# Multi-patch Convolution Neural Network for Iris Liveness Detection

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## Abstract

*Attacking iris systems with fake iris patterns has become the largest security risk of iris recognition systems. Therefore iris liveness detection which discriminate genuine or fake iris images is of significant importance to iris recognition systems. However, the state-of-the-art algorithms mainly rely on hand-crafted texture features which can only identify fake iris images with single pattern. This paper proposes a Multi-patch Convolution Neural Network (MCNN) that is capable of handling different types of fake iris images. MCNN directly learns the mapping function between raw pixels of the input iris patch and the labels. The outputs of each patch are fed into a decision layer which determines the final decision. Our proposed algorithm automatically learns the features to detect hybrid pattern of fake iris images rather than handcraft. The decision layer helps to improve the robustness and accuracy for iris liveness detection. Experimental results demonstrate an extremely higher accuracy of iris liveness detection than other state-of-the-art algorithms. The proposed MCNN remarkably achieve the best results with nearly 100% accuracy on ND-Contact and CAISA-Iris-Fake datasets.*

## 1. Introduction

Iris is one of the most promising and popular biometric traits, which has been widely used in many critical applications such as national ID card, banking, social benefit, border control, mobile payment, etc. The risk of security attacks to iris recognition systems increases accordingly driven by the great benefit of fraudulent identity authentication. As any other information security technologies, an iris recognition system has the risk to be attacked by various approaches. And all these attacks are possible to attack the iris recognition system successfully by tempering with the identity verification result. Vulnerabilities of iris recognition systems have prevented their deployments in high level security scenarios. Therefore it is absolutely necessary to develop intelligent self-protection algorithms to identify all possible attacks to iris recognition systems.

Presentation of a fake iris pattern to the iris camera is the most popular approach to attack an iris recognition system. Fake iris images may be captured from artificial eye model (it is usually designed for blind persons with realistic iris texture pattern), colorful contact lens, synthetic iris images, iris pattern print on the paper, iris image/video displayed on the LCD, etc. Iris liveness detection aims to authenticate whether the input iris images are captured from a living subject. It is an important module in an iris recognition system to reduce the risks of being attacked by fake iris patterns at the sensor input.

Although there are a number of texture analysis algorithms proposed for iris liveness detection, there still exists many problems. State-of-the-art algorithms are mainly based on hand-crafted texture features, such as GLCM [8], LBP [9], HVC [14], etc. Although some feature selection algorithms such as Adaboost [9] are used to find the most effective parameter settings for a specific type of texture features, there is no strict definition on the texture models of genuine/fake iris images. As there are various types of fake iris patterns, well designed handcrafted features may not able to handle all the occasions. Therefore, [12] utilize CNN to make a preliminary research for iris liveness detection. However, they only use print fake iris images in their research. Besides, an iris image without normalizing used in their algorithm includes useless information such as eyelash, eyelid, etc, which decreases the accuracy of iris liveness detection.

In this paper, we propose a Multi-patch Convolutional Neural Network (MCNN) for iris liveness detection, which successfully handle hybrid fake iris patterns. A decision layer is designed to model the relationship between the multiply output of the first stage CNN and the final labels. The normalized iris images are first divide into multiply patches. After a set of convolutional neural networks, the outputs are fed into a decision layer. Thus, the MCNN also successfully deal with those fake iris images which mixture with genuine and fake iris patterns together. The major contributions of our work are two-fold:

Table 1. The state-of-the-art algorithms are listed in chronological order. Iris liveness detection algorithms mainly contain sensor level and algorithm level, and the algorithm level stand in the mainstream iris liveness detection. Most of algorithms identify fake iris images based on hand-crafted feature extraction. The table shows the applicable fake patterns of these algorithms or the public results in their manuscripts.

| Algorithm | Contact | Print | Synth | Plastic | Hand-crafted or Automatic | Sensor or Algorithm |
|---|---|---|---|---|---|---|
| Daugman [6] (2004) | - | - | - | ✓ | Hand-crafted (frequency analysis) | Algorithm |
| Lee *et al.* [11] (2006) | - | ✓ | - | ✓ | - | Sensor |
| He *et al.* [8] (2008) | ✓ | - | - | - | Hand-crafted (GLCM+SVM) | Algorithm |
| Wei *et al*. [15] (2008) | ✓ | - | - | - | Hand-crafted (Iris-Textons) | Algorithm |
| He *et al*. [9] (2009) | ✓ | ✓ | - | - | Hand-crafted (LBP+Adaboost) | Algorithm |
| Zhang *et al*. [17] (2010) | ✓ | - | - | - | Hand-crafted (WLBP+SVM) | Algorithm |
| Galbally *et al*. [7] (2012) | - | ✓ | - | - | Hand-crafted (Quality measures) | Algorithm |
| Yadav *et al*. [16] (2014) | ✓ | - | - | - | Hand-crafted (modified LBP) | Algorithm |
| Sun *et al*. [14] (2014) | ✓ | ✓ | ✓ | ✓ | Hand-crafted (HVC) | algorithm |
| R. Raghavendra *et al*. [13] (2015) | - | ✓ | - | - | Hand-crafted (In-depth analysis) | Algorithm |
| David Menotti *et al*. [12] (2015) | - | ✓ | - | - | Automatic (CNN) | Algorithm |
| Adam Czajka [4] (2015) | - | ✓ | - | ✓ | - | Sensor |

- This paper directly learns the mapping function between raw pixels of iris patches and the labels without any handcrafted features. By providing an alternate solution to make the full use of texture patterns for iris liveness detection, it is capable of identifying different types of fake iris images.
- MCNN achieves the accuracy of nearly 100% in four different public iris datasets which greatly advances the field of iris liveness detection. It also demonstrates that MCNN are robust to different fake iris patterns such as contact lens, plastic, print, synthetic, etc.

The remainder of this paper is organized as follows. Section 2 introduces some related works of iris liveness detection. In Section 3 we propose our algorithm of iris liveness detection. Section 4, we evaluate MCNN on four domain public datasets. Section 5 concludes this paper with some discussions.

## 2. Related work

Iris liveness detection is achieved in iris sensor level and intelligent algorithm level at present.

**Sensor level** Special design of iris sensors can facilitate iris liveness detection. Lee *et al*. [11] propose a fake iris detection scheme via investigating the specular spots of collimated IR-LED. The algorithm based on NIR illuminator is effective for identification of the print iris pattern and glass/plastic eye models. But it fails to identify contact lens because the iris texture is still visible when the attacker wears contact lens. Adam Czajka [4] uses the pupil dynamics algorithm to identify fake iris images, which need special sensor and fail to identify 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 but special design

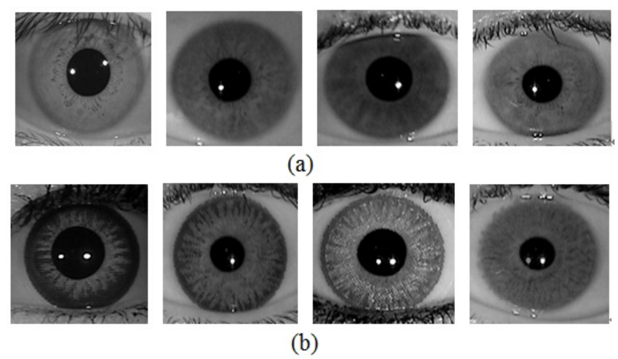


Figure 1. Comparison of texture features of genuine and fake iris images. (a) Genuine iris images. (b) Fake iris images.

of iris sensors are needed. So the generality of the sensor level iris liveness detection algorithm is limited since it depends on the specific hardware functions.

**Algorithm level** There are significant differences of texture features between genuine and fake iris images (Fig.2). The genuine iris images usually have naturally smooth texture features. In contrast, the fake iris images have coarse texture patterns due to the print iris texture on contact lens, paper and other materials. Algorithm level iris liveness detection algorithms do not need special iris sensors, which only use visual features of iris images for classification of genuine/fake samples. Daugman [6] propose to identify the print iris pattern based on frequency analysis. The basic idea is to utilize the frequency characteristics to distinguish genuine/fake iris images. However, this method is limited to print iris detection. He *et al.* [8] propose a contact lens detection method via statistical texture analysis. Four distinctive features based on gray level co-occurrence matrix (GLCM) are extracted. And support vector machine (SVM) is used for classification of genuine/fake iris images. Wei *et al*. [15] propose an algorithm based on texture analysis for contact lens detection. Iris-Textons are learned to represent statistical texture features of genuine/fake iris images. He *et al.* [9] use Adaboost to learn the most distinctive LBP features for iris liveness detection, which is able to identify print iris images and contact lens. Zhang *et al.* [17] realize high accuracy contact lens detection based on weighted-LBP encoding strategy and SVM classifier. Galbally *et al.* [7] suggest to identify print iris images based on quality measures. Yadav *et al.* [16] propose to use modified LBP for detection of contact lens. Sun *et al.* [14] develop the texture pattern representation algorithm called Hierarchical Visual Codebook (HVC) for iris image classification which is successfully applied to iris liveness detection. R. Raghavendra *et al.* [13] present an in-depth analysis of representation attacks on iris recognition systems, which is mainly focus on the print iris images and the iris images captured on LCD. David Menotti *et al.* [12] firstly adopt deep learning to extract iris features automatically, which is able to extract semantic and vision meaningful features directly from iris images without normalizing to distinguish genuine iris images and single pattern iris images (print iris images).

Table.1 concludes the state-of-the-art algorithms about feature extraction and their applicable patterns of fake iris image. It is noted that algorithm level methods with texture analysis are mainstream method for iris liveness detection. However, most texture analysis algorithms based on handcrafted feature extraction can only identify single or two patterns of fake iris images because it is difficult to find 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 network with small scale samples. Hence, we design a MCNN which is capable of learning effective parameter for various iris fake images and increases training samples accordingly.

## 3. Our Approach

### 3.1. Multi-patch presentation

The number of publicly available fake iris image datasets with reasonable size is limited and fake iris datasets lag behind the development of iris recognition. First, it is costly to organize the activities of constructing fake iris image datasets. Second, constructing an iris image dataset is a nontrivial task due to the difficulty of controlling the variation factors of iris images. Deep network, such as CNN, [10] has a huge number of network parameters, which mainly concentrate in the full connected layer. The size of input image decides the number of parameters in the full connected layer, but not in the convolutional layer. The CNN is easy to over fit while training it with only small scale samples and big size input images. Therefore, we propose the multi-patch convolution neural network for iris

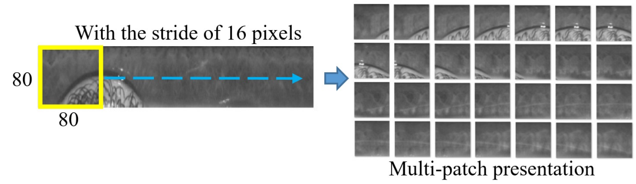



Figure 2. Multi-patch presentation of a normalized iris image.

liveness detection, which not only prevent over fitting of CNN, but also can learn optimal parameters to detect different types of fake iris images.

The size of normalized iris images is 512×80 pixels. As shown in Fig.2, an 80×80 pixels sliding window with a stride of $s$ pixels is used to decompose each normalized iris image into $n$ small patches with the same class. And the size of each small patch is 80×80 pixels. Therefore, iris training samples after decomposing increase n times the samples without decomposing.

The proposed MCNN helps to increase the accuracy of classification. If a normalized iris classified by softmax classifier and the output probability of softmax classifier is $p_1$ and $p_2$, which represent the output of probability of the normalized iris image. If $p_1 > p_2$, the normalized image is regarded as genuine. If $p_1 < p_2$, it is regarded as fake. However, when $p_1$ is very close to $p_2$, the normalized iris image locate on the classification boundary, which makes the classification result very fuzzy. That is to say, a genuine iris image may be misclassified as a fake iris image or a fake iris image may be misclassified as a genuine iris image. Therefore, it is easy to result in the fuzzy classification result when a whole normalized iris image is used as the input of CNN. MCNN increases discrimination of genuine/fake iris images, which is capable of avoiding fuzzy classification with a normalized iris image. Simultaneously, MCNN can learn parameters to identify various patterns of fake iris images effectively.

### 3.2. Deep multi-patch classification

As illustrated in Fig.3, the main preprocessing steps include iris image segmentation and normalization. A normalized iris image is decomposed into $n$ small patches. We use CNN to learn iris texture features of each patch. The convolution and pooling operations in CNN are designed to extract high-level texture features. Fig.3 shows the detail architecture of the CNN, with two convolutional layers followed by max-pooling. The input of CNN is the 80×80 rectangle patch of an iris image. The first convolutional layer filters the 80×80 input patch with 64 kernels of size 5×5 with a stride of 1 pixel. The second convolutional layer takes as input the output of the first convolutional layer and filters it with 64 kernels of size 5×5×64. The convolutional

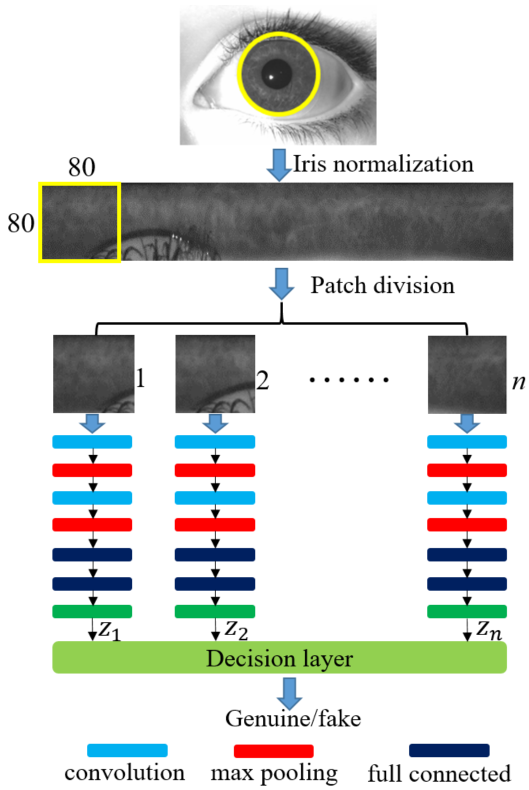



Figure 3. Our convolution neural network architecture for classification of genuine iris patches and fake iris patches. Iris localization and segmentation are the first procedure for a captured eye image. Then we normalize the iris image in the polar coordinate. Next, the normalized iris image is decomposed into 28 multi-block iris patches using a sliding window. These iris patches are used as the input of CNN. Simultaneously, the CNN output the deterministic of classification $z = y_1/y_2$ of each iris patch.

operation is expressed as

$$y^{j(r)} = \max(0, b^{j(r)} + \textstyle\sum_i k^{ij(r)} * x^{i(r)}) \qquad (1)$$

where $x^i$ and $y^j$ are the $i$-th input map and the $j$-th output respectively. $k^{ij}$ is the convolutional kernel between the $i$-th input map and the $j$-th output map. $b^j$ is the bias of the $j$-th output map. We use the ReLU nonlinearity ($y = \max(0, x)$), which is able to extract the rotation and scale invariant features compared with the sigmoid function. Our designed CNN has two full connected layers and each full connected layer has 1024 neurons. In the second full connected layer, highly compact and predictive features are extracted. The output of CNN is a two-way softmax layer, which outputs a probability distribution over the two classes (the genuine/fake iris patches). The CNN is trained to minimize the cross-entropy loss.

$$y_i = \frac{\exp(y_i^{'})}{\sum_{j=1}^{n} \exp(y_i^{'})} \qquad (2)$$

where $y_j^{'} = \sum_{i=1}^{1024} w_i x_{i,j} + b_j$. $x_i$ represents the features of the last full connected layer and $y_i$ is the output. The CNN is learned by minimizing $-\log y_t$. Stochastic gradient descent is used with gradients calculated by back-propagation.

The output of MCNN are $y_1$ and $y_2$ for each patch. We define a new variable $z = y_1/y_2$, which represents classification deterministic of each patch. When $z \gg 1$, the input iris patch is classified as the genuine iris patch confirmedly. When $z \ll 1$, the input iris patch is classified as the fake iris patch confirmedly. When $z$ is close to 1, the input iris patch has a fuzzy classification result. We fuse the classification deterministic of each patch to reduce the error classification and fuzzy classification while using a normalized iris image without decomposing. We construct classification deterministic vector $Z^{28\times 1} = \{z_1, z_2, \ldots, z_{28}\}$ of each input normalized iris image. And the training set $\{(Z^{(1)}, y^{(1)}), (Z^{(2)}, y^{(2)}), \ldots, (Z^{(m)}, y^{(m)})\}$, $y^{(i)} \in \{0, 1\}$. The logistic regression is used to solve the binary classification. The cost function $J(\theta)$ is defined as follows:

$$J(\theta) = \frac{1}{m}\sum_{i=1}^{m}[-y^{(i)}\log(h_\theta(Z^{(i)})) - (1 - y^{(i)}) \\ \log(1 - h_\theta(Z^{(i)}))] \qquad (3)$$

where $h_\theta(Z) = 1/(1+e^{-\theta^T Z})$. Our goal is to use Newton's method to minimize this function. Recall that the update rule for Newton's method is

$$\theta^{t+1} = \theta^t - H^{-1}\nabla_\theta J \qquad (4)$$

where $H$ and $\nabla_\theta J$ represent Hessian matrix and represents gradient of $J(\theta)$ respectively. And the $\theta$ the contribution rate of each multi-patch. The optimal classifier can be achieved after training. And we can use the optimal classifier to detect fake iris images.

# 4. Experiments

Two experiments are carried out to evaluate the performance of the proposed algorithm under different conditions on four public datasets: ND-Contact [3], CASIA-Iris-Interval & CASIA-Iris-Syn [2], LivDet-Iris-2013-Warsaw [5] and CASIA-Iris-Fake [1] summarized in Table 2. We focus on two experiments with these four datasets. The accuracy of MCNN is tested on three single pattern datasets (ND-Contact, CASIA-Iris-Interval & CASIA-Iris-Syn and LivDet-Iris-2013-Warsaw) compared with state-of-the-art algorithms. In order to verify the robustness of MCNN, we experiment on the hybrid dataset (CASIA-Iris-Fake).

## 4.1. Datasets

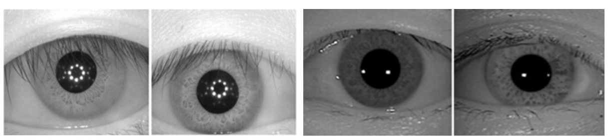
**ND-Contact**: Some datasets containing iris images with cosmetic contact lenses have been published in recent years.

Table 2. Four Datasets are used for evaluating the performance of our proposed method.

| Dataset | Iris images | Genuine | Contact lens | Plastic | Print | Synth |
|---|---|---|---|---|---|---|
| ND-Contact | 4,200 | 2,800 | 1,400 | - | - | - |
| CASIA-Iris-Interval&synth | 12,639 | 2,639 | - | - | - | 10,000 |
| LivDet-Iris-2013-Warsaw | 1,667 | 852 | - | - | 815 | - |
| CASIA-Iris-Fake | 10,970 | 6,000 | 740 | 640 | 640 | 2,950 |

(a) (b) (c)

Figure 4. Some samples from ND-Contact. (a) No contact lens. (b) Soft contact lens. (c) Contact lens.

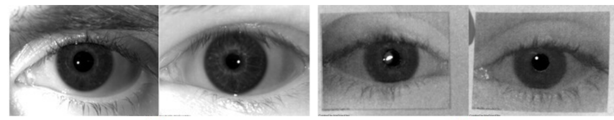


(a) (b)

Figure 5. (a) Genuine iris images in CASIA-Iris-Interval. (b) Synthetic iris images in CASIA-Iris-Syn.

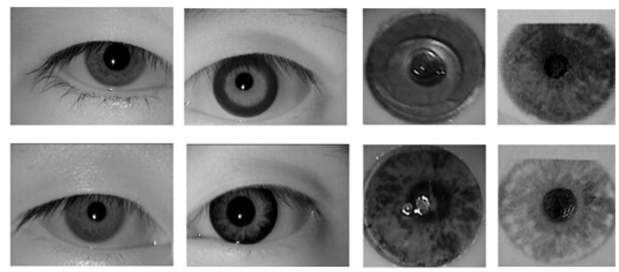
To the best of our knowledge, the Notre Dame Cosmetic Contact Lenses 2013 (or ND-Contact for short in this paper) [3] is the largest dataset. It contains iris images of subjects with soft contact lenses and cosmetic contact lenses, but without contact lenses, captured by a LG 4000 iris sensor. In our research, both iris images without contact lenses and with soft contact lenses are regarded as genuine iris images because iris texture patterns are still visible through soft contact lenses to achieve correct identification (Pioneer work in [14] regards clear contact lenses as genuine iris. Therefore, we regard the clear contact lenses as genuine iris in our experiment.). And the iris images with cosmetic contact lenses are treated as fake samples. Fig. 4 shows samples from ND-Contact.

**CASIA-Iris-Interval&CASIA-Iris-Syn (CASIA-Iris-Interval&Syn)**: The genuine iris image dataset CASIA-Iris-Interval [2] and the synthetic iris image dataset CASIA-Iris-Syn [2] are used to test the proposed iris liveness detection algorithm. Iris images of CASIA-Iris-Interval are captured with 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. Based on this design, the iris camera can capture high quality iris images. CASIA-Iris-Interval (Fig.5 (a)) is well-



(a) (b)

Figure 6. Examples of iris in LivDet-Iris-2013-Warsaw DB. (a) The genuine iris images. (b) The print iris images.



(a) (b) (c) (d)

Figure 7. Some sample from CASIA-Iris-Fake. (a) Genuine iris. (b) Contact lens. (c) Plastic. (d) Print

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.5 (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.

**LivDet-Iris-2013-Warsaw**: The LivDet-Iris DB [5] is firstly used in Liveness-Iris Competition. The Warsaw dataset is captured by EyeGuard AD100 which comprises over 1,667 samples acquired from around 560 different iris images. As shown in Fig.6, two different types of spoof attacks in the the LivDet-Iris-2013-Warsaw are considered in the dataset. It contains 815 print iris and 852 genuine iris. The genuine/print iris are shown in Fig.6.

**CASIA-Iris-Fake**: Although the above three datasets are good for research of iris liveness detection, they only have one pattern of fake iris images. Therefore, hybrid CASIA-Iris-Fake dataset is also used in our experiment [1]. This dataset includes four subsets, namely Print, Contact, Plastic and Synth. In the first three subsets, fake iris patterns are print on paper, contact lens, and plastic eyeball model respectively. An iris device IG-H100 is used to capture a large number of fake iris images. These three kinds of typical fake iris images have seemingly realistic iris texture and are useful for testing the performance of iris liveness detection algorithm. Fig.7 shows samples from CASIA-Iris-Fake dataset.

### 4.2. Experiments on the single fake pattern datasets

This section will present the experimental results on the single fake pattern dataset. It mainly investigates the performance of our proposed algorithm on different types of fake iris images. ND-Contact only contains fake iris images with cosmetic contact lenes. CASIA-Iris-Interval&Syn contain synthetic fake iris images and LivDet-Iris-2013-Warsaw DB contains the print fake iris images. The training set and testing set of these three datasets are set as follow:

(1) For ND-Contact, we use the setting of training and testing datasets defined 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 and CASIA-Iris-Syn datasets, we randomly choose 1,000 genuine and 1,000 synthetic iris images as the training set. And all other iris images are used as the testing set. The experiment is repeated five times with different random setting of the training dataset. (3) For LivDet-Iris-2013-Warsaw set, we use 400 genuine iris images and 400 print iris images for training and the rest for testing.

**Comparison algorithm**: Spoofnet [12], Weighted LBP [17], HVC+SPM [14] are used for comparison.

**Evaluation Protocol**: CCR (Correct Classification Rate) and FAR (rate of falsely accept fake iris image as genuine one) and FRR (rate of falsely reject genuine iris image as fake one) are used as the evaluation protocol.

The experimental results suggest that our proposed MCNN performs better than SpoofNet, Weighted LBP, HVC+SPM on the single pattern datasets as shown in Table 3. Our algorithm achieves 100% CCR on the ND-Contact dataset, 99.87% CCR on CASIA-Iris-Interval & Syn datasets and 98.15% CCR on the LivDet-Iris-2013-Warsaw dataset respectively. Besides, MCNN and SpoofNet based on CNN achieve a higher CRR than Weight LBP and HVC+SPM 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.

### 4.3. Experiments on the hybrid fake pattern dataset

CASIA-Iris-Fake is used to evaluate the performance of MCNN on the hybrid pattern fake iris images dataset. It consists of fake iris images with contact lens, plastic iris images, print iris images and synthetic iris images. We respectively use 400 iris images per each class (genuine/fake) for training and the rest of iris images for testing. The iris liveness detection algorithms, including SpoofNet, Weighted LBP, HVC+SPM are used to comparison. Table 4 shows the CCR, FAR, FRR of these algorithm and Fig.8 shows the

Table 4. Performance of iris liveness detection methods on the hybrid pattern fake iris images dataset

| Method | CCR | FAR | FRR |
|---|---|---|---|
| **MCNN** | **100%** | **0%** | **0%** |
| SpoofNet | 99.06% | 1.04% | 0.63% |
| Weighted LBP | 97.40% | 5.36% | 2.08% |
| HVC+SPM | 98.27% | 1.45% | 1.99% |

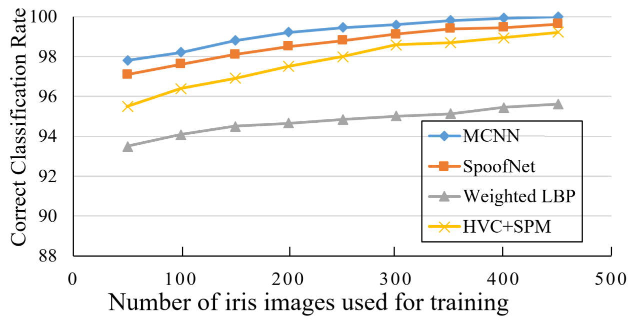



Figure 8. CCR curves as a function of the number of training samples on CASIA-Iris-Fake database.

CCR curves as a function of the number of training samples.

A number of conclusions can be drawn from experimental results. First, all these methods can achieve high accuracy in detection of various fake iris patterns. Second, with the increasing quantity of training samples, the CCR of all methods gradually increases. Third, MCNN performs better than SpoofNet, Weighted LBP, HVC+SPM on the hybrid dataset in detection of fake iris images. MCNN is able to fully exploit texture information of iris images.

## 5. Conclusion

This paper is very meaningful for iris liveness detection. We propose a novelty algorithm named MCNN which is able to identify fake iris images. CNN is used to automatically learn the most effective texture features for classification of genuine/fake iris images. Such an approach establishes a direct inference scheme from raw pixel values of iris images to iris liveness detection results. Representation of multi-patch normalized ROI are suggested as the input of CNN. A decision layer is designed to model the relationship between the multiply output of the first stage CNN and the final labels, which is effective to detect different types of fake iris images. More importantly, the MCNN can increase training dataset in the condition of limitation of the scale of existing fake iris dataset and prevent over fitting of CNN according to decrease the number of parameters in the full connected layer in CNN.

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. From the all experiments, we can get the order of CCR (from high to low) for different types

Table 3. Performance of iris liveness detection methods on the single pattern fake iris image datasets

| Dataset | SpoofNet [12] | | | Weighted LBP [17] | | | HVC+SPM [14] | | | **MCNN** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | CCR | FAR | FRR | CCR | FAR | FRR | CCR | FAR | FRR | CCR | FAR | FRR |
| ND-Contact | 99.43% | 0.63% | 0.75% | 95.71% | 6.25% | 4.37% | 98.86% | 1.25% | 1.50% | **100%** | **0%** | **0%** |
| CASIA-Iris-Interval&Syn | 99.44% | 0.79% | 0.52% | 96.99% | 4.39% | 2.80% | 98.15% | 1.20% | 2.43% | **99.87%** | **0.24%** | **0.11%** |
| LivDet-Iris-2013-Warsaw | 97.37% | 4.43% | 0.97% | 95.58% | 5.87% | 3.10% | 97.58% | 4.05% | 1.75% | **98.15%** | **3.13%** | **0.67%** |

of iris pattern as follow: contact lens pattern > synthesis iris pattern > print iris pattern.

Both sensor level and algorithm level iris liveness detection algorithms have their advantages and disadvantages. In the future work, 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. For example, if the iris sensor can capture depth images of human iris, the iris liveness detection algorithm can easily identify the fake iris patterns displayed on a plane (paper or LCD) using the 3D geometry information.

## 6. Acknowledgements

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