A Novel Iris Texture Extraction Scheme for Iris Presentation Attack Detection

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***Abstract*—Iris recognition systems suffer from a new challenge brought by various textured contact lenses, as they can change the appearance of iris texture. To deal with this challenge, conventional methods use Gray-Gradient Matrix and Gray-Level Run-Length Matrix (GLRLM) to extract iris texture features, and use Support Vector Machines (SVM) for authenticity classification. These methods only pay attention to the statistical value of feature matrix, but they ignore the details of texture features and isolate inherent connections between these texture details. This paper reveals that the intrinsic connection of iris texture features under the large scale of the features of neural networks is highly valuable for effectively eliminating the interference of textured contact lenses. Under this premise, we propose a novel iris anti-counterfeit detection method based on an improved Gray Level Co-occurrence Matrix (*Modified-GLCM*) combined with a binary classification neural network. The experimental results show that the proposed method outperforms the conventional texture analysis methods using feature statistical characteristics and the best result of LivDet-Iris-2017. What's more, we analysis and verify the potential threat of the iris adversarial sample on the iris presentation attack detection algorithm through iris texture extraction.**

***Index Terms*—iris recognition, iris texture, iris presentation attack detection, iris adversarial samples**

I. Introduction

The uniqueness and stability of iris promote the application of iris recognition in large-scale biometric recognition systems, such as India's unique iris ID (UIDAI) [1]. With the improvement of hardware performance and the continuous improvement of biometric security level, iris recognition will have greater development and application space. However, with the popularization of iris recognition, the types and frequency of attacks against iris recognition systems have also increased. Typical means include using forged biometrics, replaying video attacks, and deceiving to alter the final recognition results, etc. [2], [3]. If an attacker only tries to enter the identification system through a system security vulnerability to tamper the identification result, such attacks can be prevented by repairing the system's vulnerability. However, in most cases, when attackers use forged biometrics to attack, the above defense methods cannot resist the attacks at all. Therefore, for effective detection of false iris in the iris recognition process, it becomes more necessary to consider new PAD method for existing advanced spoofing attack techniques (e.g. paper printed with iris). Besides, in recent years, the popularity of colored contact lenses has further increased the difficulty of iris presentation attack detection [4]. Attacks have been developed to deceive the system by wearing colored contact lenses printed with artificial textures [5]. In such attacks, due to the high similarity between artificial textures and real iris textures, the current iris anti-counterfeiting algorithms are still far from having the ability to effectively detecting them. Iris Liveness Detection Competition started in 2013 and the most recent one was held in 2017 [6]. The results of the report in the 2017 competition show that various types of iris anti-counterfeiting algorithms are far from reaching the acceptable detection ability when they are put into practical use to deal with artificial texture spoofing attacks.

Currently, feature extraction matrix GLCM combined with SVM [7] is a popular iris presentation attack detection algorithm. This method mainly makes use of the statistical characteristics of the feature matrix to effectively classify real and artificial irises. However, the scale of the features of the texture feature extracted by GLCM is relatively small and lacks flexibility. It's difficult to adaptively represent the correlation between the detailed texture features in the large receptive field. In addition, SVM classification itself only pays attention to some of the statistical features in the feature matrix, so it would ignore some detailed texture features that may be more distinguishable.

The focus of this paper is to cope with the challenge brought by the colored contact lenses, and propose a new anti-counterfeiting algorithm for high-precision fake iris that considers the correlation of the detailed features in the iris. We combine a modified feature extraction matrix GLCM with neural networks to expand the differentiation between colored contact lenses and real iris, so as to improve the detection rate of colored contact lenses. Here the modified feature extraction matrix is called Modified-GLCM. This method expands the scale of the features of the GLCM through the Manhattan distance, overcomes the shortcomings of the GLCM being sensitive to the direction of the texture features, and can effectively extract more iris detailed texture features and their associated information [8]. Based on it, the neural network for feature extraction can easily classify the

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obtained feature matrix Modified-GLCM, and retain more accurate iris texture information. Besides, since most PAD algorithms are based on texture feature detection, so the rest of this article verifies the threat of adversarial samples on most PAD algorithms from a theoretical and experimental perspective.

The contributions of this paper can be summarized:

- **The effect of scale of the features is verified for better classification results:** It's revealed that difference scales of the features can result in difference performances on classification. We propose a feedback mechanism to tune the scale of the features for improving the effect of classification.
- **An improved feature extraction method is well-designed for more sensitive texture features:** We propose an improved feature matrix *Modified-GLCM* that can expand the scale of the features for feature extraction. Through expanding the scale of the features of the GLCM, it extracts more information about regularity, repeatability and continuity between the detailed texture features in the colored contact lenses.
- **An adaptive classification method is used in a targeted manner:** It retains all the feature information extracted by the feature matrix, and accurately classifies the obtained feature matrix through a binary classification neural network.
- **The threat of iris adversarial samples is verified:** Since the adversarial samples are generated by training real samples, this article explains the adversarial samples from the perspective of texture analysis: why it is difficult for the PAD algorithms to detect adversarial samples.

The structure of the rest of this paper is as follows. Section II briefly outlines the important iris anti-counterfeit detection methods in the present technology. Section III presents our proposed method. In Section IV, experimental evaluations are performed. Section V summarizes the conclusions and talks about future work directions.

II. Related Work

The earliest iris presentation attack detection algorithm was proposed by Daugman [9] in 2003, using stray energy in two-dimensional Fourier spectrum to detect the printed iris. Due to the printing characteristics of the printer itself, periodical printing marks will be generated when printing the iris, which is reflected in the spectrum as a high energy in a certain frequency band. Such method has a certain effect on detecting printed paper iris. Many subsequent researches on iris anti-counterfeiting are based on this method. However, when the input fake iris image is intentionally defocused and blurred, high-frequency components will be difficult to detect. At the same time, with the development of the manufacturing process of the fake texture of the colored contact lens, the difference between the artificial texture and the real texture is becoming smaller and smaller, therefore, the method is not ideal for detecting artificial textures of the colored contact lens.

In order to solve the problem of detecting artificial textures of colored contact lenses, He [10] proposed some feature extraction matrices to extract the texture features of the iris, and then analyzed the characteristics of the texture features by statistical method to classify the iris. These features are just few part features of real iris. Therefore, this method can use support vector machine (SVM) to classify these several greatly different statistical features. This method has made great progress in detecting artificial textures of colored contact lenses. Many subsequent researches have referenced this kind of method, extracted statistical information of image texture through various feature extraction matrices, and then combined with SVM classification to complete iris anti-counterfeiting. Typical research is from Suvarchala *et al.* [7]. They further improved the feature extraction method based on He's [10] method, and used the gray gradient matrix (GLDM) and Gray-Level Run-Length Matrix (GLRLM) replace GLCM to extract iris texture features. The improvement of this method is that more statistical features representing iris are obtained through experimental statistical analysis. Therefore, the method has improved the recognition accuracy on a certain degree. Doyle and Bowyer [11] simultaneously improved the feature extraction method and classification method, used the BSIF feature extraction algorithm. They also drew the conclusion that whether accurate segmentation of the iris has little effect on the accuracy of authenticity detection.

What the above methods have in common is that they all select a small number of statistical features that characterize the texture of the iris, and then use the SVM classifier to classify these features. Its advantage is obvious. Simple calculations can get excellent classification results. However, this method also has some unavoidable disadvantages:

- The feature matrix of this kind of method can only pay attention to the gray relationship between pixels in adjacent or very small areas (actually it's defined as scale of the features [12]). It's difficult to extract the correlation and regular information between the detailed features under the large scale.
- No matter how this kind of method improves the feature extraction method, the result is that only some statistical features through objective analysis are input into the SVM classifier for classification. In this way, the classification basis is completed by artificial screening, which is subjective and unreliable. Therefore, no matter how to improve the feature extraction method, the upper limit of performance of this kind of method would not be significantly improved.

Another solution is to use deep learning for feature extraction and classification. This kind of method abandons the artificial extraction. Feature extraction and classification are all done by the deep learning network. This avoids the loss of image information, but in order to ensure the accuracy of classification, it greatly increases

the complexity of the network, thereby the computational complexity is greatly increased.

Based on previous research, in order to further improve the presentation attack detection performance of iris, the following improvement methods are proposed. GLCM matrix is one of the most commonly used statistical methods for texture feature extraction. Therefore, a novel method called Modified-GLCM based on GLCM is proposed in this paper. Modified-GLCM makes up for the shortcomings of GLCM that is sensitive to the texture direction and the scale of the features is too small to extract the correlation information between detailed features by introducing the Manhattan distance. Meanwhile, this paper introduces an optimized neural network as the classifier, which avoids the phenomenon of high discrimination and high-level texture information loss caused by artificially selecting statistical texture features, thereby greatly improving the upper limit of the iris anti-counterfeiting performance.

In 2014, Goodfellow *et al*. [13] proposed the GAN model. GAN mainly consists of generating network G and discriminating network D. In 2015, Radford A [14] proposed the DCGAN network, replacing the G and D of the GAN network with two convolutional neural networks. By making some specific restrictions on the two convolutional neural networks, the DCGAN network was trained more stable. After that, Tero Karras proposed the ProGAN [15] model in 2017. The biggest contribution of ProGAN is to propose a new training method, that is, we should not learn the difficult high-definition image generation as soon as we come up. ProGAN starts learning from the low-resolution, and then improves the resolution. It can effectively and stably train a high-quality high-resolution generator model. These GAN models make the adversarial samples generated by them more real, which brings huge challenges to the field of image detection.

In the field of iris recognition, there are few researches on the detection of GAN-generated adversarial samples. Therefore, we generated the adversarial samples by the retrained GAN models to verify the strong aggression of the adversarial samples on iris presentation attack detection. And in the experimental part, this paper explains the reason for the aggression of iris adversarial samples from the perspective of texture feature analysis.

III. Approach

Generally, before performing feature extraction on an iris image, normalized pre-processing of the iris image needs to be done. This paper uses the mature technique [16] in the field of iris normalization. The method in [16] is specifically used for non-ideal irises. It is quite robust, has high segmentation accuracy and can be applied to different iris databases without changing the parameters, which is quite suitable for LivDet-Iris-2017-Clarkson [6] iris dataset. The main pre-processing steps in [16] include iris segmentation and normalization, as shown in Fig. 1. Iris segmentation finds the iris region by locating its inner and outer boundaries from a coarse-to-fine strategy. The iris normalization obtains a 64 × 512 normalized image by mapping the gray image of the iris from the Cartesian coordinate system to the double dimensionless polar coordinate system.

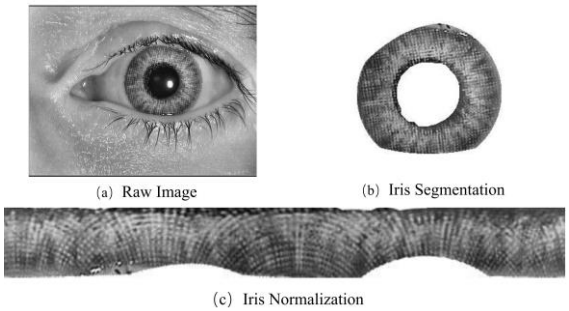

Figure 1. Example of iris pre-processing.

A. Shortcomings of GLCM on Feature Extraction

This paper takes the gray level co-occurrence matrix as the research basis for feature extraction. GLCM was first proposed by Haralick [17] and is a statistical method to describe the texture characteristics of images. It calculates the statistical characteristics of the image texture by studying the gray-level relationship between the pixel unit in the gray image and its neighborhood pixels, that is, it uses the statistical gray-level relationship between adjacent elements to represent the texture. And it's often used for studying the texture features by calculating its own statistical features.

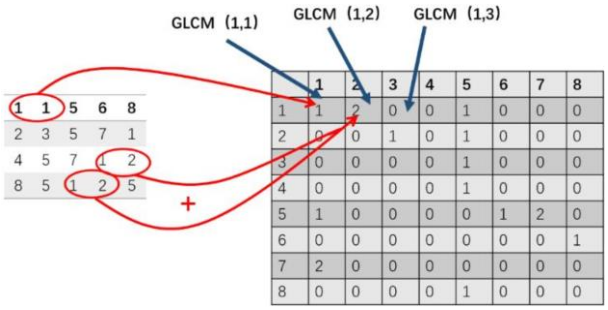

Figure 2. Example of GLCM calculation process.

An example of GLCM calculation process is shown in Fig. 2. The left part is a gray-level image, and the right part is a gray-level co-occurrence matrix. GLCM is used to represent the gray-level co-occurrence matrix below. It's a two-dimensional matrix of $H \times H$, where H is the largest gray level in the gray-level image. GLCM has four calculation directions (horizontal, vertical, left diagonal, right diagonal). The calculation direction selected in the figure is the horizontal direction, namely $GLCM(i, j)$ represents the occurrence frequency of a pair of element pairs with pixel values i and j that satisfy the horizontal adjacent relationship in the gray-level image.

From the calculation process of GLCM, it can be seen that the calculation of GLCM is very simple. Meanwhile, it also has statistical features that relevantly describe the thickness, size, and sharpness of the texture. All above these advantages make GLCM a simple and efficient method to describe the texture of the image. However, the limitations of GLCM are also obvious. First of all, from the calculation principle of GLCM, GLCM is obtained by

calculating the gray-level changes of adjacent elements, which can only represent the gray-level relationship of adjacent areas. So the direction of scale of the features is single and the range is short. In terms of iris texture, it's likely that feature information such as the high-level texture features under the large scale and the correlation between detailed textures will not be extracted. Besides, it uses several statistical features of the matrix obtained by GLCM represent some texture features of the image, separately. These textures are often just surface features that have explainable physical meaning. And more useful texture information is often not completely retained. In this way, some highly distinguished high-level image content is likely to be ignored.

B. *Modified-GLCM*

As mentioned above, there is a big difference between the local iris spot of colored contact lenses and real iris. A real iris is composed of small iris spots with different sizes and shapes, while colored contact lenses are printed by combining small iris spots with very high similarity. Therefore, if the texture features in the large scale in the image can be extracted, more combined correlation information between spot and spot can be obtained. This will be of great help for authentic iris recognition. Taking countermeasures against the existing shortcomings of GLCM and the texture characteristics of colored contact lenses, this paper proposes a modified method based on GLCM. We call it Modified-GLCM. This method can expand the texture feature scale of GLCM.

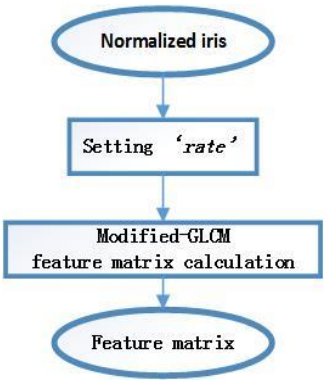

Figure 3. The calculation process of Modified-GLCM algorithm.

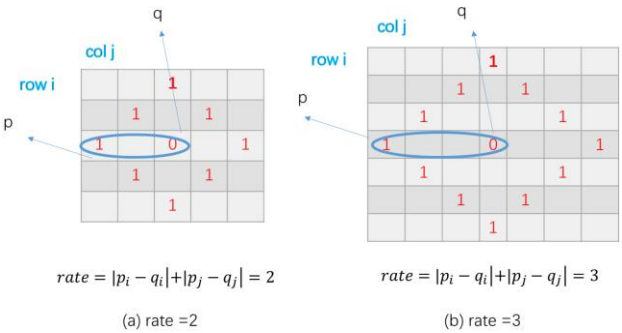

Figure 4. Spatial position relationship in Modified-GLCM.

The Modified-GLCM algorithm is shown in Fig. 3, including setting *rate* and *Modified-GLCM* feature matrix calculation. We introduce a parameter called *rate* to represent the scale of the features of Modified-GLCM, shown in Fig. 4. *rate* represents the Manhattan distance [18] between two elements with gray value p and q in the gray image. The distance is expressed in L1 norm, as in (1).

$$rate = |p_i - q_i| + |p_j - q_j| \tag{1}$$

where i and j represent the number of rows and columns of the two elements whose gray level is p and q.

Here *Modified-GLCM* is no longer calculated in the single direction, but all element pairs that meet the scale of the features conditions are calculated. Fig. 4(a) and 4(b) respectively indicate the spatial positional relationship that an element with a gray level of 1 paired with an element with a gray level of 0 when the scale of the features are 2 and 3 respectively.

The calculation of *Modified-GLCM* is expressed as follows.

$$Modified\text{-}GLCM(p,q) = \sum_{\substack{p\in G \\ q\in G}} \begin{cases} 1, if\ (|p_i - q_i| + |p_j - q_j| = rate) \cap \\ \quad ((p_i - q_i) - (p_j - q_j) \le 0) \\ 0, others \end{cases} \tag{2}$$

where G means the gray level map with size of $m \times n$, p and q are the elements in the gray level map, $p \in G$ (G (i, j) = p, $i \in (1, m)$, $j \in (1, n)$) means the gray level of the element in G is p, $|p_i - q_i| + |p_j - q_j| = rate$ means that the elements with gray levels p and q meet the given rate.

If $(p_i - q_i) - (p_j - q_j) \le 0$, it means that the element with gray level p is at the upper left of the element with gray level q.

An example of the calculation process of *Modified-GLCM* is shown in Fig. 5. The occurrence frequency of element pairs that meet the scale of the features conditions is calculated statistically: for instance, *Modified-GLCM* (1, 1) represents the number of (1, 1) element pairs in the gray level image when *rate* = 2.By comparing the *Modified-GLCM* and GLCM obtained from the same gray level image in Fig. 2 and Fig. 5, it can be drawn that *Modified-GLCM* has a larger neighborhood and more calculation directions than GLCM. *Modified-GLCM* extracts more spatial information about image textures than GLCM, and also filters out some redundant statistical values, for example, band textures in a small area with the same gray level. It can be found that (1, 1) element pairs in the horizontal direction do not participate in the calculation in Fig. 5. Note that we are more concerned about the edge, shape and size information of the texture. In this way, the calculation of the internal of the band texture can be reduced.

From the calculation principle of the above algorithm, it can be drawn that *Modified-GLCM* has another advantage, that it has more comprehensive statistical texture information than GLCM. When rate is 3, *Modified-GLCM* can extract texture information in 12 directions equally divided by 360 degrees in a more balanced manner, while GLCM can only calculate one

direction once. This is very favorable for complete extraction of iris texture.

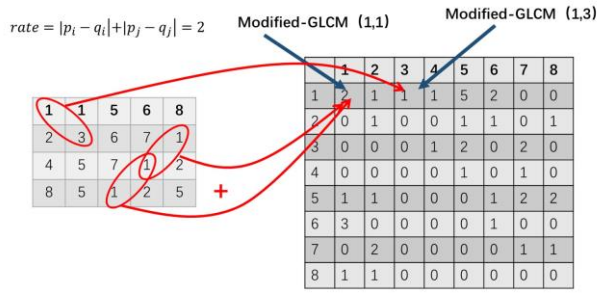

Figure 5. Example of *Modified-GLCM* calculation, rate is 2.

C. Classification

Both methods of Suvarchala [7] and He [10] directly take the statistical characteristics of the obtained feature matrix as the input of a SVM classifier to distinguish the irises, which is a process from complex to simple. However, this method inevitably misses many high-dimensional texture features that cannot be obtained just by data analysis. Therefore, this paper uses a binary classification neural network [19], [20] instead of a SVM as the classifier for *Modified-GLCM*. The feature matrix *Modified-GLCM* is directly used as the input to the binary classification neural network, which can further retain the iris texture features in *Modified-GLCM*.

Since the features have been already extracted, there is no need to apply a complex CNN network to do the repetitive work. To simplify the algorithm and accurate classification, a MLP network was chose for the final classification. The MLP network has three layers, including an input layer, an output layer, and a hidden layer. The dimension of input X is ($H \times H$, m), $H \times H$ represents the size of feature matrix, and m represents the number of training samples.

IV. Experimental Evaluations

A. Dataset

This paper utilizes the LivDet-Iris-2017-Clarkson [6] iris dataset to test the performance of our method. The dataset contains two parts, a training set and a test set. After removing some iris samples that failed to be segmented, the training set and test set retained a total of 5769 samples as our experimental dataset. The training set contained 2433 live iris samples and 1118 colored contact lens samples. The test set contains 1458 live iris samples and 760 colored contact lens samples. Four random samples of live iris and colored contact lens samples were randomly selected from the training set, as shown in Fig. 6.

In the experiment, the training set and test set are still divided according to the original data set. GLCM and *Modified-GLCM* are used for feature extraction, and SVM and MLP network are used for feature classification.

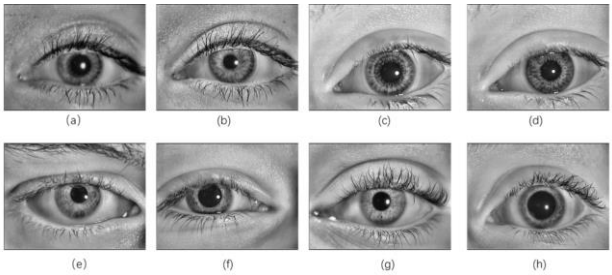

Figure 6. Samples of contact lens iris ((a), (b), (c), (d)) and live iris ((e), (f), (g), (h)).

B. Performance Analysis

In order to evaluate the effectiveness of our proposed method, the Receiver Operating Characteristic (ROC) curve and accuracy, precision, recall, False Acceptance Rate (FAR), False Rejection Rate (FRR) of classification detection are used to conduct the iris verification evaluations. In order to reduce the calculation, the gray values were converted to between 0 and 63. Besides, the GLCM was calculated in four directions and the results of four directions were stitched vertically into a matrix as result of GLCM to retain all the information.

1) Effectiveness of Modified-GLCM

The ROC curve of the methods is plotted above, as shown in Fig. 7. It shows that the curve of our proposed method achieves the maximum Area under Curve (AUC). By comparing the ROC curve of different rates (including 2, 3 and 4) and the ROC curve of GLCM, we find that when the scale of the features becomes larger, the ROC curve gets closer to the upper left corner. This result indicates that the performance of *Modified-GLCM* feature extraction has improved based on GLCM, confirming the assumption that expanding the scale of the features can better extract iris texture features and the effectiveness of the *Modified-GLCM*. However, the result gets worse when rate is 4, meaning that the bigger the scale of the features, not necessarily better results. This phenomenon is also consistent with our assumption: when the scale of the features is too large, there is little detail information extraction, but the distinction between true and false iris will decline. Besides, we compare the four NN methods with the SVM method. It can be clearly seen that the performance of the NN method is much better in feature classification.

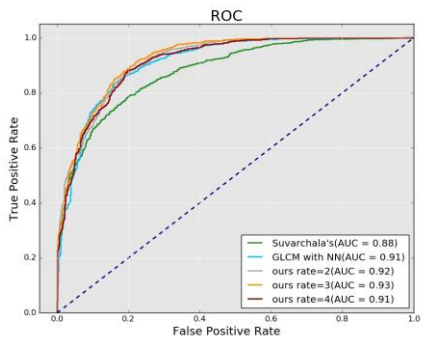

Figure 7. ROC curves of different methods.

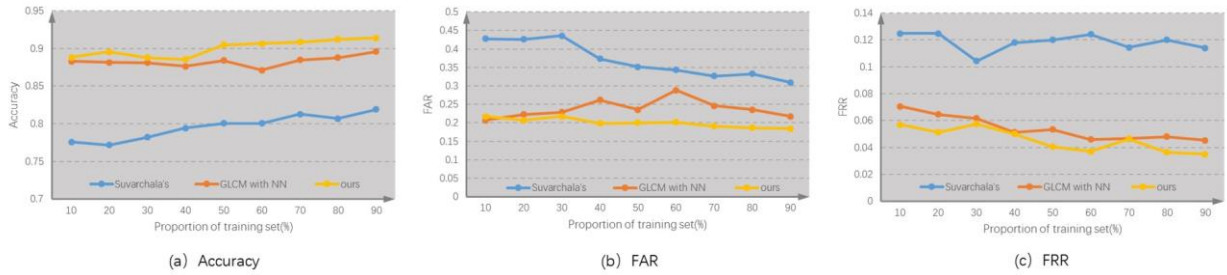

Figure 8. Recognition results under different proportions of the complete set.

We also conducted training tests on different proportions of the complete training sets, and the experimental results are shown in Fig. 8. The abscissa of the line graph in Fig. 8 represents the proportion of training files to the complete training set. The result shows that the accuracy and precision of our proposed method are much higher than the method of combining the feature matrix with SVM in Suvarchala [7], and our method obtains the lowest FAR and FRR. Meanwhile, by comparing the results of GLCM combined with NN and *Modified-GLCM* combined with NN, it can be clearly seen that *Modified-GLCM* can obtain the highest accuracy. The lowest FAR, FRR, and the descending trend of FAR, FRR is also more obvious. These results prove that *Modified-GLCM* is more capable of extracting the correlation information of the detailed iris textures in the large scale. The most important is that these results proved the universality of our method under different sizes of training sets.

2) Overall benchmark comparison

The performance comparison of the algorithms proposed in this paper on the complete LivDet-Iris-2017-Clarkson iris dataset is shown in Table I and Table II.

It can be seen from Table II that our algorithm achieves the best results in precision, recall, and accuracy, and also obtains the lowest FAR and FRR. All the methods of Table II calculate the feature map, but Suvarchala's extracts the statistical features of the feature map while ours doesn't extract the statistical features, which can also be seen from Table IV. And from the comparison between Suvarchala's and the other 2 methods, we can conclude that NN is significantly better than the SVM classification method. Besides, from the comparison of the different rates of our method in Table I, the performance gets better when the rate gets bigger to three, with worse result when the rate gets much bigger to four. It suggests that there is an optimal rate to extract the most distinguishable features of the iris textures. How to choose a suitable rate decides whether we can extract the large receptive field correlative information with more accurate and distinguishable features of local detailed textures.

TABLE I. PERFORMANCE (%) UNDER DIFFERENT FEATURE SCALES

	PRE	REC	ACC	FAR	FRR
rate=2	89.28	95.47	89.50	21.97	4.53
rate=3	**89.58**	**95.54**	**89.77**	**21.31**	**4.46**
rate=4	86.98	93.00	86.25	26.71	7.00

TABLE II. PERFORMANCE COMPARISON (%)

	PRE	REC	ACC	FAR	FRR
Suvarchala's	89.39	88.13	80.66	33.68	11.87
GLCM(NN)	89.39	95.34	89.50	21.71	4.66
ours	**89.58**	**95.54**	**89.77**	**21.31**	**4.46**

To further verify the effectiveness of the algorithm in this paper, we compared it with the three best algorithms (CASIA, Anon1 and UNINA) in Iris Liveness Detection Competition 2017 [6]. APCER and BPCER are used to evaluate the performance, where:

- APCER is the rate of misclassified spoof images (spoof called live).
- BPCER is the rate of misclassified live images (live called spoof).

Results are summarized in Table III. Compared with the best result of LivDet-Iris-2017, our algorithm received the best results with a rate of rejected live samples of 2.22% and accepted rate of spoof samples of 1.97%. The result of APCER is much better than the best result of LivDet-Iris-2017.

TABLE III. ERROR RATES (%) OF COMPARISON BETWEEN DIFFERENT ALGORITHMS OF LIVDET-IRIS-2017 AND OURS

Algorithm	Clarkson	
	APCER	BPCER
Best (LivDet-Iris-2017)	14.71	3.36
CASIA (LivDet-Iris-2017)	9.61	5.65
Anon1 (LivDet-Iris-2017)	15.54	3.64
UNINA (LivDet-Iris-2017)	38.37	0
ours	**1.97**	**2.22**

3) Algorithm complexity comparison

In order to comprehensively analyze the advantages and disadvantages of our proposed algorithm, the test time complexity of several algorithms was calculated. The result is shown in Table IV. In Table IV, n and m are the height and width of gray map, d represents the dimension of feature, N is the max gray value of the gray map, k is the number of the support vector, and M represents the number of hidden layer neurons.

TABLE IV. ALGORITHM COMPLEXITY COMPARISON

	Feature map	Extract feature	Classify
Suvarchala's	O(n×m)	O(d×N×N)	O(d×k)
GLCM (NN)	O(n×m)	---	O(M)
ours	O(n×m)	---	O(M)

Obviously, the few methods have the same time complexity on calculating feature map and our method doesn't need to extract feature before classification. What's more, d×N×N is larger than M. So, our proposed method has smaller algorithm complexity than others. The algorithm in this paper is simple to implement. It uses python 3.6 for algorithm writing and experiments. The algorithm mainly uses the numpy module. The hardware platform is an ASUS laptop with 4G memory. The model in this paper uses CPU for training and the learning rate is set to 0.01. Because the model is lightweight, it tends to converge after 2K iterations of training, and the training ends after 3K iterations.

4) Aggressiveness of iris adversarial samples and Analysis

In order to verify the aggressiveness of the iris adversarial samples, we selected two GAN models (DCGAN and ProGAN) to train and generate the iris adversarial samples. The training set of the two GAN networks is the real iris in Livdet-iris-2017. The samples generated by DCGAN have size of 128*128, and the samples generated by ProGAN have size of 256*256. Some samples are shown in Fig. 9. We added the generated samples as a new type of sample to the original training set to retrain the above algorithms. The original training set remains unchanged, and 1200 iris adversarial samples are added to it as a new type of sample. Then we compared the accuracy of the above algorithms training with iris adversarial samples and training without iris adversarial samples. The results are shown in Table V, the accuracy of the above algorithm has dropped by more than 28%. It can be seen from the above results that the existing iris recognition and iris presentation attack detection algorithms are difficult to deal with the attacks of iris adversarial samples.

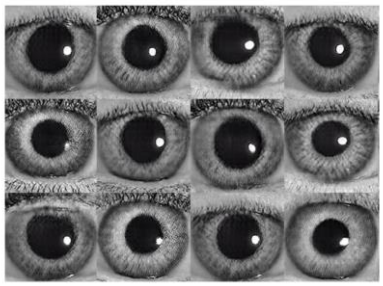

Figure 9. Iris adversarial samples generated by ProGAN.

TABLE V. ALGORITHM COMPLEXITY COMPARISON

	Origin	Train with DCGAN generated samples	Train with ProGAN generated samples
Suvarchala's	80.7	52.4	51.7
GLCM(NN)	89.5	54.1	51.0
ours	**89.8**	**54.3**	**51.7**

Extraction and classification of texture features is the mainstream idea of iris recognition and iris presentation attack detection algorithms. Therefore, we wonder whether the aggression of iris adversarial samples comes from texture features. Based on the above assumptions, we randomly selected 32 samples from the iris adversarial samples and the real iris samples, extracted the feature matrix of the samples through the feature extraction operator of the above algorithms, and then verified our assumptions through comparing the similarity of the features of iris adversarial sample and the real sample. This article chooses cosine function as the similarity of the two features, expressed as follows:

$$similarity = \frac{1 + \frac{A \bullet B}{|A| \times |B|}}{2} \tag{3}$$

where A represents the texture feature of one iris adversarial sample and B represents the texture feature of one iris real sample.

The results are shown in Fig. 10. The similarity of Suvarchala's feature operator exceeds 0.93, accounting for 73.64% of the result, and the similarity of our algorithm feature operator exceeds 0.93, accounting for 85.42% of the result. It can be seen that it is the high similarity of texture features that causes the indistinguishability of iris adversarial samples and iris

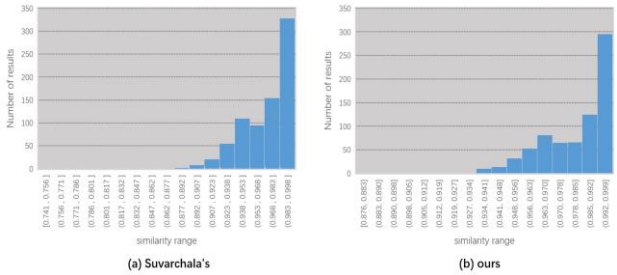

Figure 10. The similarity of features of iris adversarial samples and iris real samples.

V. CONCLUSIONS AND FUTUREWORK

In this paper, an iris presentation attack detection algorithm that uses *Modified-GLCM* to extract iris features combined with MLP networks is proposed. It can be used in the iris recognition system to detect attacks by wearing colored contact lenses. A detailed comparison and verification of its performance on the more difficult and challenging LivDet-Iris-2017-Clarkson iris database was performed. The experimental results show that the algorithm proposed in this paper is significantly better than the texture analysis method of feature matrix combined with SVM classification, and the *Modified-GLCM* has been greatly improved based on GLCM. Compared to the best results of LivDet-Iris-2017, our method also received the much better results with a rate of rejected live samples of 2.22% and rate of accepted spoof samples of 1.97%. And we verified and analyzed of the aggressiveness of iris adversarial samples on the iris presentation attack detection algorithms.

Our method is an innovative and improved algorithm based on GLCM. It's easy to calculate and has excellent performance, which can be applied to many other image processing fields. However, this method still has some deficiencies. The computational complexity of training a

neural network is much larger than the previous algorithm, as we have to adjust the learning rate and other training parameters again and again. Besides, the PAD algorithm still has space for improvement on how to choose a suitable rate and how to detect iris adversarial samples. Therefore, how to reduce the computational complexity and optimize the rate of texture extraction to find the distinguishing features between iris adversarial samples and real samples will be the focus of future work.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Dian Li conducted the research, did the experiments above, analyzed the results and wrote the paper. Cheng Wu and Yiming Wang provided much guidance on research, experiments and writing. And all authors had approved the final version.

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