Counterfeit Iris Detection Based on Texture Analysis

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Abstract

This paper addresses the issue of counterfeit iris detection, which is a liveness detection problem in biometrics. Fake iris mentioned here refers to iris wearing color contact lens with textures printed onto them. We propose three measures to detect fake iris: measuring iris edge sharpness, applying Iris-Texton feature for characterizing the visual primitives of iris textures and using selected features based on co-occurrence matrix (CM). Extensive testing is carried out on two datasets containing different types of contact lens with totally 640 fake iris images, which demonstrates that Iris-Texton and CM features are effective and robust in anti-counterfeit iris. Detailed comparisons with two state-of-the-art methods in literatures are also presented, showing that the proposed iris edge sharpness measure acquires a comparable performance with these two methods, while Iris-Texton and CM features outperform the state-of-the-art.

1. Introduction

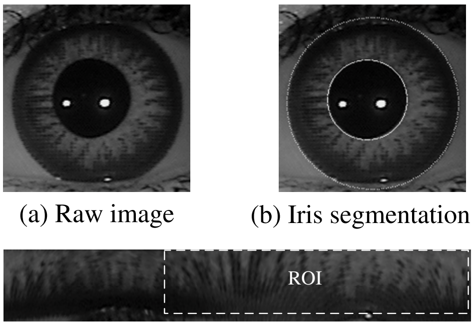
Personal identification using biometrics has been developing rapidly since the past decade. Biometric systems have already been deployed to border control, access to personal computers and the control of airport. However, biometric systems still have vulnerabilities. Spoofing biometric system may occur in every step from data acquisition to decision level, including using fake biometrics, replaying attacks, corrupting match scores and overriding final decision, etc[11]. Iris pattern is considered as the most accurate and stable biometric modality, however, iris recognition system meets new challenge in anti-counterfeit iris as color contact lens become popular recently. Attackers wearing contact lens with artificial textures printed onto them may try to access the system unauthorized, which is one of the potential means to spoof the systems.

This paper addresses the issue of detecting fake iris wearing printed color contact lens, with the purpose of making iris recognition system more robust in anti-spoofing. This issue is a liveness detection problem in biometrics, which aims to ensure that images acquired by the camera are real patterns. In previous studies of this issue, Daugman[5] proposed to detect printed iris pattern using spurious energy in 2D Fourier spectra. Lee et al.[8] suggested detecting fake iris based on Purkinje image. He et al.[7] used four features (image mean, variance, contrast and angular second moment) to detect fake iris. In this paper, we propose three anti-spoofing measures to prevent printed color contact lens from accessing iris recognition system. Detecting iris edge sharpness is the first measure proposed. Another measure comes from our previous work [10] for coarse iris classification, using feature named Iris-Texton by learned visual vocabulary to classify iris texture. Lastly, textural features based on co-occurrence matrix (CM) are adopted, and feature selection procedure is applied to find a combination of 3 features from the 28 features proposed by Haralick et al.[6].

The remainder of this paper is organized as follows. Section 2 briefly describes iris image preprocessing. Section 3 presents the proposed measures for counterfeit iris detection. Section 4 gives experimental results and analysis. Section 5 concludes the paper.

2. Iris Image preprocessing

Iris images are preprocessed into a normalized image before feature extraction. The main preprocessing steps include iris segmentation and normalization, with illustration in Fig.1. Iris segmentation is to find iris region by precisely localizing its inner and outer boundaries. Iris normalization is to project iris from Cartesian to polar coordinates using bilinear interpolation. More detail can be found in [9].



(a) Raw image (b) Iris segmentation

(c) Iris normalization

Figure 1. Iris Image preprocessing.

3. Counterfeit iris detection

3.1 Iris edge sharpness

A typical fake iris wearing color contact lens is shown in Fig1(a), presenting as grey-scale images in the state-of-the-art systems using NIR illumination. Textures printed on contact lens usually distribute over the outer half iris region, especially on the iris edge (transition from sclera to iris region). From the appearance of fake iris, it can be seen that its iris edge usually sharper than that of live iris. So we introduce iris edge sharpness (IES) as the first measure to detect counterfeit iris, describing as:

$$IES = \sum_{\theta=0}^{2\pi}(I(r_{i+\xi}, \theta) - I(r_{i-\xi}, \theta)), \qquad (1)$$

where $I(r, \theta)$ is an iris image in polar coordinates, r_i is iris radius and θ is the angle from an edge point to iris center. $I(r_{i+\xi}, \theta)$ and $I(r_{i-\xi}, \theta)$ represent pixel values in sclera region and iris region, respectively.

3.2 Iris-Texton for iris texture characterization

Texton refers to fundamental micro-structure in generic natural images and thus constitute textures as the basic elements in early visual perception. Our previous work[10] successfully extends texton theory to represent the visual appearance of iris images. Iris-Texton feature extraction includes two steps. Firstly a small, finite vocabulary of visual words in iris images, called Iris-Texton, are learned. Then Iris-Texton histogram are used as feature vectors to represent the global characteristics of iris images.

Fig.2 shows a diagram illustrating the steps of learning Iris-Texton vocabulary. An input image ROI, excluding eyelids/eyelashes noise (see Fig.1), is sent into filter banks, where the image is characterized by its responds to a set of orientation and spacial-frequency selective Gabor filters. The filtered image $r(x, y)$ is described as:

$$r(x, y) = \int\int I(x_1, y_1)h(x-x_1, y-y_1)dx_1dy_1, \quad (2)$$

$$h(x, y) = g(x, y) \cdot \cos[2\pi f(x\cos\theta + y\sin\theta)], \quad (3)$$

where $I(x, y)$ is image, $h(x, y)$ is even Gabor filters and $g(x, y)$ is isotropic Gaussian function.

Then the filter response vectors are clustered into a set of prototypes, using a vector quantization algorithm, e.g, K-means in our experiments. The K centers found by K-mean are Iris-Textons. There are 64 Iris-Textons learned, which are named Iris-Texton vocabulary.

After that the global feature of iris image is represent by Iris-Texton histogram, shown in Fig.3. Each Iris-Texton is represented by the mean of vectors in the cluster and serves as one bin in the histogram. Each pixel can generate a 40 dimension vector by Gabor filtering and concatenation, and this vector is assigned to the bin representing the nearest texton. By mapping 40 dimensional vectors to 64 bins, we can obtain a histogram with frequent variations of bins. The Iris-Texton histogram denotes the richness of micro-texture in iris image with proper filters chosen, therefore it is sufficient to characterize the global feature of iris image.

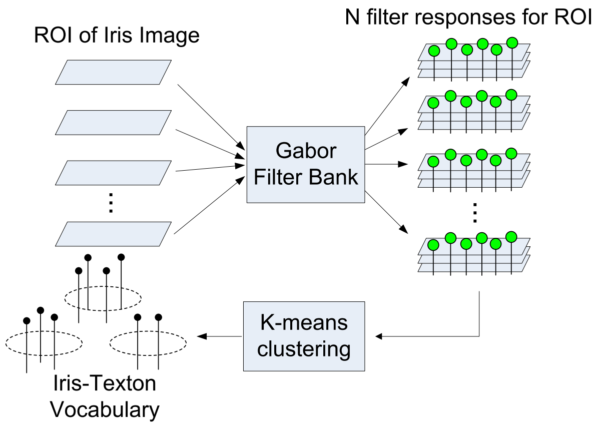


Figure 2. The Iris-Texton vocabulary construction.

Lastly the dissimilarity of two Iris-Texton histograms is measured by Chi-square statistic:

$$\chi^2(H_1, H_2) = \sum_{i=1}^{64} \frac{(H_{1i} - H_{2i})^2}{H_{1i} + H_{2i}}, \qquad (4)$$

The summation only includes non-zeros bins to avoid $H_{1i} + H_{2i} = 0$.

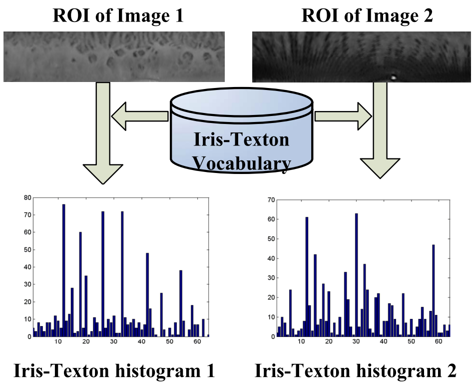


Figure 3. Obtaining Iris-Texton histogram.

3.3 Textural features based on co-occurrence matrix

Textural features based on grey level co-occurrence matrices (GLCM) is the third measurement we used to detect fake iris. Those features are generated on image ROI, which is obtained by image preprocessing described in Fig.1. Co-occurrence matrices represent a second order statistic measurement, as they characterize the relationship between the neighboring pixels.

In his work, Haralick et al.[6] defined 14 measures of textural features based on co-occurrence matrix (homogeneity, contrast, correlation, variance, inverse difference moment, etc.) to represent image. These features are orientation dependent, and hence 4 values can be obtained in each measure based on orientation $(0^o, 45^o, 90^o, 135^o)$. The mean and range of the 4 values are served as features of the 14 measures, therefore an image can be represented by 28 features totally. However, the 28 features shows certain redundancies, indicating only some of them are necessary. In this paper, feature selection procedure using combination of features (at most 8 feature combination: $C_{28}^1 + C_{28}^2 + ... + C_{28}^8$) are applied to find the best features to characterize iris texture. Based on feature selection results, which is shown in Fig.4, three features are finally selected to characterize iris texture. They are inverse difference moment (f_{idm}), sum average (f_{sa}) and sum entropy (f_{se}), defining as follows:

$$f_{idm} = \sum_i \sum_j \frac{1}{1+(i-j)^2} p(i,j), \tag{5}$$

$$f_{sa} = \sum_{i=2}^{2N_g} i p_{x+y}(i), \tag{6}$$

$$f_{se} = -\sum_{i=2}^{2N_g} p_{x+y}(i) log(p_{x+y}(i)), \tag{7}$$

where $p(i,j)$ is the co-occurrence matrix, $p_{x+y}(k) = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} p(i,j)$,$(i+j=k, k=2,3,...,2N_g)$ (N_g is the total grey levels).

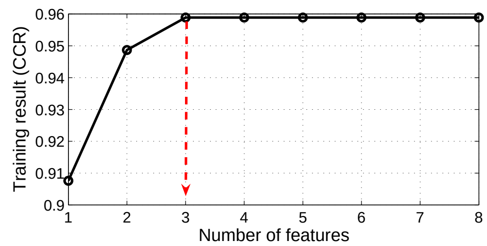


Figure 4. Feature selection results.

4. Experimental results and discussion

4.1 Database

Image data used in our experiments consist of two datasets which are denoted as DB1 and DB2. Contact lenses in DB1 and DB2 are from two companies [2, 3], with very different textural appearance printed onto them. DB1 contains 160 fake iris images (shown in Fig.5(e)) with 4 different contact lenses (shown in Fig.5(a)[2]) and 160 live iris images. DB2 contains 480 fake iris images (shown in Fig.5(f)) with 16 contact lenses (shown in Fig.5(b)(c)(d)[3]) and 480 live iris images. Fake iris images are self-collected since there are no such open databases. Live iris images are randomly selected from two open iris databases, CASIA[4] (Fig.5(g)) and BATH[1] (Fig.5(h)).

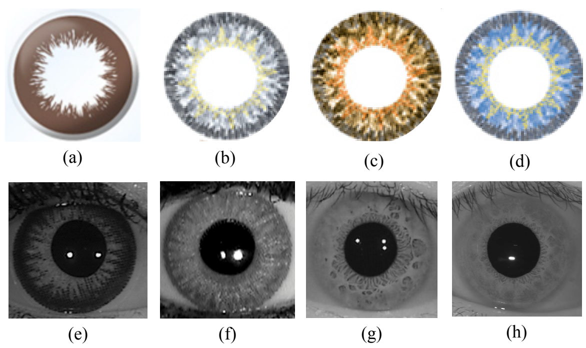


Figure 5. Samples of contact lenses, fake iris and live iris.

4.2 Experiments and analysis

Experiments were conducted to evaluate the effectiveness of the above measures. Since the IES (iris edge sharpness) measure does not need any training procedure, we used a appropriate threshold to obtain testing

Table 1. Testing results (%) on DB1 & DB2, with comparison of five measures. (IES: iris edge sharpness; ITF: Iris-Texton feature; CMF: co-occurrence matrix feature; D: Daugman's[5]; He: He et al.[7].)

	DB1			DB2		
	CCR	FAR	FRR	CCR	FAR	FRR
IES	97.8	1.87	2.5	76.8	27.1	19.4
ITF	98.3	1.25	1.87	95.8	4.17	5.83
CMF	100	0	0	94.1	8.13	3.75
He[7]	96.7	4.4	2.5	78.1	24.6	19.2
D [5]	96.3	7.5	0	/	/	/

results. While evaluating Iris-Texton feature and co-occurrence matrix(CM) features, we selected SVM[12] as classifier, using half of the images for training and the rest for testing. Experiments were performed on DB1 and DB2 separately. Table1 shows the testing results, where CCR (Correct Classification Rate), FAR (False Accept Rate for accepting fake iris as live one) and FRR (False Reject Rate for rejecting live iris as fake one) are presented. We implemented the algorithm of He et al.[7] for comparison as well. Since samples in DB2 do not show distinctive frequencies in their 2D Fourier spectra, Daugman's[5] method is only applied in DB1 for comparison.

Experimental results show that: **(i)** CCR is closely related to the type of contact lens, or the technique of making them. DB1 gains a far better performance, because contact lenses in DB1 appear similar in texture color and pattern. On the contrary, textures of contact lens in DB2 are diversified, therefore it is more challenge to detect. That is why neither IES nor He's[7] method work well in DB2. Daugman's[5] method fail in DB2 because textures in those contact lenses are well printed without any printed dots on them. **(ii)** IES is a simple measurement and highly depend on segmentation accuracy. It can be employed in systems with speed requirement given its low computational cost and its performance is comparable to the state-of-the-art. It can also be deployed by setting the threshold to a low FAR while sacrificing FRR. **(iii)** Iris-Texton and CM features gain high CCR in both datasets, outperforming the state-of-the-art. Iris-Texton feature generalizes well in two different datasets, demonstrating a strong learning ability for texture primitives. CM features show about 6% decrease from DB1 to DB2, therefore it is suggested that the 28 features of CM undergo a feature selection procedure each time when new data come.

5. Conclusion

In this paper, we have proposed three measures, iris edge sharpness, Iris-Texton feature and co-occurrence matrix based features, for detecting counterfeit iris with printed color contact lens in iris recognition system. Detailed comparisons on their performance were given on two types of fake iris database. Experimental results indicate that the three proposed methods are effective. Analysis and suggestion are also provided that on what occasion they may be used, and how these methods may help or affect the system.

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References

[1] *Bath Iris Database, http://www.bath.ac.uk/elec-eng/research/sipg/irisweb/database.htm*.

[2] *http://www.define.com.cn/about.asp*.

[3] *http://www.duebacon.com/*.

[4] *Institute of Automation CAS, CASIA-IrisV3, http://www.cbsr.ia.ac.cn/IrisDatabase.htm*. 2006.

[5] J. Daugman. Demodulation by complex-valued wavelets for stochastic pattern recognition. In *Intl Journal of Wavelets, Multi-resolution and Information Processing*, volume 1, pages 1–17, 2003.

[6] R. M. Haralick, K. Shanmugam, and I. Dinstein. Textural feature for image classification. *IEEE Trans. on Systems, Man, and Cybernetics*, 3(6):610–621, 1973.

[7] X. He, S. An, and P. Shi. Statistical textura analysis-based approach for fake iris detection using support vector machine. In *Proc. of International Conference on Biometrics 2007*, pages 540–546, 2007.

[8] E. C. Lee, K. R. Park, and J. Kim. Fake iris detection by using purkinje image. In *Proc. of International Conference on Biometrics 2006*, pages 397–403, 2006.

[9] L. Ma, T. Tan, Y. Wang, and D. Zhang. Personal identification based on iris texture analysis. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 25(12):1519–1533, 2003.

[10] X. Qiu, Z. Sun, and T. Tan. Learning appearance primitives of iris images for ethnic classification. In *Proc. of ICIP*, pages 405–408, 2007.

[11] S. A. C. Schuchers. Spoofing and anti-spoofing measures. *Information Security Technical Report*, 7(4):56–62, 2002.

[12] V. Vapnik. *Statistical learning theory*. 1998.