflection image



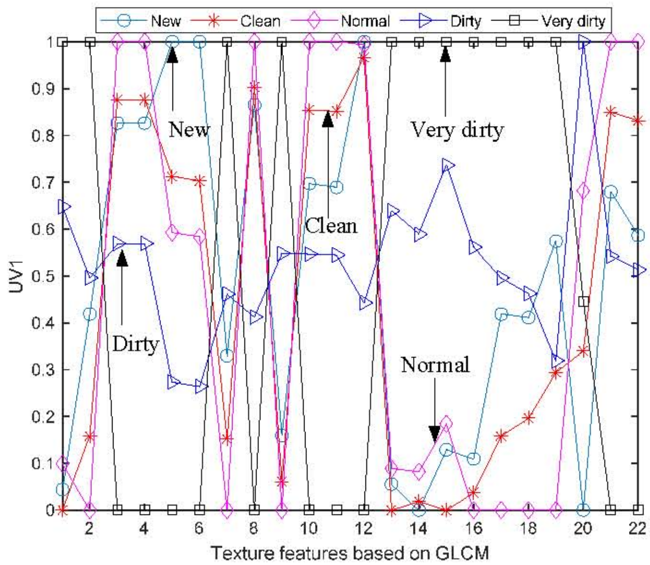
(g) Red light front reflection image



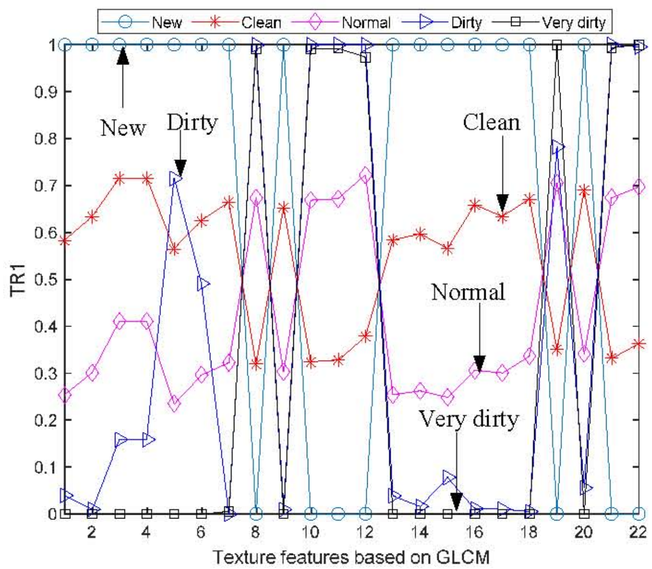
(j) Red light transmission image



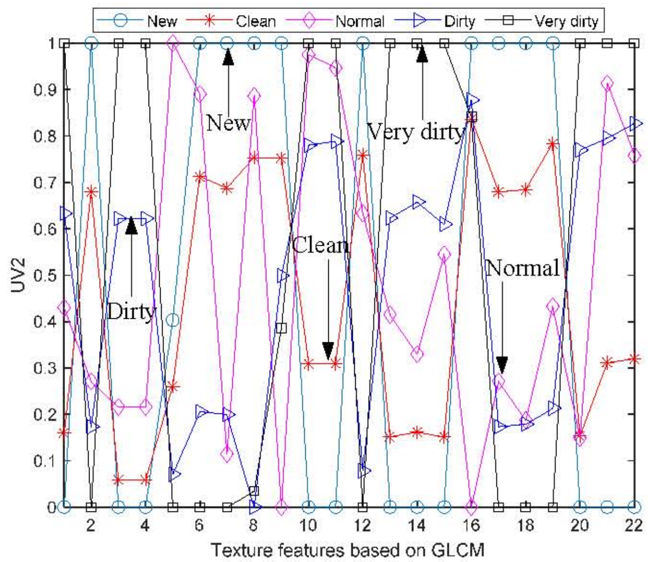
(h) Red light reflection image



(k) UV front reflection image



(i) Green light transmission image



(l) UV light reflection image

Fig. 5 Texture characteristics of multi-spectral images of five types of banknote.

(2) MLSVMs Banknotes Dirty Degree Recognition Based on Threshold Selection

1) First threshold selection method. Calculate the average value of the GLCM texture features extracted for each type of banknotes by column and combine the average matrix of 5 types of banknotes to form a large matrix. Then normalize it by column, and filter all 264 features by the preset threshold for the column texture characteristics. Under each threshold, the banknote dirty degree recognition simulation results are statistically performed 25 times randomly. The recognition accuracy results of the full banknote area with different threshold values are shown in Table 4, and the number of remaining texture features after screening is listed in Table 5. Although the number of texture feature parameters is reduced, the accuracy of banknotes dirty degree recognition is significantly lower than that of full texture features, so this threshold texture feature selection method cannot effectively reduce the number of features.

2) Second threshold selection method. Firstly, the texture feature data extracted from each type of banknotes are normalized by column, the average is calculated by column and the average matrix of 5 types of banknotes is combined into a large matrix. Then they are normalized again and all 264 texture features are screened according to the preset threshold value of the pair columns. Statistics are carried out on the simulation results of banknote dirty degree identification for 25 random times under each threshold. Table 6 lists the recognition accuracy results after screening of different threshold features with the full banknote area, the recognition accuracy curve is shown in Fig. 6, and the number of remaining texture features after screening is listed in Table 7. Compared with the feature recognition accuracy rate, this feature screening method basically does not reduce the recognition accuracy rate at the threshold value of 0.01-0.13, and fluctuates within 5%. When the threshold value is 0.14, the accuracy rate is significantly reduced, indicating that the threshold value of 0.13 is the critical point.

TABLE 4. RECOGNITION ACCURACY RATE AFTER DIFFERENT THRESHOLD FEATURE SELECTION WITH WHOLE TICKET

Accuracy (MLSVMs with different threshold values)				
Threshold value	0.112	0.15	0.17	0.2
Accuracy	42.20%	45.68%	45.52%	45%

TABLE 5. NUMBER OF REMAINING FEATURES AFTER FULL FACE FEATURE SELECTION

Illuminate	Features (MLSVMs with different threshold values)			
	0.112	0.15	0.17	0.2
Blue reflection image	36	33	30	13
Green light reflection image	30	22	14	5
Infrared light reflection image	2	2	1	0
Red light reflection image	13	6	3	0
Transmitted light image	4	3	0	0
UV light reflection image	11	4	1	1
Number of remaining features	96	70	50	19

TABLE 6. RECOGNITION ACCURACY RATE AFTER DIFFERENT THRESHOLD FEATURE SELECTION WITH WHOLE TICKET

Accuracy (MLSVMs with different threshold value)						
Threshold value	0.01	0.02	0.03	0.04	0.06	0.07
Accuracy	56.31%	55.96%	56.15%	55.31%	52.08%	53.77%
Threshold value	0.08	0.11	0.12	0.13	0.14	0.15
Accuracy	51.46%	54.50%	57.08%	55.23%	49.15%	46.12%

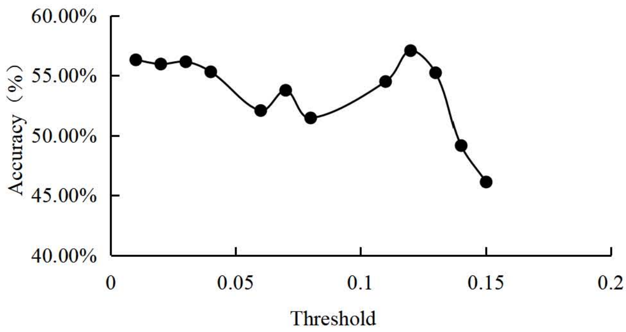


Fig. 6 Recognition accuracy curve of different thresholds for full face ticket.

TABLE 7. NUMBER OF REMAINING FEATURES AFTER FULL FACE FEATURE SELECTION

Accuracy (MLSVMs with different threshold values)						
Threshold	0.01	0.02	0.03	0.04	0.06	0.07
Blue reflection image	37	34	27	27	23	20
Green light reflection image	41	35	33	25	19	16
Infrared light reflection image	38	23	15	14	9	9
Red light reflection image	39	34	33	28	23	19
Transmitted light image	42	38	33	30	20	17
UV light reflection image	36	32	27	25	14	9
Number of remaining features	233	196	168	149	108	90
Threshold	0.08	0.11	0.12	0.13	0.14	0.15
Blue reflection image	15	12	12	11	7	6
Green light reflection image	13	9	6	5	5	5
Infrared light reflection image	9	6	4	2	1	1
Red light reflection image	19	16	11	9	6	6
Transmitted light image	13	8	7	5	4	3
UV light reflection image	8	4	3	2	2	2
Number of remaining features	77	55	43	34	25	23

At this point, the number of remaining texture features is 34. It can basically be determined that the remaining texture features at the threshold 0.13 can replace all 264 texture features, so that the number of texture features can be greatly reduced. Through targeted selection of texture feature parameters, the number of texture feature parameters on the recognition model can be reduced. In the same way, the texture feature selection was also carried out for the left middle white area, and the simulation results can be seen in Table 8, Fig. 7, Table 9.

Different from the full banknote area, the feature selection of the white area in the left middle does not reduce the accuracy of banknote dirty degree recognition at a threshold of 0.01-0.1, which fluctuates within 5%. When the threshold value reaches 0.11, the recognition accuracy is significantly reduced, indicating that the threshold value of 0.1 is the critical point. At this time, the number of remaining feature parameters is 40, and it can basically be determined that the remaining feature parameters at the threshold 0.1 can replace all 264 features so that the number of features can be greatly reduced. Through targeted selection of texture features, the number of texture features for the recognition model can be reduced. Whether it is the full banknote area or the left middle white area, when there are about 40 texture features remained after feature screening, the accuracy of the recognition of banknotes dirtiness can be kept stable.

In order to show whether the remaining features are consistent, Fig. 8 counts the number of remaining features under different light sources in the two regions. The full banknote area and the left middle white area reach the critical point when there are 34 texture features and 40 texture features respectively, and the number of remaining texture features is similar. However, it is obvious from Fig. 7 that the remaining texture feature parameters of the full banknote area and the left middle white area under different light sources are not the same. For example, under the frontal reflection of ultraviolet light, there are 0 feature remained from 22 features on the full banknote area, and 6 features remained from 22 features in the left middle white area.

TABLE 8. RECOGNITION ACCURACY RATE AFTER DIFFERENT THRESHOLD FEATURE SELECTION IN THE LEFT MIDDLE WHITE AREA

Accuracy (MLSVMs with different threshold values)						
Threshold value	0.01	0.02	0.03	0.04	0.05	0.06
Accuracy	53.73%	53.69 %	53.35 %	52.23 %	52.23 %	52.62%
Threshold value	0.07	0.08	0.09	0.1	0.11	0.13
Accuracy	52.19%	51.42 %	52.27 %	50.50 %	45.27 %	44.88%

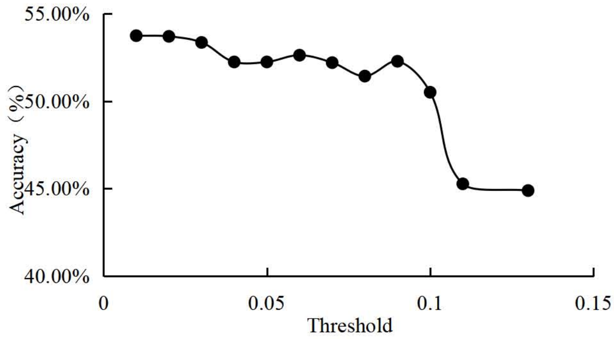
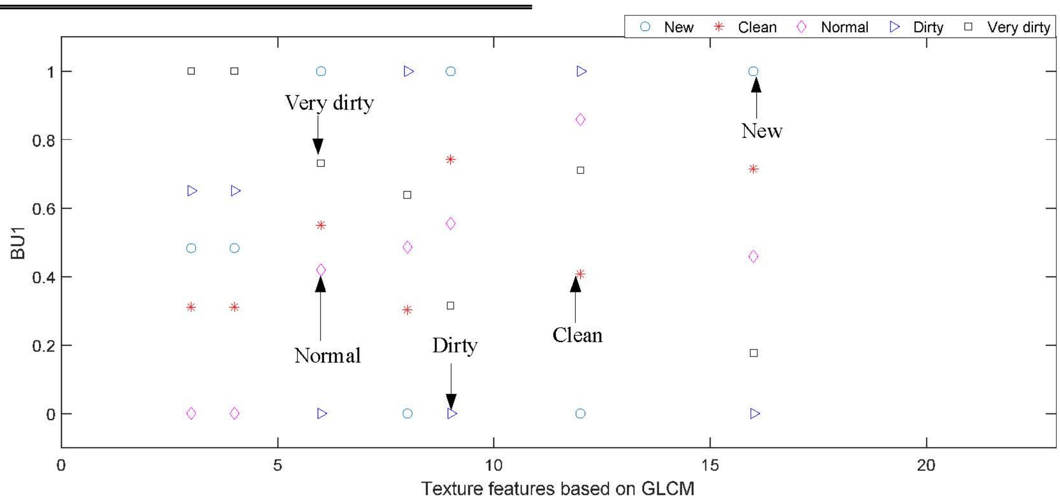


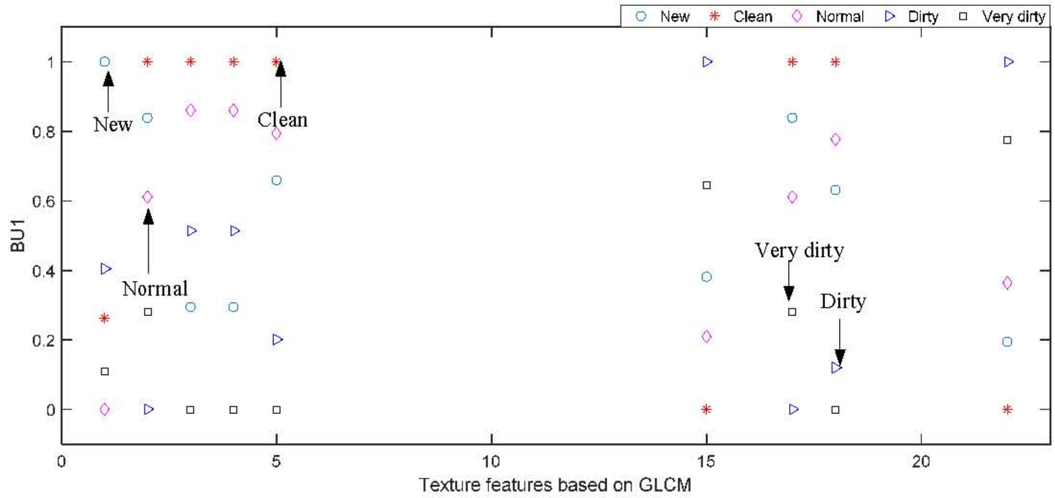
Fig. 7 Recognition accuracy curve of different thresholds in the left middle white area.

TABLE 9. NUMBER OF REMAINING FEATURES AFTER FEATURE SELECTION IN THE LEFT MIDDLE WHITE AREA

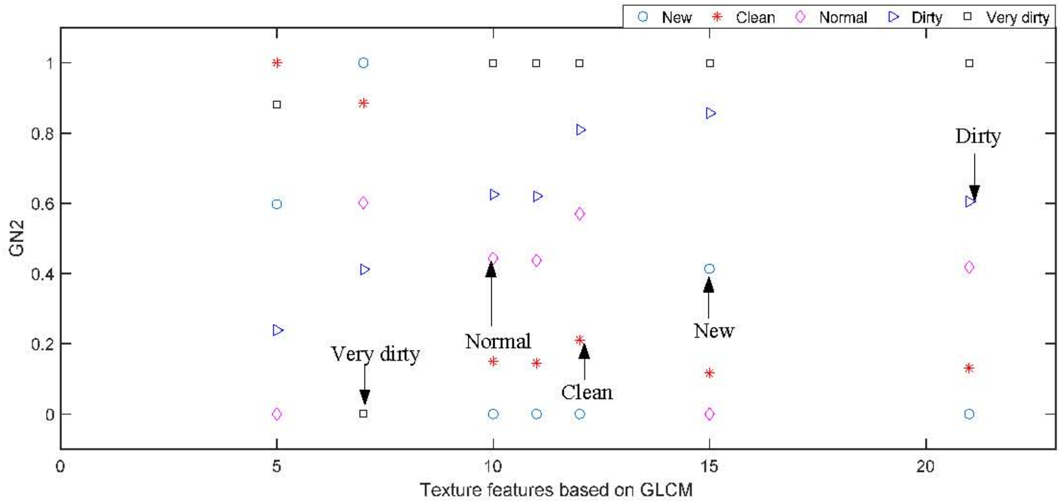
Accuracy (MLSVMs with different threshold values)						
Threshold	0.01	0.02	0.03	0.04	0.05	0.06
Blue reflection image	39	30	28	28	27	22
Green light reflection image	40	31	28	24	21	20
Infrared light reflection image	37	30	26	21	17	14
Red light reflection image	42	32	31	26	23	20
Transmitted light image	38	29	23	20	18	15
UV light reflection image	38	35	31	25	19	16
Number of remaining features	234	187	167	144	125	107
Threshold	0.07	0.08	0.09	0.1	0.11	0.13
Blue reflection image	20	16	13	12	11	10
Green light reflection image	19	14	11	8	8	5
Infrared light reflection image	9	7	5	4	1	1
Red light reflection image	17	15	6	5	4	2
Transmitted light image	14	9	5	4	2	0
UV light reflection image	14	13	8	7	3	0
Number of remaining features	93	74	48	40	29	18



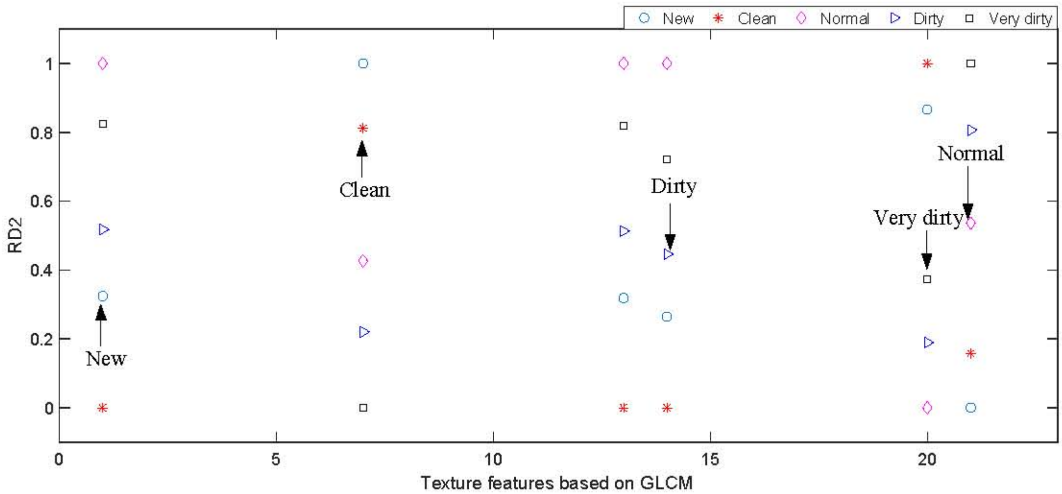
(a) Remaining features of the full-spectrum blue front reflection image



(b) Remaining features of the blue front reflection in the left middle white area



(c) Remaining features of the reflection image of the green light in the left middle white area



(d) Remaining features of the reflected image of the red light on the full-spectrum

Fig. 8 Remaining texture features after threshold selection.

This shows that in different regions, the remaining texture features after filtering through the threshold are not consistent. Different regions have different remaining texture feature combinations. These texture features are exclusive to the area of the banknote so as to adapt to the identification of the dirtiness of banknotes in the relative area.

IV. CONCLUSION

This paper proposes a novel MLSVMs dirty degree recognition method of banknotes based on regional image texture feature parameters and threshold selection. Firstly, the CIS acquires the double-sided reflection gray-scale images of the banknote under blue light, green light, red light, infrared light, and ultraviolet light, and the gray-scale images under green light and infrared light transmission. Secondly, the extracted banknote images were segmented, and 22 texture feature parameters were extracted from the banknote images based on GLCM to describe the visual features of their dirty degree. Finally, 22 texture features under different light sources in different regions are selected according to the threshold value. MLSVMs was used to recognition the dirty degree of banknotes and the experimental results show that the proposed method is effective.

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