Hierarchical Multi-class Iris Classification for Liveness Detection

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***Abstract*—In modern society, iris recognition has become increasingly popular. The security risk of iris recognition is increasing rapidly because of the attack by various patterns of fake iris. A German hacker organization called Chaos Computer Club cracked the iris recognition system of Samsung Galaxy S8 recently. In view of these risks, iris liveness detection has shown its significant importance to iris recognition systems. The state-of-the-art algorithms mainly rely on hand-crafted texture features which can only identify fake iris images with single pattern. In this paper, we proposed a Hierarchical Multi-class Iris Classification (HMC) for liveness detection based on CNN. HMC mainly focuses on iris liveness detection of multi-pattern fake iris. The proposed method learns the features of different fake iris patterns by CNN and classifies the genuine or fake iris images by hierarchical multi-class classification. This classification takes various characteristics of different fake iris patterns into account. All kinds of fake iris patterns are divided into two categories by their fake areas. The process is designed as two steps to identify two categories of fake iris images respectively. Experimental results demonstrate an extremely higher accuracy of iris liveness detection than other state-of-the-art algorithms. The proposed HMC remarkably achieves the best results with nearly 100% accuracy on ND-Contact, CASIA-Iris-Interval, CASIA-Iris-Syn and LivDet-Iris-2017-Warsaw datasets. The method also achieves the best results with 100% accuracy on a hybrid dataset which consists of ND-Contact and LivDet-Iris-2017-Warsaw datasets.**

I. Introduction

With the wide application of iris recognition systems, the risk of security attacks to the systems is increasing rapidly due to the great benefit of fraudulent identity authentication. Recently iris recognition systems have the risk to be attacked by various approaches. In view of these potential risks, it is obviously necessary to develop intelligent self-protection algorithms to protect iris recognition systems from attacks.

Among the various attacking approaches, showing fake iris appearance is the most popular approach to attack iris recognition systems. There are several categories of fake iris patterns, such as artificial eye model (it is usually designed for blind persons with realistic iris texture pattern), colorful contact lens, synthetic iris images, iris pattern printed on the paper (we call it print iris for short in the following), iris image/video displayed on the LCD, etc. Iris liveness detection mainly aims to identify whether the input iris images are captured from living individuals. As an important part in iris recognition systems, iris liveness detection can effectively reduce the risks of being attacked by fake iris images, which are captured at the input level.

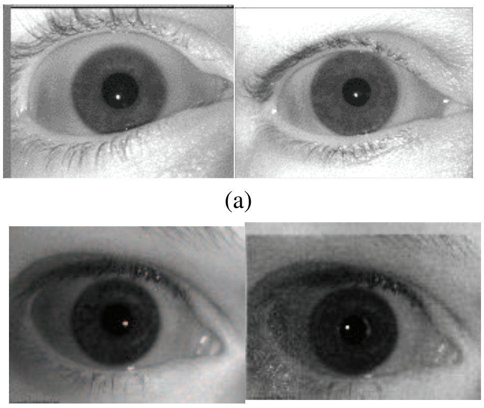
A number of texture analysis algorithms have been proposed for iris liveness detection. Among the various algorithms, the algorithms based on hand-crafted features, such as GLCM [7], LBP [8], HVC [13], are the mainstream methods. The hand-crafted features may not be able to handle multi-pattern situations. Apart from the algorithms based on hand-crafted features, there are also some feature selection algorithms, such as Adaboost, MCNN, etc. Adaboost [8] is used to find the most effective parameter settings for a specific type of texture features. However, Adaboost does not strictly define the texture models of genuine/fake iris images. Therefore, more and more work utilizes CNN to make a preliminary research for iris liveness detection. Nevertheless, these work does not classify different fake iris patterns into specific categories. Moreover, the texture features of different patterns are diverse. Unified training ignores the unique fake characteristics of each model. These uniqueness information can increase the accuracy of iris liveness detection with hybrid patterns.

This paper proposes a hierarchical multi-class iris classification (HMC) for liveness detection. This algorithm is effective for iris liveness detection of hybrid fake patterns. The motivation of the proposed algorithm is that the distribution of various fake iris patterns is different. Different kinds of fake iris patterns can be roughly divided into two categories by their fake areas distribution, global fake iris and local fake iris. For example, print iris and synth iris belong to global fake iris, while contact lens and plastic iris belong to local fake iris. We select print iris and contact lens as the representative pattern of each category. The fake parts of iris images with contact lens distributed in iris area shows in Fig. 1. However, the fake parts of print iris images distribute in the whole image. If we train an unified model for these two patterns, the authenticity differences of various iris image parts will reduce the identification accuracy. The classification stage is divided into two steps, identifying print fake iris and contact lens fake iris respectively. In view of the differences between various fake patterns, we identify colorful contact lens fake iris from the mixed dataset firstly. Then we identify print fake iris and genuine iris from the rest of the dataset. Thus, HMC can successfully deal with the iris liveness detection of hybrid patterns. The advantages of our

0-7695-6403-8/18/31.00 ©2018 IEEE
DOI 10.1109/ICB2018.2018.00018

method are as follows. Firstly, HMC is able to achieve higher accuracy on single fake iris pattern dataset. Secondly, HMC proposes a new scheme based on hierarchical classification for various fake iris patterns. Thirdly, the HMC is proven highly effective on iris liveness detection of hybrid fake patterns. This work is an extension of our previous work which we used in the Liveness Detection Competition of IJCB2017 [20]. In this work, we utilize more categories of fake iris images and focus on detecting multi-class fake iris images under a hierarchical framework.

The reminder of this paper is organized as followings. In section 2, some related work of iris liveness detection is introduced. In Section 3, our algorithm of iris liveness detection is proposed. Section 4 evaluate HMC on three domain public datasets, and then in Section 5 we conclude this paper with some discussions.



(a)

(b)

Figure 1. Comparison of different fake iris patterns (genuine/fake). (a) A genuine iris image (left) & iris image with contact lens (right) (b) A genuine iris image (left) & printed pattern iris image (right).

II. Related Work

Iris liveness detection has realized in sensor and intelligent algorithm level. The research is introduced as follows.

A. Sensor level iris liveness detection

Special design of iris sensors is a common way for iris liveness detection. Lee et al. [10] propose a fake iris detection scheme by investigating the specular spots of collimated IR-LED. This algorithm is effective for identification of two fake iris patterns, the print iris pattern and glass/plastic eye models. However, it fails to identify contact lens because the iris texture is still visible when the attacker wears contact lens. In addition, Adam Czajka [3] proposes a fake iris image detection scheme by using the pupil dynamics algorithm, which needs special sensor. Nevertheless, it fails to identify the iris images with colorful contact lens and synthetic iris images. Sensor level iris liveness detection algorithms can actively capture the optical characteristics of the genuine iris pattern. However iris sensors need to be specially designed, thus iris liveness detection algorithm is limited by the specific hardware functions.

B. Algorithm level iris liveness detection

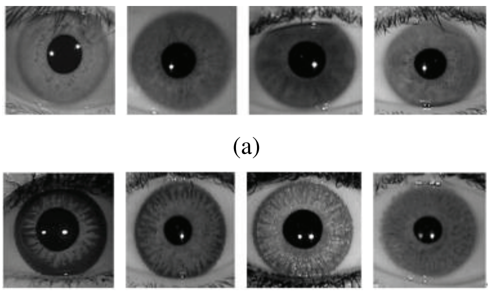
There are significant differences of texture features between genuine and fake iris images, as shown in Fig.2. In detail, the genuine iris images usually contain naturally smooth texture features, while the fake iris images contain coarse texture patterns, such as the print iris texture on contact lens, paper and other materials. Unlike the sensor level iris liveness detection methods, algorithm level methods do not need special designed iris sensors. In this respect, Daugman [5] proposed a fake iris images detection scheme via frequency analysis to identify the print iris pattern. In simple terms, the basic idea is to utilize the frequency characteristics to identify genuine/fake iris images. He et al. [7] proposed a contact lens detection method via statistical texture analysis. In this method, four distinctive features based on gray level co-occurrence matrix (GLCM) are extracted. Meanwhile, support vector machine (SVM) is used for classification of genuine/fake iris images. Wei et al. [14] proposed a contact lens detection method based on texture analysis. In this method, Iris-Textons are learned to represent statistical texture features of genuine/fake iris images. He et al. [8] propose an iris liveness detection method, which uses Adaboost to learn the most distinctive LBP features for iris liveness detection. This method is able to identify print iris images and contact lens. Zhang et al. [16] realized high accuracy contact lens detection based on weighted-LBP encoding strategy and SVM classifier. Galbally et al. [6] propose an iris liveness detection method, which suggests to identify print iris images based on quality measures. Yadav et al. [15] proposed an iris liveness detection method by using modified LBP for detection of contact lens. Sun et al. [13] developed a texture pattern representation method, which is called Hierarchical Visual Codebook (HVC), for iris image classification. This method is successfully applied to iris liveness detection. R.Raghavendra et al. [12]presented an in-depth analysis of representation attacks on iris recognition systems. It mainly focus on two kinds of iris images, the print iris images and the iris images captured on LCD. David Menotti et al. [11] firstly adopt deep learning to extract iris features automatically, which is able to extract semantic and vision meaningful features directly from iris images without normalization to distinguish genuine iris images and single pattern iris images (print iris images). He et al. [17] proposed a Multi-patch Convolution Neural Network (MCNN) that is capable of handling different types of fake iris images. However, it does not consider about various features of different fake iris patterns.

Table I concludes the state-of-the-art algorithms about feature extraction and their applicable patterns of fake iris

Table I
THE STATE-OF-THE-ART ALGORITHMS ARE LISTED IN CHRONOLOGICAL ORDER. IRIS LIVENESS DETECTION MAINLY CONTAINS SENSOR LEVEL AND ALGORITHM LEVEL, AND ALGORITHM LEVEL STANDS IN THE MAINSTREAM IRIS LIVENESS DETECTION. MOST ALGORITHMS IDENTIFY FAKE IRIS IMAGES BASED ON HAND-CRAFTED FEATURE EXTRACTION. THE TABLE SHOWS THE APPLICABLE FAKE PATTERNS OF THESE ALGORITHMS.

Algorithm	Contact	Print	Synth	Plastic	Features Category	Sensor or Algorithm
Daugman[5] (2004)	-	-	-	√	Hand-crafted	Algorithm
Lee et al.[10] (2006)	-	√	-	√	-	Sensor
He et al. [7] (2008)	√	-	-	-	Hand-crafted	Algorithm
Wei et al. [14] (2008)	√	-	-	-	Hand-crafted	Algorithm
He et al. [8] (2009)	√	√	-	-	Hand-crafted	Algorithm
Zhang et al. [16] (2010)	√	-	-	-	Hand-crafted	Algorithm
Galbally et al. [6] (2012)	-	√	-	-	Hand-crafted	Algorithm
Yadav et al. [15] (2014)	√	-	-	-	Hand-crafted	Algorithm
Sun et al. [13] (2014)	√	√	√	√	Hand-crafted	Algorithm
R.Raghavendra et al. [12] (2015)	-	√	-	-	Hand-crafted	Algorithm
David Menotti et al. [11] (2015)	-	√	-	-	Automatic	Algorithm
Adam Czajka [3] (2015)	-	√	-	√	-	Sensor
He et al. [17] (2016)	√	√	√	-	Automatic	Algorithm

image. As listed in Table I, algorithm level methods with texture analysis are mainstream methods for iris liveness detection. However, most texture analysis algorithms, which based on hand-crafted feature extraction, can only identify only one pattern of fake iris images. It is difficult to find out the most effective parameter settings for all patterns fake iris images. Furthermore, over fitting is a challenging problem for learning texture features based on deep networks with small scale samples. Therefore, we design a HMC which is capable of learning effective parameters for various fake iris images. Meanwhile, we also increase the number of training samples accordingly. The existing problems of iris liveness detection are well resolved.



(a)

(b)

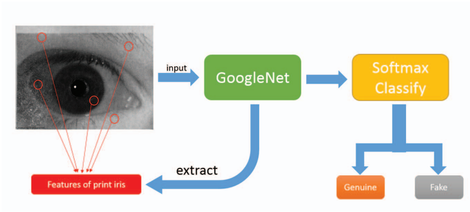
Figure 2. Comparison of texture features of genuine and fake iris images. (a) Genuine iris images. (b) Fake iris images.

III. OUR APPROACH

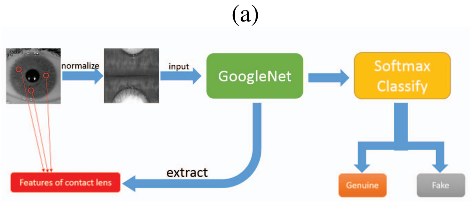
A. Hierarchical multi-class classification

Fake iris pattern is distributed differently in iris images. It causes that features of different fake iris patterns should be extracted from different iris image areas. For instance, all parts are fake in a print iris image. Nevertheless, for an iris image with contact lens, the fake part is only distributed in the iris ring. Therefore, we use different parts of the iris image as input to handle different fake iris patterns. In view of these differences, the iris image with contact lens need to be normalized before classification. The normalized iris images with contact lens is 256*256 pixels. The normalized image mainly focuses on the iris area. On the contrary, for the print iris images, we use the entire image as input without preprocessing. We train two corresponding models for identifying print iris images and iris images with contact lens respectively. The network process is shown in Fig.3. As we know, deep network, such as CNN, [9] generally extracts features of a single fake iris pattern. This is why most CNN methods are not able to handle iris liveness detection with hybrid fake iris patterns. Hence, we propose the HMC for iris liveness detection. We treat iris liveness detection with hybrid patterns by a hierarchical process rather than handling all patterns simultaneously.

The proposed HMC can increase the accuracy of iris liveness detection of hybrid patterns. In detail, we design a deep network which includes two cascading networks as shown in Fig 4. These two parts of networks handle the iris liveness detection of whole fake iris and local fake iris respectively. As mentioned above, we select a representative pattern of each fake iris category, the iris image with contact lens and the print iris image. The handling of these two fake iris patterns can make an analogy to all fake iris patterns. If a given iris dataset consists of print, contact lens and genuine iris images, we picked out the print iris images by the first network. The input of the first network is an iris image without normalization. Such a hierarchical processing is able to classify the print iris images more accurately on account of the individual training for print iris. The rest of the dataset are contact lens and genuine iris images. Then we normalized the remainder images. The normalized images are used as the input of the second network. These images are able to extract the features of the iris images with contact lens. So we separate the remaining two kinds of iris images into contact lens and genuine iris image. Thus, we can successfully classify the hybrid patterns into three categories via HMC. The print iris images and the iris images with contact lens is classified as the fake iris. The rest of the datasets is classified as the genuine iris. As a result, HMC is able to classify various patterns of fake iris images effectively.



(a)



(b)

Figure 3. Network process of two fake iris patterns (a) print iris (b) contact lens.

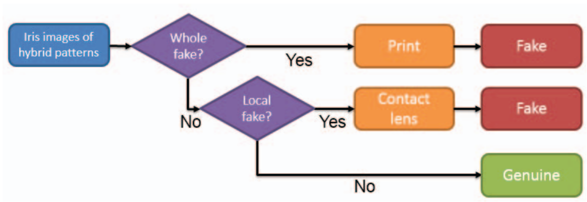


Figure 4. The process of HMC.

B. Network architecture

As mentioned above, we propose the hierarchical multi-class iris classification to handle iris liveness detection of hybrid patterns. The whole classification process is concatenated by two parts of the same network structure in order to handle contact lens and print iris images respectively. For the purpose of extracting more representative features, we need to train a high quality model. The key to obtain high quality models is to increase the depth (number of layers) or the width (the number of layers or the number of neurons) of the model. However, in order to achieve these two goals, more parameters will be calculated and updated, which is easy to make the network over fitting. For avoiding the network over fitting and controlling the size of the convolution kernel, GoogleNet[18] is used as the basic network structure. It is a better way to extract texture features of different fake iris patterns. The network structure of GoogleNet is shown in Fig.5. We fine tune the GoogleNet for iris liveness detection. In our proposed scheme, the input of HMC is the 224*224 iris image. This way of preprocessing has achieved good performance in [21]. The output is a two-way softmax layer, since iris liveness detection is a binary classification problem. Meanwhile, we add accuracy layers of top-1 and top-5 at the test phase respectively for monitoring the networks performance. By these two parts of networks, contact lens and print iris images are classified respectively. The first network learns the texture features of print iris images and the second network focuses on iris images with contact lenses. Thus, iris liveness detection with hybrid patterns is able to be classified hierarchically.

IV. Experiments

To evaluate the performance of the proposed algorithm under different conditions, two experiments are carried out on three public datasets: ND-Contact [2], CASIA-IrisInterval & CASIA-Iris-Syn [1], LivDet-Iris-2017-Warsaw [4] [19]. These three datasets are summarized in Table II. The accuracy of HMC is tested on three single pattern datasets and compared with state-of-the-art algorithms. Meanwhile, in order to prove the algorithm performance of hybrid fake iris patterns, experiment is conducted on the hybrid patterns datasets.

A. Datasets

In this section, the three datasets which we use in the experiments are introduced respectively.

ND-Contact: In recent years, there are some published datasets containing iris images with cosmetic contact lens. The largest one of them, ND-Contact (the Notre Dame Cosmetic Contact Lenses 2013), is used to test the iris liveness detection with contact lens in this experiment. This dataset contains iris images with soft contact lenses and cosmetic contact lenses. The images of ND-Contact are captured by a

Table II
Four Datasets are used for evaluating the performance of our proposed method.

Dataset	Iris images	Genuine	Contact lens	Plastic	Print	Synth
ND-Contact [2]	4200	2800	1400	-	-	-
LivDet-Iris-2017 -Warsaw[4][19]	4513	1844	-	-	2669	-
CASIA-Iris Interval&synth [1]	12639	2639	-	-	-	10000
Hybrid Patterns Dataset	2400	800	800	-	800	-

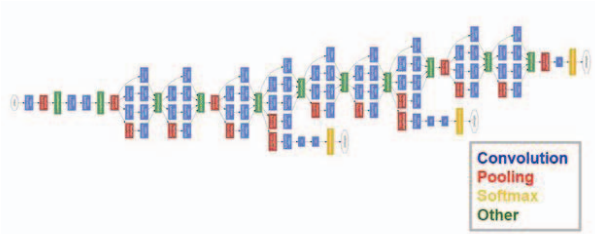
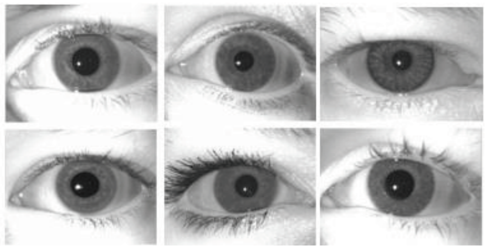
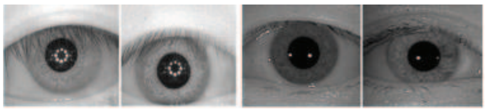


Figure 5. Network structure of GoogleNet [18].



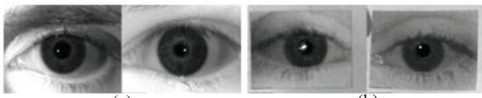
(a) (b) (c)

Figure 6. Some samples from ND-Contact. (a) No contact lens. (b) Soft contact lens. (c) Contact lens.



(a) (b)

Figure 7. (a) Genuine iris images in CASIA-Iris-Interval. (b) Synthetic iris images in CASIA-Iris-Syn.



(a) (b)

Figure 8. Examples of iris in LivDet-Iris-2017-Warsaw DB. (a)The genuine iris images. (b) The print iris images.

LG 4000 iris sensor. It is worth mentioning that iris texture patterns are still visible through soft contact lenses, so both iris images without contact lenses and with soft contact lenses are regarded as genuine samples. Furthermore, the iris images with cosmetic contact lenses are regarded as fake samples. ND-Contact contains 4200 iris images in total, including 2800 genuine iris images and 1400 iris images with contact lens. Fig.6 shows a number of typical samples from ND-Contact.

LivDet-Iris-2017-Warsaw: The LivDet-Iris DB [4] [19] is firstly used in Liveness-Iris Competition. The Warsaw dataset is captured by EyeGuard AD100. It contains 2669 print iris and 1844 genuine iris. The genuine/print iris are shown in Fig.8.

CASIA-Iris-Interval & CASIA-Iris-Syn (CASIA-IrisInterval & Syn): Dataset CASIA-Iris-Interval [1] contains genuine iris images. And dataset CASIA-Iris-Syn [1] contains synthetic iris images. Iris images of CASIA-Iris-Interval are captured by a home-made close-up iris camera. An important feature of this iris camera is that we have designed a circular NIR LED array, with suitable luminous flux for iris imaging. Therefore, the iris camera can capture high quality iris images. CASIA-Iris-Interval (Fig.7 (a)) is well suited to study the detailed texture features of iris images. It contains iris images captured in two sessions, containing 2639 iris images corresponding to 395 eye classes from 249 subjects. CASIA-Iris-Syn (Fig.7 (b)) contains 10000 synthesized iris images of 1,000 classes. The iris textures of these images are synthesized automatically from a subset of CASIA-Iris-Interval.

Hybrid Patterns dataset: Although the above three datasets are good for research of iris liveness detection, they only have one pattern of fake iris images. In order to test the proposed iris liveness detection with hybrid fake iris patterns, we selected 800 iris images of each pattern from the two datasets (ND-Contact and LivDet-Iris-2017-Warsaw) of single fake pattern randomly as the training set and testing set. The number of the training samples is set as 500. These two kinds of typical fake iris images have seemingly realistic iris texture and are useful for testing the performance of iris liveness detection algorithm.

B. Experiments on single pattern datasets

In this section we will present the experiment results on single fake iris pattern dataset. The main purpose of this experiment is to investigate the performance of our proposed algorithm on different patterns of fake iris. In the foregoing, we introduce three datasets of single fake iris pattern, ND-Contact, CASIA-Iris-Interval & CASIA-Iris-Syn and LivDet-Iris-2017-Warsaw. ND-Contact only contains fake iris images with cosmetic contact lenses. CASIA-Iris-Interval & Syn contain synthetic fake iris images and LivDet-Iris-2017-Warsaw contains the print fake iris images. The training set and testing set are set as follows:

(1) For ND-Contact, we set as the definition by provider, i.e. a training set of 3,000 images including 2,000 genuine samples and 1000 fake samples and a testing set including 800 genuine samples and 400 fake samples.
(2) For CASIA-Iris-Interval & CASIA-Iris-Syn, we randomly choose 1500 genuine iris images and 1500 synthetic iris images as the training set. The rest of the dataset is set as the testing set. The experiment is repeated five times with different random setting of the training dataset.
(3) For LivDet-Iris-2017-Warsaw, we only have the training

Table III

PERFORMANCE OF IRIS LIVENESS DETECTION METHODS ON THE SINGLE PATTERN FAKE IRIS IMAGE DATASETS.

Dataset	Spoofnet [11]			Weighted LBP [16]			HVC+SPM [13]			MCNN [17]			**HMC**		
	CCR	FAR	FRR	CCR	FAR	FRR	CCR	FAR	FRR	CCR	FAR	FRR	CCR	FAR	FRR
ND-Contact [2]	99.43%	0.63%	0.75%	95.71%	6.25%	4.37%	98.86%	1.25%	1.50%	100%	0%	0%	**100%**	**0%**	**0%**
CASIA-Iris-Interval & Syn [1]	99.44%	0.79%	0.52%	96.99%	4.39%	2.80%	98.15%	1.20%	2.43%	99.87%	0.24%	0.11%	**99.91%**	**0.18%**	**0.11%**
LivDet-Iris-2017-Warsaw [4][19]	97.12%	4.53%	0.99%	95.40%	5.36%	3.09%	97.38%	4.31%	1.51%	98.02%	3.01%	0.67%	**99.15%**	**1.02%**	**0.31%**

datatset but no test dataset which is provided by the competition. So we use 70% of the training dataset for training. And the rest is used for testing.

Furthermore, in order to confirm the effectiveness of our proposed algorithm, we choose Spoofnet [11], Weighted LBP [16], HVC+SPM [13] and MCNN [17] for comparison. Meanwhile, CCR (Correct Classification Rate) and FAR (rate of falsely accept fake iris image as genuine eone) and FRR (rate of falsely reject genuine iris image as fake one) are used as the evaluation protocol.

The experimental results are shown in Table III. The comparisons with Spoofnet [11], Weighted LBP [16], HVC+SPM [13] and MCNN [17] suggests that our proposed HMC has better performance on single pattern datasets. As shown in Table III, our algorithm achieves 100% CCR on ND-Contact dataset, 99.91% CCR on CASIA-Iris-Interval & Syn datasets and 99.15% CCR on LivDet-Iris-2017-Warsaw dataset respectively. It is obvious that the algorithms based on CNN, such as HMC, MCNN and Spoofnet, achieve a higher CRR than the algorithms based on hand-crafted feature extraction. It proves that deep learning is able to make full use of the raw pixel information of iris images for iris liveness detection than handcrafted features. In addition, HMC achieves a higher CRR than MCNN on single iris pattern datasets. The reason is the networks of HMC are deeper and wider to obtain more effective features.

C. Experiments on hybrid fake pattern dataset

In order to evaluate the performance of HMC on the hybrid fake iris pattern dataset, we create a dataset by choosing 800 iris of each pattern (print, contact lens) from the single pattern datasets randomly. We use 500 iris images per class for training and the rest for testing. The methods of comparison include SpoofNet, Weighted LBP, HVC+SPM and MCNN. Table IV shows the CCR, FAR, FRR of these algorithms. Furthermore, Fig.8 shows the CRR curves as a function of the number of training samples. This is an open set test.

As shown in Table IV, all these algorithms achieve a high accuracy in detection of various fake iris patterns. However, HMC performs better than SpoofNet, Weighted LBP, HVC+SPM and MCNN. It prove that HMC is able to obtain more targeted features of different fake iris patterns. In addition, with the increasing quantity of training samples, the CCR of all methods gradually increases.

Table IV

PERFORMANCE OF IRIS LIVENESS DETECTION METHODS ON THE HYBRID PATTERN FAKE IRIS IMAGES DATASET.

Dataset	CCR	FAR	FRR
Spoofnet[11]	98.92%	1.47%	0.96%
Weighted LBP[16]	97.40%	4.32%	2.08%
HVC+SPM[13]	98.12%	2.01%	1.99%
MCNN[17]	99.92	0.11%	0.12%
HMC	**100%**	**0%**	**0%**

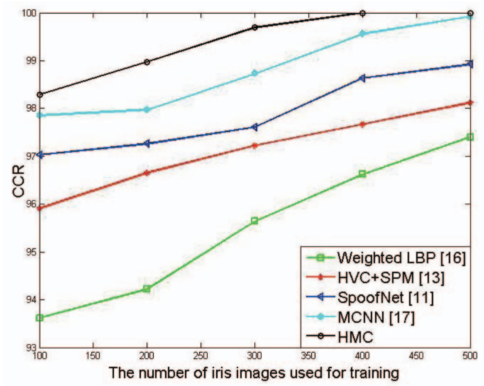


Figure 9. CCR curves as a function of the number of training samples on hybrid dataset.

V. CONCLUSIONS

This paper proves that HMC is meaningfully for iris liveness detection and classification. In view of the disadvantages of the state-of-the-art algorithms on iris liveness detection of hybrid patterns, our proposed HMC is a novelty algorithm which is able to identify fake iris images of hybrid patterns by hierarchical multi-class classification. It uses an idea of divide-and-conquer. Each part of the HMC is used to automatically learn the most effective texture features for classification of genuine/fake iris images in a single pattern. Meanwhile, more appropriate features of single pattern are able to be obtained because the network is deeper and wider than other algorithms of iris liveness detection based on CNN. Our approach establishes a scheme of hierarchical process which is effective to classify various fake iris patterns. The state-of-the-art algorithms identify different fake iris patterns in union rather than hierarchically. In this paper, the classification process of divide-and-conquer for different fake iris patterns is the biggest innovation. The experiment results show that HMC is more efficient on iris liveness detection of hybrid patterns than the state-of-the-art algorithms due to the idea of identifying different fake iris patterns hierarchically. In addition, we discover that contact lens pattern is the most easily to be identified than the print iris pattern and the synthesis iris pattern.

In the future work, we will not only focus on these two specific fake iris patterns (contact lens & print iris). Although HMC is able to identify most of the fake iris patterns in theory, only two representative fake patterns of the two fake iris categories are chosen in this paper. The iris liveness detection of more fake iris patterns based on hierarchical classification will be studied in order to make our algorithm more robust. Furthermore, as two main categories of iris liveness detection, both sensor level and algorithm level algorithms have their advantages and disadvantages. It is better to combine sensor level and algorithm level iris liveness detection algorithms together to achieve a more reliable solution to secure iris recognition systems.

ACKNOWLEDGMENT

This work is supported by the National Natural Science Foundation of China (Grant No. 61420106015) and the Beijing Municipal Science and Technology Commission (Grant No. Z161100000216144).

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