Cross-Sensor Iris Matching Using Patch-based Hybrid Dictionary Learning

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Abstract: Recently, more and more new iris acquisition devices appear on the market. In practical situation, it is highly possible that the iris images for training and testing are acquired by different iris image sensors. In that case, the recognition rate will decrease a lot and become much worse than the one when both sets of images are acquired by the same image sensors. Such issue is called “cross-sensor iris matching”. In this paper, we propose a novel iris image hallucination method using a patch-based hybrid dictionary learning scheme which is able to hallucinate iris images across different sensors. Thus, given an iris image in test stage which is acquired by a new image sensor, a corresponding iris image will be hallucinated which looks as if it is captured by the old image sensor used in training stage. By matching training images with hallucinated images, the recognition rate can be enhanced. The experimental results show that the proposed method is better than the baseline, which proves the effectiveness of the proposed image hallucination method.

1 INTRODUCTION

Iris recognition (Bowyer et al, 2008) has attracted considerable attention for its practical applications. The iris image sensor used to capture the texture of iris is actually one of the most important issues in iris recognition because images captured by different sensors contain different visual characteristics. In the practical applications, most of the time, it is impossible to re-enroll a large number of users every time when a new sensor is deployed. Therefore, one often encounters such problem where iris images for enrollment and testing are acquired by different image sensors. We call this problem “cross-sensor iris matching”.

1.1 Previous work

Recent studies have addressed the issue of cross-sensor iris matching, and indicated it indeed is an important problem. Bowyer (2009), (Connaughton et al., 2011) investigated the interoperability of iris sensors from different manufacturers using multiple available matching algorithms. Pillai (2014) used kernel learning methods (Weinberger, 2004) for learning transformations of having desired iris properties.

2 PROPOSED METHOD

The existing work about cross-sensor iris matching, though successful, however, is a method of high computational complexity. In fact, cross-sensor matching problem also occurred in other biometrics modalities, for example, in face sketch recognition (Li et al., 2006) (Li and Savvides, 2006). Inspired by such solution in face sketch recognition, we propose a novel patch-based hybrid dictionary learning method using sparse representation to approach this problem.

2.1 Training Stage

What we are trying to do in training stage is to build a hybrid dictionary including both low quality and high quality iris images so that later in testing stage we can use this dictionary to hallucinate iris images when we get a new testing image.

In our experiment, the high quality images are captured by iris image sensor PIER 2.3 (Securimetrics pier device, securiMetrics Inc.) and the low quality images are captured by Iris-On-the-Move system (IOM) (Matey et al., 2006). Training data consists of a pair of PIER and IOM images from each subject, for all subjects in the database.

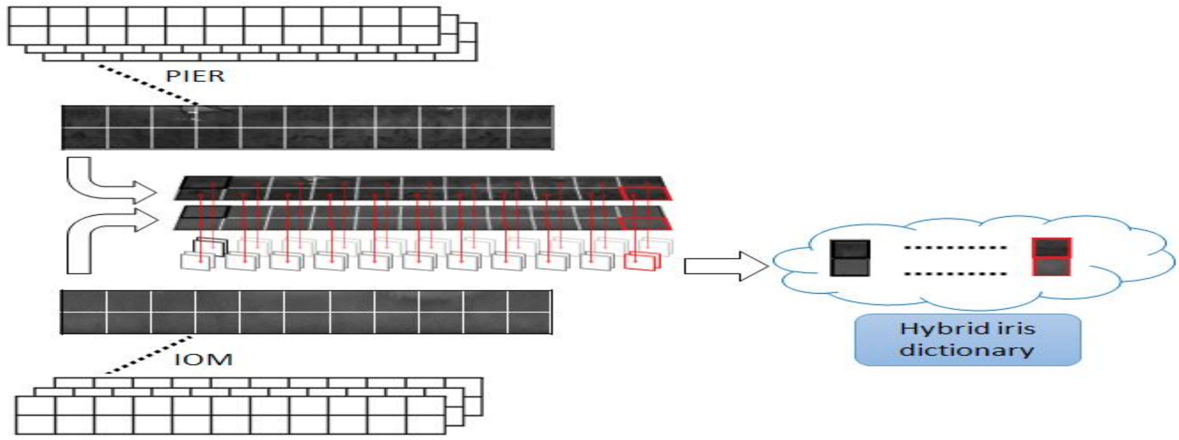

Figure 1: Illustration of experimental procedure during training stage.

We will assume that in the training stage, we have corresponding image pairs captured from PIER and IOM, respectively. In the test stage, we assume that the test images are captured by IOM. Thus, the targeted problem becomes, given test IOM image (low quality), how to hallucinate its corresponding image that looks as if it is captured by PIER (high quality)?

In training stage, we perform the following steps. First, given a pair of hybrid iris training images we perform global alignment. A pair of hybrid iris database that consists of two iris image sets, captured by two iris image sensors A and B, we denote these two datasets I^A and I^B. Specifically,

$$I^A = \{I_1^A, I_2^A, \ldots, I_M^A\} \quad (1)$$
$$I^B = \{I_1^B, I_2^B, \ldots, I_M^B\} \quad (2)$$

where I_k^A and I_k^B denotes the k^{th} iris images in image set I^A and I^B, respectively.

Second, hybrid iris training images are divided into local patches. The patch-based hybrid iris database is represented as P_A and P_B.

$$P^A = \{P_1^A, P_2^A, \ldots, P_N^A\} \quad (3)$$
$$P^B = \{P_1^B, P_2^B, \ldots, P_N^B\} \quad (4)$$

where P_k^A and P_k^B denotes the k^{th} iris images patch in image set P^A and P^B, respectively. Note that $N >> M$.

Third, a hybrid dictionary comprises iris patches. In this stage, we create a new hybrid patch set Θ from P^A and P^B. Specifically,

$$\Theta = \left\{ HP_i \middle| HP_i = \begin{bmatrix} P_i^A \\ P_i^B \end{bmatrix}, \forall\, 1 \le i \le N \right\} \quad (5)$$

The set Θ can be viewed as iris image patch set in a hybrid space, which is composed by combining image patches from different optical sensors. Therefore, in this work, we call Θ as “hybrid iris dictionary”. Patches that belong to the same location would be stored in the corresponding hybrid iris dictionary. Figure 1 gives us a graphical illustration of experimental procedure during training stage.

2.2 Testing Stage

During the test stage, we perform the following steps. First, given a test iris image I_{test}^B captured by image sensor B, our goal is to hallucinate its corresponding image I_{test}^A so that it looks as if it is captured by sensor A and has the same image quality as all images in set I^A. Here the basic assumption is that the image quality of set I^A is much higher than that of I^B, therefore, in order to achieve higher recognition rate, it is highly desired to hallucinate I_{test}^A based on the given image I_{test}^B.

Second, the given test image I_{test}^B is broken into overlapped patches. We use sparse representation to decompose each test patch p_i^{test} as a linear combination of dictionary atoms. In mathematical form, it can be described as:

$$\alpha_i = arg\min_{\beta_i}(\|p_i^{test} - D\beta_i\|_2^2 + \mu\|\beta_i\|_0) \quad (6)$$

The dictionary D in (6) comes from the lower parts of the hybrid iris dictionary. According to (Davis et al., 1997) (Pati et al., 1993), the coefficient α_i can be calculated by using Orthogonal Matching Pursuit (OMP). The coefficient α_i contains information indicating which atoms in D should be used to reconstruct p_i^{test}, under the constraint that the number of the reconstruction atoms is minimized. Therefore, we can look for which element in α_i

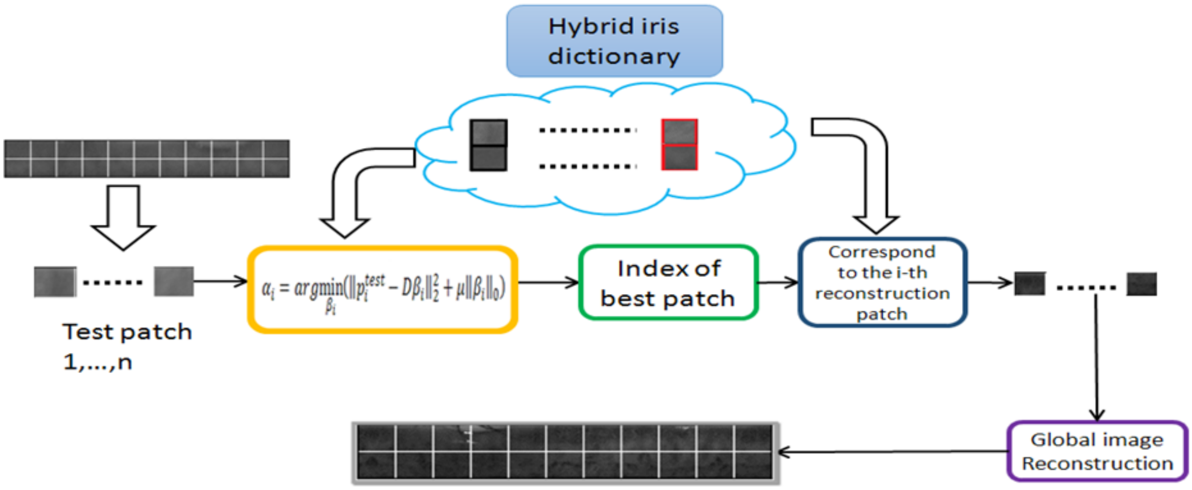

Figure 2: Illustration of experimental procedure during testing stage.

has the highest value, and the index of this element represent the index of the training patch which has the highest resemblance to p_i^{test} in hybrid iris dictionary. Suppose the index of the element with the largest value in α_i is j, then we are confident to declare that the atom P_j^B has the highest resemblance to p_i^{test}. Using P_j^A which is the counterpart of P_j^B in the upper part of the heterogeneous dictionary Θ to represent p_i^{test} in reconstructed space, and continuing applying such method $\forall 1 \leq i \leq N$, we can hallucinate the corresponding high quality I_{test}^A using global image reconstruction. Figure 2 illustrates the proposed procedure during the testing stage. A testing image belongs to low quality iris image captured by IOM device is divided into a set of patches. Remember that the size of the test patch must be consistent with the size of the training patch in the hybrid iris dictionary.

Table 1: Statistics about IOM and PIER

Database Properties	IOM	PIER
Number of Iris Classes	111	
Size of the Picture	640x480	
Maximal Number of Images Per Subject	54	3
Minimal Number of Images Per Subject	10	3
Average Number of Images Per Subject	24	3
Total Number of Images	2682	333

3 EXPERIMENT

3.1 A typical iris recognition system

The process of a typical iris recognition system consists of following stages: (1) Eye image acquisition, (2) iris segmentation, (3) iris normalization, (4) feature extraction, (5) iris matching, and (6) calculate hamming distance. Figure 3 shows the flow chart of a typical iris recognition system.

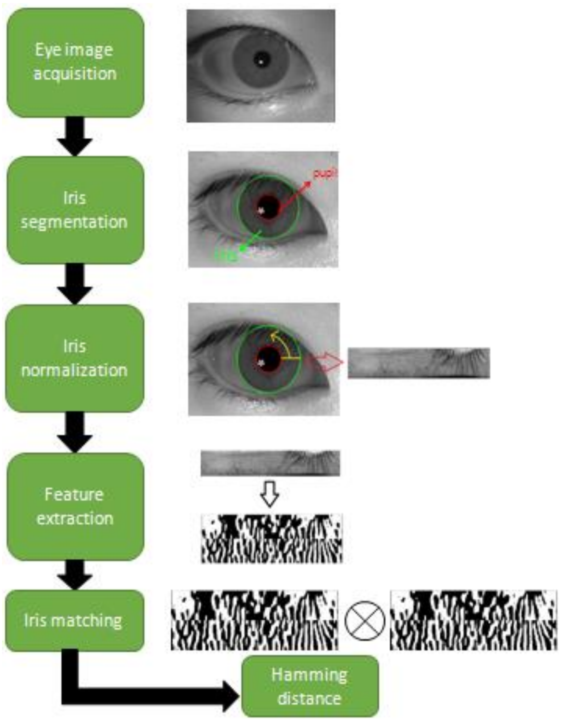

Figure 3: The flow chart of the process of a typical iris recognition system.

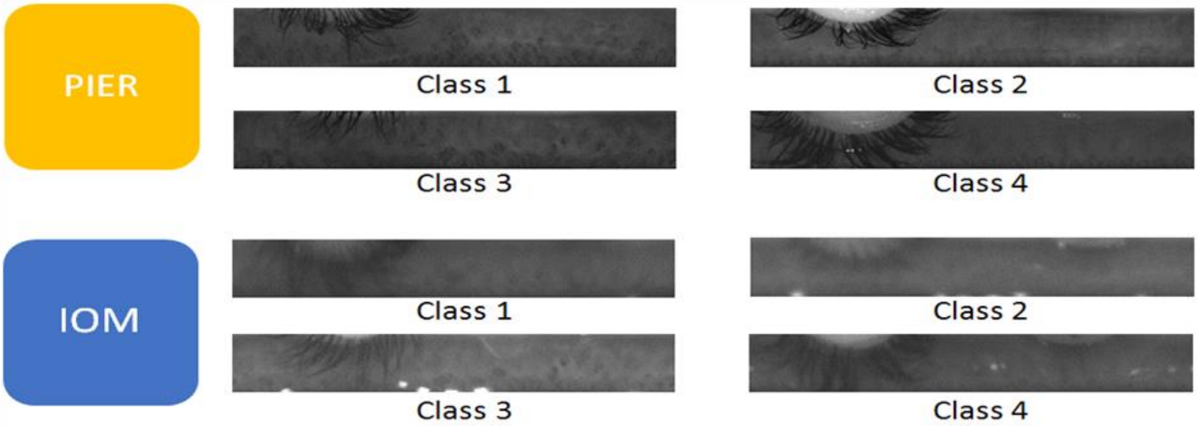

Figure 4: Illustration of the same iris class image captured by the PIER and IOM devices.

3.2 Database

In order to measure the iris recognition performance based on the proposed patch-based hybrid dictionary learning algorithm, experiments have to be performed on databases which contain both high quality and low quality iris images for the same iris class. The database we used in our experiment collected at Carnegie Mellon University during March and April in 2009. The iris images are captured by two kinds of iris acquisition devices: 1) IOM [9], whose image quality is low; 2) SecuriMetrics PIER 2.3 [8], whose image quality is better than IOM. The details of the IOM and PIER database are given in Table 1. Figure 4 illustrates the same iris class image captured by the PIER and IOM devices. From Figure 4, we can discover that the quality of iris images captured by the PIER device is much higher than that of iris images captured by the IOM device in the same class.

3.3 Procedures

For training data, we choose the second picture of PIER images and the third picture of IOM images for each class. Therefore, we have a set of PIER iris images $I^A = \{I_1^A, I_2^A, \ldots, I_M^A\}$, and a set of corresponding IOM iris images $I^B = \{I_1^B, I_2^B, \ldots, I_M^B\}$, where I_k^A and I_k^B is column vector, derived from the i^{th} PIER and IOM iris images, respectively. For test data, we choose all IOM iris images except the third picture for each iris class. We do following steps:

(1) All both training data and test data will be pre-segmented and normalized to the size of 30x180.

(2) All training images are divided into patches and stored in the corresponding hybrid dictionary.

(3) Let the set of the lower parts (captured by IOM device) of each atom in the hybrid dictionary as the dictionary D of sparse representation.

(4) A test image can is divided into patches, represented as x_i .

(5) Use OMP to calculate the coefficient α_i .

(6) Find the index of the best patch by locating the highest value in α_i

(7) Find the corresponding patch location, which belong to upper parts captured by PIER device in the hybrid dictionary.

(8) Corresponding patches of y_i will replace the original test patches of x_i .

(9) Synthesize the high quality iris image by global image reconstruction.

3.4 Results

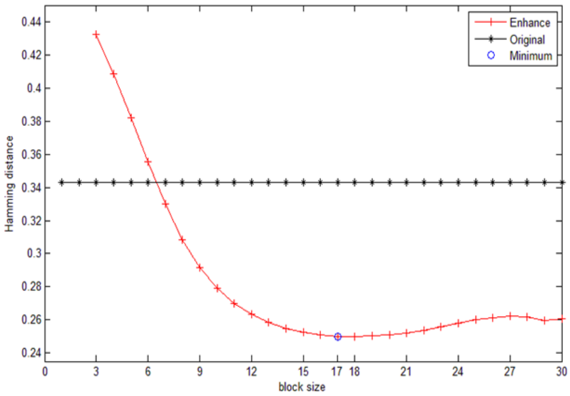

Figure 5: Experimental result of patch size optimization.

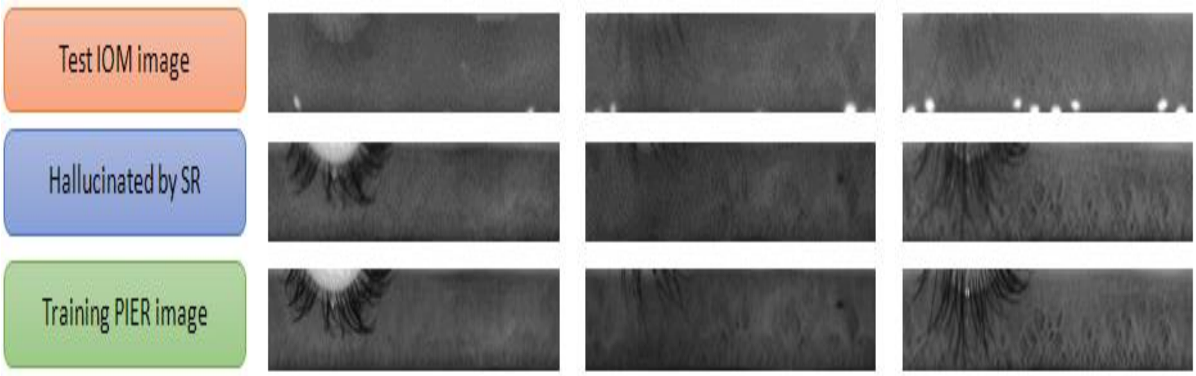

Figure 8: Illustration of experimental procedure during testing stage.

Because all training and test images are divided into patches, the size of the patch may affect the performance.

In order to analyze the accuracy of the size for patch, we perform an experiment of patch size optimization. The size of test patch ranges from 3x3 to 30x30 in the iris images. The value of Hamming Distance (HD) for the training and testing matching varies in different sizes as shown in Figure 5. We can see that the best patch size for the proposed method is 17x17, where HD reaches its minima.

In Figure 6, there are ROC curves that are based on four different methods. The four algorithms and experimental conditions we compared are

1. Gallery set: PIER images; probe set: IOM images without any enhancement. This result is served as "baseline".
2. Gallery set: PIER images; probe set: IOM images transformed by the eigeniris method (which can be called hybrid subspace method as well), as proposed in the work in (Li and Savvides 2006).
3. Gallery set: PIER images; probe set: IOM images. The matching score (normalized Hamming distance) is adapted and transformed using kernel learning method (Pillai et al., 2014).
4. The proposed method using sparse representation.

The blue curve represents the iris recognition performance when directly matching training and testing images without using any algorithm to improve iris image quality. The red curve represents the recognition performance after using the proposed patch-based hybrid iris dictionary learning method to enhance the test image quality. The black curve shows the recognition performance after using hybrid subspace method (Li and Savvides, 2006) to hallucinate the image. The pink curve shows the recognition performance after using kernel learning (Pillai et al., 2014).

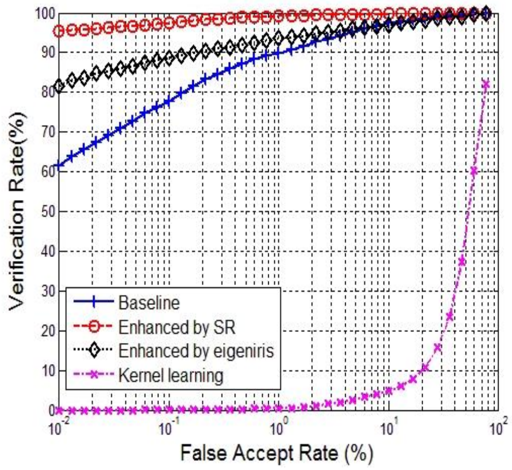

Figure 6: ROC curves comparison of the baseline , eigeniris, kernel learning, and the proposed method.

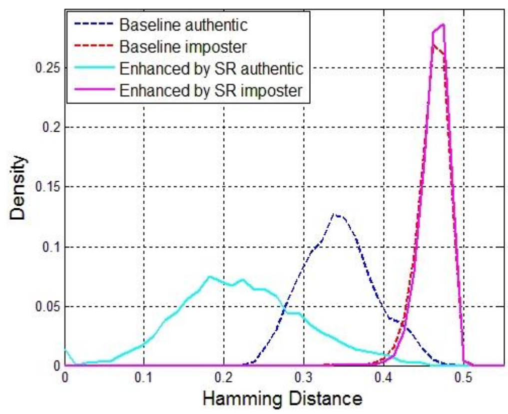

Figure 7: HD distribution of the large-scale iris recognition experiment under baseline and the proposed method.

We can see that when FAR = 10^{-2} %, the verification rate of the proposed method achieves 95.45% which is superior than that of eigeniris about 81.57% and that of baseline about 61.48%, as show in Figure 6. Moreover, we discover that the kernel learning method in the cross-sensor iris matching problem can not exhibit high recognition performance.

Figure 7 shows the histogram of HD distribution for the authentic and impostor comparison, before (baseline) and after applying the proposed method. We can see that the authentic score distribution obviously being moved toward left side, while the imposter score distribution remains almost the same. Moreover, the EER of the proposed method achieves 0.8576%, compared to EER=4.7726% in the baseline experiment. The results show that the two distributions are moved further away from each other, demonstrating the effectiveness of the proposed method.

Figure 8 shows the example iris images hallucinated by the proposed methods SR (heterogeneous dictionary learning method using sparse representation). From these three examples, given test IOM image whose quality is low, we can see that hybrid iris dictionary learning method using sparse representation can synthesize high quality image that look as if it is captured by the PIER device.

4. CONCLUSIONS

In this paper, we propose a novel patch-based hybrid iris dictionary learning method using sparse representation to approach the issue of cross-sensor iris matching. The proposed method achieves better recognition performance for two situations: 1) the iris images for training and testing are acquired by different iris image sensors; 2) the training set images have higher quality while the test images have lower quality. Furthermore, the experimental results shows the proposed method successfully enhance the iris recognition performance in terms of EER and separability of Hamming distance distribution, as shown in Figure 6 and 7. Future work includes using more delicate algorithm (for example, k-SVD) for dictionary atom update and collecting more heterogeneous iris images for large-scale experiment.

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