Contact lens detection based on weighted LBP

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***Abstract*—Spoof detection is a critical function for iris recognition because it reduces the risk of iris recognition systems being forged. Despite various counterfeit artifacts, cosmetic contact lens is one of the most common and difficult to detect. In this paper, we proposed a novel fake iris detection algorithm based on improved LBP and statistical features. Firstly, a simplified SIFT descriptor is extracted at each pixel of the image. Secondly, the SIFT descriptor is used to rank the LBP encoding sequence. Then, statistical features are extracted from the weighted LBP map. Lastly, SVM classifier is employed to classify the genuine and counterfeit iris images. Extensive experiments are conducted on a database containing more than 5000 fake iris images by wearing 70 kinds of contact lens, and captured by four iris devices. Experimental results show that the proposed method achieves state-of-the-art performance in contact lens spoof detection.**

***Keywords*-fake iris, spoof detection, cosmetic contact lens, weighted LBP**

I. INTRODUCTION

Iris recognition has drawn much attention due to its convenience and security. Compared with other biometric modality, iris pattern has been regarded as one of the most accurate biometric modalities for its uniqueness, stability and non-intrusiveness [1], [2]. However, as other biometric systems, iris system is also under threat of forged iris attack. Efficient iris spoof detection can improve security of iris recognition systems.

Some artifacts have been considered to spoof iris recognition system, such as paper printed iris, cosmetic contact lens, and redisplayed videos. Cosmetic contact lens is a contact lens with color texture printed on it. Spoof caused by wearing a cosmetic contact lens is particularly dangerous. It is easily accepted by the system and hard to detect. Fig. 1 shows some genuine and fake iris images. This paper proposes a framework of contact lens detection.

In previous studies on iris spoof detection, several kinds of methods have been proposed. Daugman [1] proposed a FFT based method that checks the spectral energy in frequency domain, which uses the periodic characteristics of printer. Lee et al. [3] proposed a method to distinguish genuine and fake iris based on the Purkinje image. Sung et al. [4] introduced a method of detecting fake iris by measuring the ratio of the reflectance measured at 750nm and 850nm

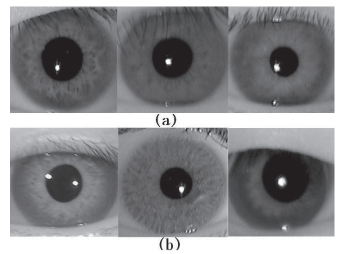

Figure 1. Iris image examples. (a) Genuine irises; (b)Irises with cosmetic contact lenses.

illumination. Wei et al. [5] proposed iris spoof detection methods based on textons and co-occurrence matrix. He et al. [6] used the LBP feature and boosting method for iris spoof detection.

In this paper, we propose a set of more efficient features that combines local textural features and structural features. Firstly, we extract SIFT descriptors at each pixel for the purpose of weighting the LBP encoding sequence. Then, the weighted LBP maps are generated with the SIFT descriptors as weighting coefficients [7], [8]. Finally, we extract statistical features from the LBP map and use SVM to classify genuine and fake irises.

The remainder of this paper is organized as follows. Section 2 introduces the proposed methods. Section 3 introduces a new large counterfeit iris database and presents the experimental results. Section 4 concludes the paper.

II. TECHNICAL DETAILS

The flowchart of the proposed cosmetic contact lens detection method is shown in Fig. 2. It consists of four steps: iris image preprocessing; generating scale space and calculating SIFT-like descriptors; calculating weighted local binary patterns; extracting features and classification. We will describe each step in the following subsections.

A. Iris image preprocessing

The main preprocessing steps include iris segmentation and de-noising, which are illustrated in Fig. 3. Iris segmentation is to find iris region by precisely localizing its inner and outer boundaries. More details can be found in [9]. The

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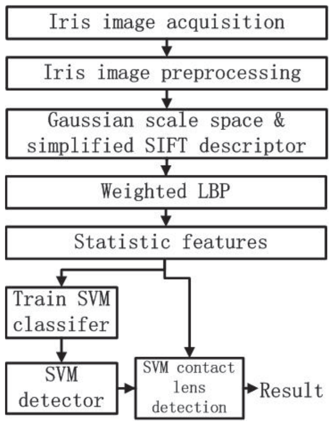

Figure 2. Flowchart of proposed cosmetic contact lens detection method.

bounding square block of iris circle is regarded as the region of interest for feature extraction rather than iris normalization to polar coordinate system, to keep the regular texture pattern of colorful contact lens in Cartesian coordinate and save time used for transformation of coordinate systems.

For de-noising, we choose low-pass filter and Total Variation [10] as de-noising method. Experimental results show that combining the results of two methods is a good candidate for image de-noising. To make the computation convenient, we normalized iris images into the same size 400×400.

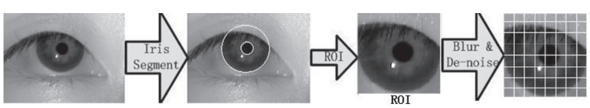

Figure 3. Iris image preprocessing.

B. Gaussian scale space and simplified SIFT descriptor

After smoothing, we use a simplified SIFT descriptor to analyze the local structural characteristics.The SIFT descriptor is adopted because it is largely invariant to changes of scale, illumination, and local affine distortions, and also in a certain degree of stability to view changes and noise [8]. Application of SIFT descriptor will enhance the stability and robustness of LBP.

The first step is to generate the scale space $L(x, y, \sigma)$ from the convolution of a variable-scale Gaussian template $G(x, y, \sigma)$, with an image $I(x, y)$. The second step is to extract a simplified SIFT descriptor for each pixel in its 5×5 neighborhood, as shown in Fig. 4. Arrows denote the magnitude and orientation at each image pixel, and the overlaid circle is weighted Gaussian window. Fig. 4(b) shows the orientation histograms summarizing the contents over subregions. In order to achieve orientation invariance, the coordinates of the descriptor and the gradient orientations are rotated relative to the main orientation, which is determined by all the gradient direction of every scale. The last step is to get a descending rank of the orientation histogram, denoted as $Rank_{SIFT}(i), Rank_{SIFT}(i) \in \{0, 1, 2, 3, 4, 5, 6, 7\}$, where i is ID of the orientation.

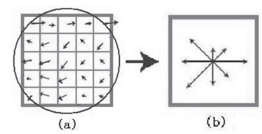

Figure 4. Simplified SIFT descriptor. (a) Gradients; (b) Descriptor.

C. Weighted-LBP (w-LBP)

In this work, the local binary patterns (LBP) are adopted to represent texture patterns of iris images. The LBP has emerged as an effective texture descriptor and is widely used in texture analysis [7]. LBP is defined for each pixel by comparing its 3×3 neighborhood pixels with the center pixel value, and considering the result as a binary bit string. Iris has very fine textures, and the local rotations, affine transformations and distortions of the iris image are common phenomenon. Therefore, the SIFT descriptor is used to improve the invariability of LBP to rotation, affine transformation, and illumination.

For each pixel, we regard the direction with the larger SIFT histogram entries as the higher bit of binary string. According to the SIFT orientation histogram, we encode LBP as

$$wLBP_8 = \sum\nolimits_{i=0}^{7} sign(g_i - g_c) 2^{Rank_{SIFT}(i)}$$

$$sign(g_i - g_c) = \left\{ \begin{array}{ll} 0, & if\ g_i < g_c \\ 1, & if\ g_i >= g_c \end{array} \right.$$

Where g_i is gray value of a neighbor pixel, g_c is gray value of the central pixel, and the neighbor pixel ID i corresponds to ID of orientation histogram. Fig. 5 is an illustration of weighted LBP encoding.

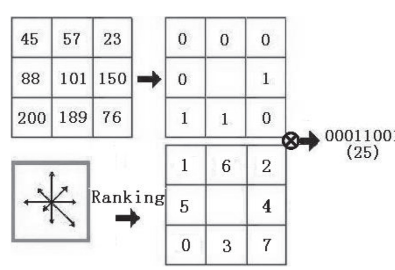

Figure 5. Weighted LBP encoding.

For the sake of gray-scale invariance, we extract w-LBP at each level of Gaussian scale space, denoted by G1-G6. For G1-G3, we get 3 w-LBP maps as mentioned above, Fig. 6(a). For G4-G6, we extract w-LBP in 24 neighbors shown in Fig. 6(b). For a specific direction, when at least two of three neighborhood pixels are larger than the center pixel, the value of a binary bit string is set as 1, otherwise 0.

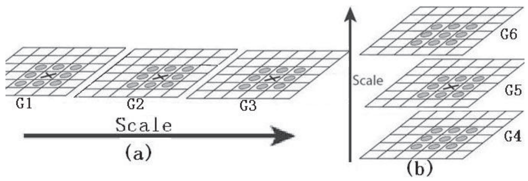

Figure 6. w-LBP of different scales.

D. Statistical features and classification

Here, novel statistical features are extracted from the w-LBP map. We divide a w-LBP map into 8×8 partitions as the last image of Fig. 3 shows, and abandon the first and last rows to avoid the impact of eyelid. In each block, three statistics of the w-LBP map are exacted, namely, standard deviation of w-LBP histogram, mean and standard deviation of w-LBP map acorrding to the following formulas.

$$\bar{I}_{map} = \frac{1}{m \times n} \sum_{i,j} I_{map}(i,j)$$
$$\sigma_{map} = \sqrt{\frac{1}{m \times n} \sum_{i,j} \left(I_{map}(i,j) - \bar{I}_{map} \right)^2}$$
$$\sigma_{hist} = \sqrt{\frac{1}{256} \sum_{i=0}^{255} \left(hist(i) - m \times n/256 \right)^2}$$

Where m and n are the size of block, and I_{map} and $hist$ are w-LBP map and histogram. Thus, we get a 576 dimensional feature for each image.

We employ the SVM with RBF kernel function for classification [11]. SVM is suitable for testing the proposed feature extracting method because of avoiding inclining to over-learning or over-fitting. CCR (Correct Classification Rate), 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 performance metrics.

III. Experiments

A. Database

Our experiments were based on a self-collected fake iris database since there are no such public available databases. The database contains 55 kinds of cosmetic contact lenses, worn by 72 people. During the collection, four different iris cameras are used to capture the contact lens wearing iris images, including IrisGuard IG-H100, OKI IRISPASS-h, IrisKing IKEMB-100 and CASIA-Cam V3. Therefore, our database contains four datasets corresponding to each device: DB1, DB2, DB3, DB4. For each dataset, we keep twenty images of each person, ten from left eyes and ten from right eyes, resulting in 1400 images in total. Some of these images are shown in Fig. 7. We also used the dataset mentioned in [5], denoting as DB5. Genuine iris images are randomly selected from two iris databases. One database is CASIA iris databaseV3 [12]. The other database is a new iris database including 1005 persons. Some images are shown in Fig. 8. The genuine iris images are taken by the same cameras as mentioned above. Besides, the genuine iris database includes glasses wearing iris images. The large spots caused by specular reflection and glass-frames make the database more challenging. The iris images used in our experiments are of moderate quality, including images with slight motion blur, defocus and occlusions.

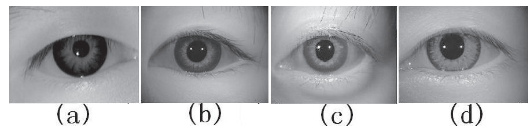

Figure 7. Examples of iris image with cosmetic contact lenses database. (a) DB1; (b) DB2; (c) DB3; (d) DB4.

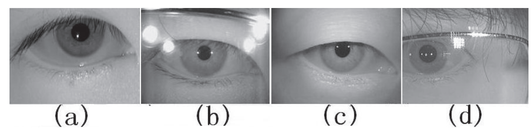

Figure 8. Examples of genuine iris database. (a) DB1; (b) DB2; (c) DB3; (d) DB4.

B. Experimental results

To evaluate effectiveness of the proposed method, the original LBP feature extraction was also developed for comparison. For fair comparison, we used multi-resolution LBP with the same features dimension as the weighted LBP, that named by $LBP_{8,2}^{u2}$, $LBP_{8,3}^{u2}$, $LBP_{8,5}^{u2}$ and $LBP_{8,7}^{u2}$, following the standard LBP [7]. SVM is adopted as classifier, and same training and testing datasets are used.

Firstly, experiments were performed on each database separately, using half of the images for training and the rest for testing. Both of the methods show good classification performances with CCR over 99%. Then, we mixed these databases and use one fourth of the images for training and the rest for testing. Table I shows the testing results, where CCR, FAR and FRR are presented. It is interesting to compare our method with the methods of He [6]. At last, in order to evaluate the inter operability of the proposed method kinds of databases, we did a more challenging experiment that training the SVM classifier with dataset DB1 and testing it on the other datasets. The experimental results are shown in Table II, and some ROC are shown in Fig. 9.

Experimental results show that both the proposed w-LBP and standard LBP method gain high CCR on single datasets. The w-LBP shows its advantages during handling the mixed database, and also shows robustness in the cross camera experiments, indicating a strong learning ability for texture primitives. It is therefore suitable for counterfeit iris

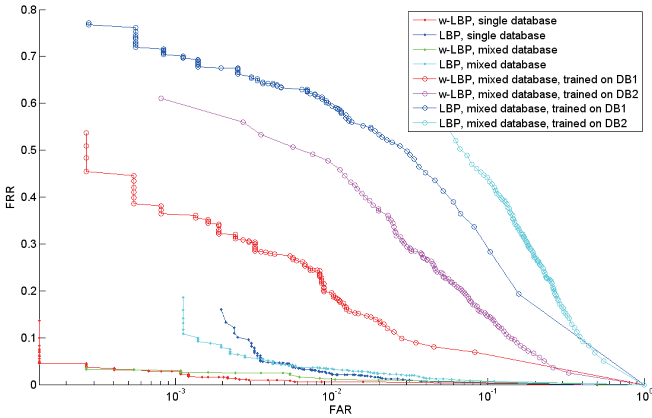

Figure 9. Dot line: ROCs of single and mixed database experiments; circle line: ROCs of cross database experiments.

Table I
MIXED DATABASE EXPERIMENTAL RESULTS

	CCR	FAR	FRR
Standard LBP	97.55%	1.52%	3.23%
He [6]	98.36%	1.20%	2.96%
w-LBP	99.14%	0.44%	1.13%

Table II
CROSS-CAMERA VALIDATION EXPERIMENTAL RESULTS

	CCR	FAR	FRR
Standard LBP	83.75%	15.65%	17.84%
w-LBP	88.05%	10.56%	15.63%

detection, whose samples are time-consuming and costly to collect. Most of existing iris spoof detection methods in the literature do not involve the impact of wearing glasses that have heavy reflections. Experimental results indicate that our method is robust to glasses impact, including specular, glass-frame shelter, hazy caused by dirty optic, and extra texture of dirty optic.

IV. CONCLUSIONS

In this paper, we have proposed a novel method to detect counterfeit irises wearing cosmetic contact lenses. Firstly, we de-noise iris images and segment iris image parts. Then, we extract SIFT descriptor at every pixels and use it for weighting the LBP encoding procedure. Finally, three simple statistics of weighted LBP map are extracted. SVM classifier is used for counterfeit iris detection. The combination of SIFT with LBP improves its invariance of scale illumination and local affine distortion, and make the algorithm more robust to camera view change. The experimental results show that the proposed method is robust to detect contact-lens and promising for cross-camera fake iris classification.

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