Fusion of Iris and Periocular Biometrics for Cross-Sensor Identification

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Abstract. As a reliable personal identification method, iris recognition has been widely used for a large number of applications. Since a variety of iris devices produced by different vendors may be used for some large-scale applications, it is necessary to match heterogeneous iris images against the variations of sensors, illuminators, imaging distance and imaging conditions. This paper aims to improve cross-sensor iris recognition performance using a novel multi-biometrics strategy. The novelty of our solution is that both iris and periocular biometrics in heterogeneous iris images are combined through score-level information fusion for approaching the problem of iris sensor interoperability. Then the improved feature extraction method, namely Multi-Directions Ordinal Measures, is applied to encode both iris and periocular images to describe the distinctive features. The experimental results on images captured from three iris devices, including two close-range iris devices and one long-range iris device, demonstrate the effectiveness of the proposed method.

Keywords: Iris Recognition, Periocular Recognition, Ordinal Measures, Cross-Sensor.

1 Introduction

Iris recognition has attracted great research effort for twenty years and a number of iris devices have been developed for real world applications. Although iris texture pattern is an ideal identifier, the large intra-class variations of iris images determine that it is a nontrivial task to match iris images captured from the same subject. There are three main factors jointly determining the variations of iris images, i.e. sensor, subject and environment. Most research work in iris recognition only considers the subject issues such as pose, gaze, iris texture deformation, eyelids and eyelashes or environmental issues such as illumination changes. However, the cross-sensor iris recognition problem is less addressed. With the wide deployments of iris recognition systems for mission-critical applications such as border crossing, banking, etc., the interoperability of iris recognition systems provided by different vendors has become a real problem. There are significant differences between various iris devices in terms of wavelength of illuminators,

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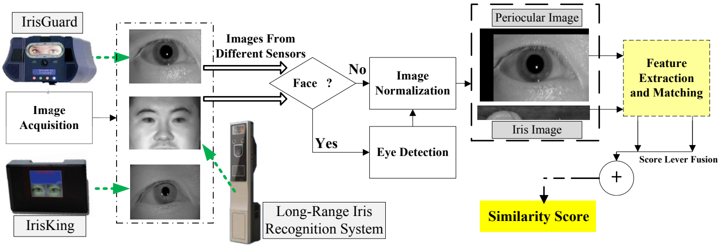


Fig. 1. Flowchart of the proposed method for cross-sensor comparison

optics, CCD or CMOS, etc. The accuracy of iris recognition degrades dramatically when cross-sensor iris images were used for identity authentication, as reported in [1].

The interoperability of cross-sensor biometric recognition systems has been discussed in the literature. Ross et al. investigated this problem on fingerprint [2]. Fernandez et al. used two different tablet computers to evaluate the sensor fusion and sensor interoperability for signature verification [3]. Philips et al. pointed out that face verification algorithms are sensitive to camera types [4]. Gonzalez et al. explored the interoperability among different hand biometric systems [5]. Recently, Bowyer et al. discussed the problem of iris sensor interoperability, and conducted some experiments to evaluate the impacts of cross-sensor iris images to iris recognition performance [6,7]. The conclusion is that both the selection of sensor and algorithm should be taken into consideration to construct a successful biometric system. The current research for cross-sensor iris recognition only considers iris biometrics and other soft biometrics in iris images such as periocular biometrics have not been considered for improving the identification accuracy.

The objective of this paper is to provide an improved solution to the interoperability problem between different iris sensors. We propose to combine multi-biometric features defined as ocular biometrics in our method in cross-sensor iris images. Ocular region contains both iris and periocular biometrics. Then an improved feature representation method named Multi-Directions Ordinal Measures (abbreviated as Multi-OM) is proposed based on our previous work [8]. Ordinal Measures (abbreviated as OM) can represent the distinctive and robust features of iris patterns, and achieve state-of-the-art performance for single-sensor iris recognition. However, the information of the original version of horizontal OM is not enough to obtain good recognition performance for cross-sensor iris recognition problem. This motivates us to extend the original version of horizontal OM to multiple directions, which is more discriminative for representing features of both iris and periocular biometrics.

Fig. 1 illustrates the flowchart of the proposed method. We use three different iris imaging devices to capture iris images, which usually contain both iris texture pattern and periocular pattern. The features of both iris and periocular regions are extracted by Multi-OM. The only difference is that iris texture and periocular biometrics are encoded into binary strings and statistical distribution of ordinal codes, respectively. Then, these two ocular biometrics modalities are fused according to a weighted sum rule to improve overall performance. Experimental results validate the effectiveness of our method.

The main contributions of this paper are threefold. At the first place, a feature extraction method is applied to solve iris sensor interoperability. Furthermore, weighted sum rule is implemented to fuse iris and periocular biometrics for improving the overall performance. In addition, proper weights for iris and periocular biometrics are addressed to depend on the selection of sensors. This will be of great help to obtaining better performance for cross-sensor comparisons.

The rest of this paper is organized as follows. Section 2 details the procedure of the proposed method. Experimental results are discussed in Section 3. The concluding remarks are drawn in Section 4.

2 Proposed Method

Due to various imaging conditions, both iris and periocular images should be preprocessed. Images from different database should have different preprocessing procedure. Based on our previous work [9], we used three different iris acquisition systems to capture iris and periocular images. The first sensor is IrisGuard H100 (Abbreviated as IG) which is a monocular handheld iris capture system with the capture distance of approximately 12 to 30 centimeters [10]. The second sensor is IKEMB-110 (Abbreviated as IK) [11] from Irisking Tech.co.. It is also a monocular iris imaging sensor with the capture distance of approximately 22 to 40 centimeters. We also use the long-range iris recognition system [9] to capture image at 3 to 5 meters away(Abbreviated as LRI). This imaging system mainly consists of two wide-range web cameras, a narrow-range high resolution NIR (near-infra-red) camera, a pan-tilt-zoom (PTZ) unit and NIR light source. These three iris capture systems can represent the mainstream of iris capture systems which have been applied in the market. IG and IK share the same procedure, but LRI should add eye detection so as to speed up the iris recognition process besides the procedure. For iris image preprocessing, the critical step is iris localization. Iris localization is to find iris pupillary and limbic boundaries. Here, we employ the localization method of Daugman [12], which is well-known as integral-differential operator to perform iris localization. We adopt the rubber sheet model and linear normalization to obtain normalized iris images. For periocular image preprocessing, we predefine a normalized iris radius R_0. Given an input periocular image and its iris radius R_1, the image will be resized by multiplying R_0/R_1. Finally, the normalized periocular image centered with iris will be cropped at a fixed size from the input image.

2.1 Feature Extraction and Matching

The problem of iris sensor interoperability is addressed by weighted fusion of information from multiple directions of OM [8].

The possible rotation differences, pupil dilation and sensor intrinsic characteristics are considered in the proposed method. Consequently, multiple directions of

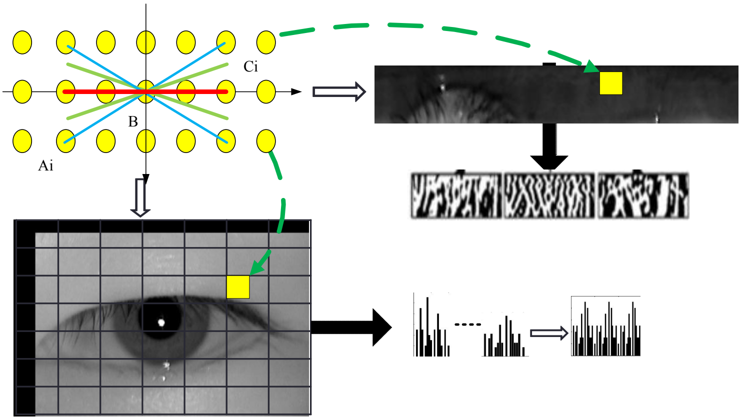


Fig. 2. This figure describes the proposed feature extraction method. Multi-OM is utilized to extract features of iris and periocular biometrics. Center point B is set by weighted fusion of codes generated from ordinal measures of multiple directions, the width of sampling line shows the weight in generating the final code of center point B.

ordinal measures should be utilized and fused to seek for more robust features for iris recognition in various environments. Weight for direction closer to horizontal one should be set larger because of its robustness. As can be seen in Fig. 2, the binary code of the sampling pixel B in the center can be calculated as follows:

$$\text{IrisCode} = F\left(\sum_{i=0}^{N} w_i F(A_i + C_i - 2B)\right), \qquad \sum_{i=0}^{N} w_i = 1, \tag{1}$$

where $F(.)$ is a sign function, N is the number of sampling directions, and w_i is weight for the direction. Point A_i and C_i are used to compare with center point B to generate sub-binary codes, for the gray values of A_i and C_i which are not in the center of pixels can be estimated by bilinear interpolation. $F(x)$ is 1 if $x \geq 0$ and 0 otherwise. All the sub-binary codes will be fused with different weights to generate the final binary code of point B. The Hamming-distance is used as a measure of dis-similarity between two iris images.

To encode the normalized periocular images, we change the specific strategy. After generating sub-binary codes, the pattern of the sampling pixel B in the center of the following Fig. 2 can be given in decimal form by

$$\text{PerioCode} = \sum_{i=0}^{N} 2^{N-i} F(A_i + C_i - 2B). \tag{2}$$

The normalized periocular image is divided into blocks. In each block, the frequency of patterns are concatenated into a histogram by their number of occurrences. Then the final descriptor of the image is computed by concatenating all the histograms. The Chi-square method is adopted to measure the similarity of periocular images.

2.2 Score Level Fusion

Given captured ocular images, both the iris and periocular biometrics can be used. Particularly in cross-sensor comparisons, periocular region will also play an important role in identifying a person. Therefore fusing these two modalities will yield significantly better performance and broaden the application compared with single modality. Due to the differences of sensor imaging capability and changing environment, weights pertaining to the two modalities may vary, mainly depend on imaging sensors. When matching cross-sensor ocular images, proper weights for iris and periocular biometrics should be set to guarantee optimal performance.

3 Experiments

3.1 Experimental Datasets

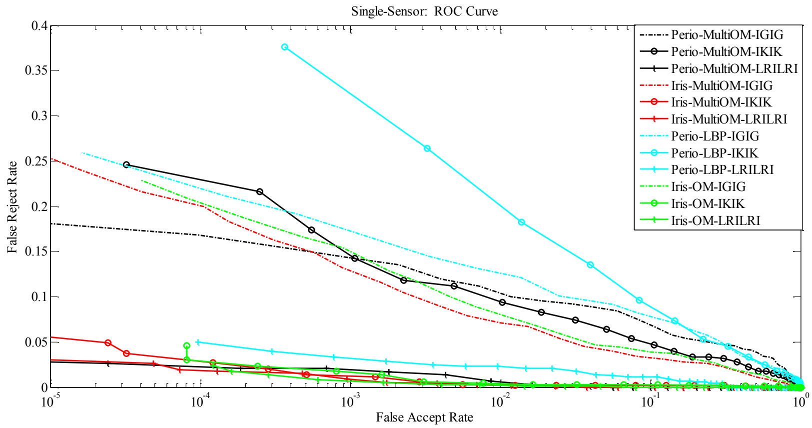
Three databases are collected by different high resolution camera, IG, IK, LRI. There are 3000 iris images from 600 eyes of 300 people for each database. Image resolution from IG and IK is 640×480. Image resolution from LRI is 2352×1728. Images from these three databases can be seen in Fig. 1.

3.2 Experiment Settings

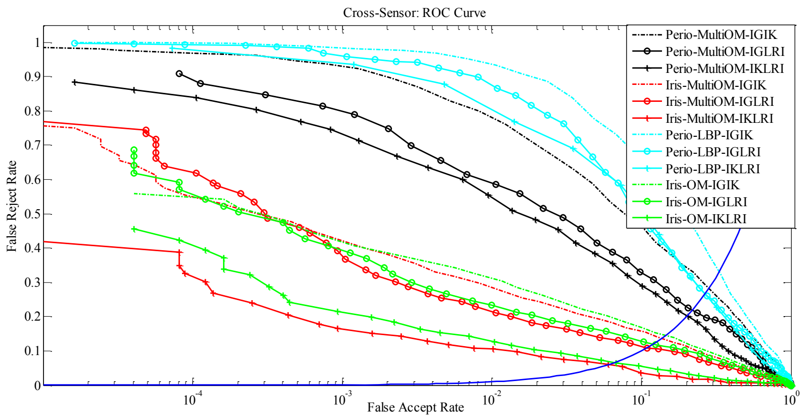
Experiments are conducted to demonstrate the robustness of the proposed method. Left and right eyes from the same individual are considered separately. Then we can simply employ weighted sum rule to obtain a higher performance. The raw images are preprocessed to obtain the normalized periocular images (resolution 480×320) and iris images (resolution 540×66). To investigate cross-sensor iris image comparisons, we compared Multi-OM with OM [8], the parameters are set similarly, tri-lobe ordinal filters are adopted for better representing iris texture, each lobe in the filter is a Gaussian filter with $\sigma = 1.2$ and size 7×7, and the interval between adjacent lobes is 10 pixels. We randomly choose the sampling directions close to the horizontal one,here we select the directions of 0,$\pm$5,$\pm$10 degrees. For periocular image comparisons, Multi-OM is also adopted to extract features of periocular images, and is compared with original LBP [13] which has been widely applied in representing periocular images. The periocular images are divided to 10×10 patches, and the degrees of Multi-OM are set uniformly between 0 to 90 degrees, here, we select the directions of 0,$\pm$25,$\pm$50,$\pm$75 degrees.

3.3 Results and Discussions

We make a comparison of periocular and iris recognition. Experiment results show the effectiveness of the proposed Multi-OM method. Then scores from iris and periocular image comparisons are fused using different weights to improve the overall performance.



(a)



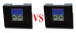
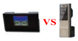
(b)

Fig. 3. (a). Experiments on ocular images from same sensors. (b). Experiments on ocular images from different sensors.

Receiver Operating Characteristic (ROC) curves are illustrated in Fig. 3 to show the performances of single and cross-sensor comparisons, the blue lines are equal error rate lines which refer to the point in receiver operating characteristic (ROC) when FAR (False Accept Ratio) is equal to FRR (False Reject Ratio). In the label, "Perio" denotes experiments on periocular images, "MultiOM","LBP" and "OM" denote feature extraction method adopted in the experiments, "IGIK" and other similar labels denote comparisons between corresponding sensors. Black and cyan lines denote ROC curves from experiments on periocular images with different feature extraction methods. Red and green lines denote ROC curves from experiments on iris images.

As shown in Fig. 3, the performance of cross-sensor comparisons decrease dramatically compared with that of single-sensor comparisons. In both figures, comparing black lines with cyan ones, Multi-OM outperforms LBP [13] for

Table 1. Different weight experimentally setting for score level fusion to obtain better performance between different sensor comparisons

Method	Iris-Weight	Perio-Weight	FusionEER	Iris-EER	Perio-EER
 *(IG-IG)*	0.51	0.49	0.0307	0.0436	0.0760
 *(IK-IK)*	0.81	0.19	0.0022	0.0041	0.0592
 *(LRI-LRI)*	0.65	0.35	0	0.0041	0.0073
 *(IG-IK)*	0.61	0.39	0.1132	0.1383	0.2826
 *(IG-LRI)*	0.55	0.45	0.0808	0.1088	0.2172
 *(IK-LRI)*	0.67	0.33	0.0409	0.0600	0.2018

representing the features of periocular images. Specially, by adopting Multi-OM, the EER is reduced by an average of 5 percent for cross-sensor comparisons. Multi-OM also outperforms OM [8] for representing the features of iris images when comparing red lines with green ones.

From the ROC curves we can conclude that: cross-sensor comparisons will dramatically decrease the performance of ocular recognition. For iris recognition, EER of cross-sensor comparisons will be larger than that of single-sensor comparisons. For periocular recognition, the performance will decrease significantly more. Comparing ROC curves of the two figures in Fig. 3, the decline is obvious. Secondly, for periocular recognition, we compare the proposed method with LBP (Local Binary Patterns) [13], the parameters of LBP are set experimentally to obtain optimal results. For iris recognition, we compare Multi-OM using the same lobe distance with OM [8]. Our method outperforms other traditional methods on the comparisons of cross-sensor ocular recognition. Features extracted by the proposed method can better represent ocular information. Thirdly, missing data dramatically affects the performance of ocular recognition. Compared with LRI, a binocular acquisition system which can obtain lager periocular region, IG and IK capture partial periocular images at close range, leading to the dramatically declining performance. Fourth, weights are determined by sensor characteristics for iris and periocular matching scores. Table 1 shows the different weights for cross-sensor comparisons. "IGIK" denotes the comparison between images captured from IG and IK, "Iris-Weight" and "Periocular-Weight" denote weights for iris and periocular biometrics. Therefore, sensor selection will affect weights for both biometric models.

4 Conclusions

This work focuses on the problem of iris sensor interoperability, demonstrates the fusion of iris and periocular biometrics for cross-sensor human identification. An improved feature extraction method (Multi-OM) is applied to representing the discriminative features. Features of iris and periocular images are extracted and encoded by Multi-OM and different encoding strategies. Iris and periocular biometrics are fused for cross-sensor comparisons. Experiments demonstrate the robustness of the proposed method. Although performance of cross-sensor ocular recognition is disappointing to some extent, ongoing research will encourage the development of more robust feature extraction methods and matching algorithms for cross-sensor biometrics, leading to wider application of iris biometrics.

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