HETEROGENEOUS IRIS RECOGNITION USING HETEROGENEOUS EIGENIRIS AND SPARSE REPRESENTATION

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ABSTRACT

When the iris images for training and testing are acquired by different iris image sensors, the recognition rate will be degraded and not as good as the one when both sets of images are acquired by the same image sensors. Such problem is called "heterogeneous iris recognition". In this paper, we propose two novel patch-based heterogeneous dictionary learning methods using heterogeneous eigeniris and sparse representation which learn the basic atoms in iris textures across different image sensors and build connections between them. After such connections are built, at testing stage, it is possible to hallucinate (synthesize) iris images across different sensors. By matching training images with hallucinated images, the recognition rate can be successfully enhanced. Experimenting with an iris database consisting of 3015 images, we show that the EER is decreased 23.9% relatively by the proposed method using sparse representation, which proves the effectiveness of the proposed image hallucination method.

***Index Terms*—** heterogeneous iris recognition, patch-based heterogeneous dictionary, sparse representation

1. INTRODUCTION

Biometric identification has drawn more and more attention in the last few years [1]. Among all possible biometric modalities, iris recognition [2] achieves the highest recognition rate and hence is highly valued in both research community and industry. However, when the iris images used for training (gallery set) and test (probe set) are captured by different image sensors, its high recognition performance is not guaranteed anymore. Due to the booming of the interest of widely using iris recognition in real life scenario, more and more companies start making new image sensors for iris acquisition. When a system designer decides to replace an old iris camera with a newer model, such problem could potentially happen. In this work, we define such problem as "heterogeneous iris recognition".

Although the amount of research work relating to heterogeneous iris recognition is little, there indeed exist works about heterogeneous face recognition. In [3, 4, 5], Li et al. are trying to solve sketch face recognition problem, where the training data is a set of real face images but the test data is a set of sketch faces. Such problem can be viewed as a counterpart of the main problem addressed in this paper, except it is focusing on face biometrics.

In this paper, we propose two approaches to solve the problem of heterogeneous iris recognition. We implemented both approaches and tested the performance on large-scale heterogeneous iris database. Our contribution includes:

(1) Propose two learning based approaches for the problem.
(2) Performance evaluation on large-scale heterogeneous iris database.
(3) To the best knowledge of the authors, it is the first work that applies the latest sparse representation theory into the problem of heterogeneous iris recognition.
(4) The proposed idea is intuitive and easy to interpret, compared to the existing work.

The rest of the paper is organized as following. The previous work is reviewed in section 2. The two proposed methods are described in section 3. The experimental procedure and results are presented in section 4, which is followed by discussion and conclusion in section 5.

2. PREVIOUS WORK

There are not too many existing publications that address the issue of heterogeneous iris recognition. Bowyer et al. [6, 7] investigated the interoperability of iris sensors from different manufacturers using multiple available matching algorithms. Pillai et al. [8] used a kernel learning method [9] for learning transformations from iris images captured by one sensor to another and applied such framework for sensor adaptation.

For the research work about heterogeneous face recognition, Li et al. [3, 4, 5] proposed a face-sketch heterogeneous space eigenface method that is able to synthesize face images based on its sketch counterpart. In recognition stage, an advanced correlation filter is built in order to perform illumination tolerant face recognition.

3. PROPOSED METHOD

In this work, we propose two patch-based dictionary-learning methods for the purpose of heterogeneous iris image hallucination. They are described in the following sub-sections, respectively.

3.1. Heterogeneous space eigeniris approach

The first method we propose is inspired by the work in [3, 4, 5]. Therefore, we call it "heterogeneous space eigeniris" approach. Given a heterogeneous 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,

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

where I_k^A and I_k^B denotes the k^{th} iris images in image set I^A and I^B, respectively. Note that these two iris images subsets are preprocessed so that

(a) The corresponding iris images I_k^A and I_k^B are coming from the same subject

(b) I_k^A and I_k^B are globally aligned.

Here, the "globally aligned" means that iris feature extraction and matching algorithm has been applied to two iris images I_k^A and I_k^B, and the best circular shift amount between them has been computed. Next, one of the two images has been circularly shifted so that the iris texture patterns between I_k^A and I_k^B are aligned globally.

Next, the iris images are all broken down into overlapped patches. The patch-based heterogeneous iris database is represented as P_A and P_B.

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

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.

The next step is to form a heterogeneous dictionary for iris patches. In this stage, we create a new heterogeneous patch set Θ from P^A and P^B. Specifically,

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

The set Θ can be viewed as iris image patch set in a heterogeneous space, which is composed by combining image patches from different optical sensors. Inspired by [3, 4, 5], we would like to train the heterogeneous space eigeniris by using this heterogeneous patch set. Applying PCA on Θ, we get a set of heterogeneous space eigeniris images $\mathbf{\Psi}$.

$$\mathbf{\Psi} = \{\psi_i \mid \psi_i = \begin{bmatrix} \phi_i^A \\ \phi_i^B \end{bmatrix}, \forall\, 1 \le i \le N\} \quad (6)$$

Where ψ_i is the i^{th} eigenvector computed by solving the eigenvalue/eigenvector problem of the covariance matrix derived from Θ. Note that each ψ_i can be viewed as a combination of two eigen-patch images ϕ_i^A and ϕ_i^B, belonging to the pseudo eigen-patch set of patch set P_A and P_B, respectively. The word "pseudo" here means that the eigen-patch set $\{\phi_i^A\}$ and $\{\phi_i^B\}$ does not really span the subspace P_A and P_B, because the property of orthonormality does not hold for either of them. Only after they are combined together (i.e., $\mathbf{\Psi}$) then does it have the orthonormality.

During the test stage, 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.

First, the given test image I_{test}^B is broken into overlapped patches. Second, since we already have $\{\phi_i^B\}$ which can be viewed as pseudo eigen-patch set, we can project every patch in I_{test}^B to the subspace spanned by $\{\phi_i^B\}$ and compute their coordinate in this subspace. However, as described in the previous paragraph, $\{\phi_i^B\}$ does not have the orthonormality property. Therefore, we need to use pseudo-inverse to compute the projection coefficients. Specifically, for each patch p_i^{test} sampled from I_{test}^B, assuming ϕ^B is a matrix with ϕ_i^B being its i^{th} column, the projection coefficients pc_i^{test} can be computed as:

$$pc_i^{test} = ((\phi^B)^T \phi^B)^{-1} (\phi^B)^T p_i^{test} \quad (7)$$

Once pc_i^{test} is computed, it can be used to hallucinate the corresponding patch image p_i^{hal} using linear combination:

$$p_i^{hal} = \phi^A pc_i^{test} \quad (8)$$

where ϕ^A is a collection of $\{\phi_i^A\}$ whose i^{th} column is ϕ_i^A

After all patch images $\{p_i^{hal}\}$ are hallucinated, the corresponding global iris image I_{test}^A can be generated by overlapping the patch images $\{p_i^{hal}\}$ in their corresponding location.

3.2. Heterogeneous dictionary learning by sparse representation

We propose another method to attack this problem, which is a patch-based heterogeneous dictionary learning method using sparse representation.

Given iris image pair database I^A and I^B, again, we build a heterogeneous dictionary η for local patch. During test stage, given a test iris image I^B_{test}, again, we broke the image into a set of local patches. For each patch p_i^{test}, we perform sparse decomposition using $\{ P_i^B \}$ as dictionary D to compute the sparsest reconstruction coefficient α_i:

$$\alpha_i = arg\min_{\beta_i}(\|p_i^{test} - D\beta_i\|_2^2 + \mu\|\beta_i\|_0) \qquad (9)$$

Equation (9) can be solved by Orthogonal Matching Pursuit (OMP) [10, 11]. Thus, 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, the index of the non-zero element in α_i gives us a hint about which element in D has the highest resemblance to p_i^{test}. 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 $\forall 1 \le i \le N$, we are able to hallucinate I^A_{test}.

Figure 1 and 2 shows the proposed idea in training and test stage.

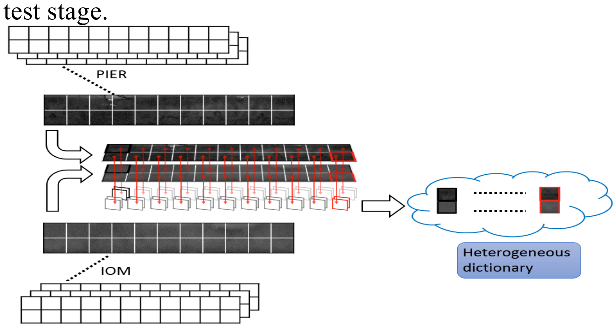

Figure 1: Illustration of experimental procedure during training stage.

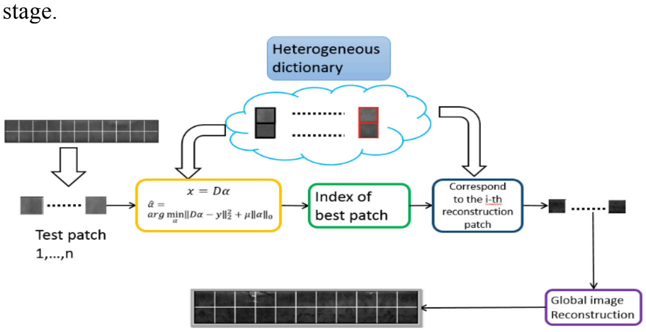

Figure 2: Illustration of experimental procedure during testing stage.

4. EXPERIMENT

4.1. Database

In order to measure the iris recognition performance based on the proposed patch-based heterogeneous 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 [12], whose image quality is low; 2) SecuriMetrics PIER 2.3 [13], whose image quality is better than IOM. The details of the IOM and PIER database are given in Table 1.

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

4.2. 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 $I^A = \{I_1^A, I_2^A, \dots, I_M^A\}$, and a set of corresponding IOM iris images $I^B = \{I_1^B, I_2^B, \dots, I_M^B\}$, where$I_k^A$ and $I_k^B$is column vector. For test data, we choose all IOM iris images except the third picture for each iris class. All both training data and test data will be pre-segmented and normalized to the size of 30x180.

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 value of Hamming Distance (HD) for the training and testing matching varies in different sizes. The best patch size is 29x29 and 17x17 for proposed method 1 (heterogeneous space eigeniris method) and 2 (heterogeneous dictionary learning method using sparse representation), respectively.

4.3. Large-scale heterogeneous iris recognition results

In Figure 3, there are ROC curves that are based on three different methods. The Baseline 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 iris recognition performance after using the patch-based heterogeneous dictionary learning method, and the gray curve represents the iris recognition performance after using the heterogeneous space eigeniris method to enhance the test image quality. We can see that when FAR = 10^{-2}%, the heterogeneous dictionary learning method using sparse representation is much better than the method using heterogeneous space eigeniris (which only achieves 80.4%) in the verification rate. The result reveals that the method using heterogeneous dictionary learning by sparse representation is suitable for approaching the sensor matching problem.

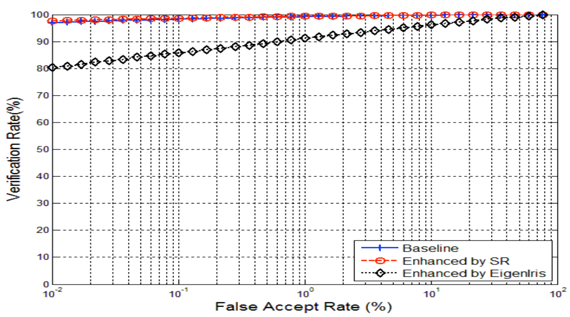

Figure 3: ROC curves comparison of the baseline, heterogeneous space eigeniris method, and the heterogeneous dictionary learning method using sparse representation.

In Figure 4 we show the zoom-in version of Figure 3, where we only plot the baseline and the result of using sparse representation. We can see the when FAR = 10^{-2}%, the verification rate of the heterogeneous dictionary learning method using sparse representation achieves 97.7% which is superior than that of baseline about
96.9%.

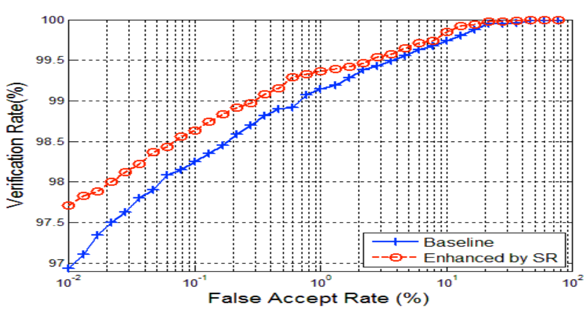

Figure 4: ROC curves comparison of the baseline and the heterogeneous dictionary learning method using sparse representation.

Figure 5 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 0.6711%, compared to EER=0.8824% in the baseline experiment. The results show that our proposed method is able to make EER decrease 23.9% relatively, demonstrating the effectiveness of the proposed method.

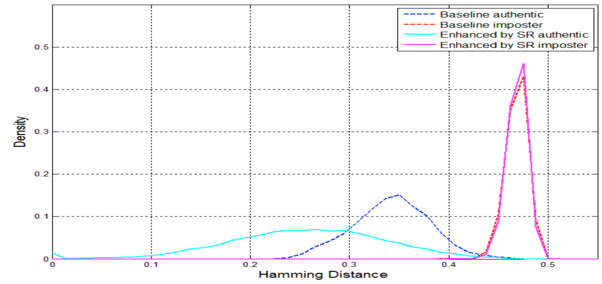

Figure 5: The density of Hamming distance of baseline and the heterogeneous dictionary learning method using sparse representation.

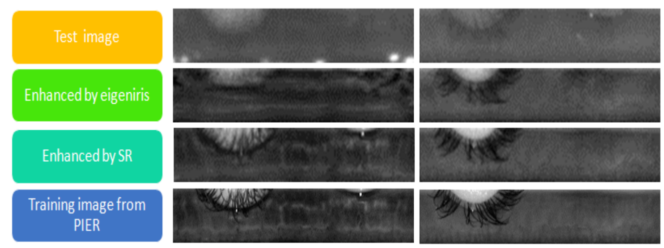

Figure 6: Comparison of the Iris images that are synthesized by the proposed methods.

Figure 6 shows the example iris images synthesized by the proposed methods with 1 (heterogeneous space eigeniris method) and 2 (heterogeneous dictionary learning method using sparse representation), respectively. From these two examples, given test IOM image whose quality is low, we can see that heterogeneous dictionary learning method using sparse representation can synthesize high quality image that look as if it is captured by PIER device.

5. CONCLUSION

In this paper, we propose two patch-based dictionary-learning methods to approach the sensor matching problem. 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 using sparse representation successfully enhance the iris recognition performance in terms of EER. Future work includes using more delicate algorithm (for example, k-SVD [14, 15]) for dictionary atom update and collecting more heterogeneous iris images for large-scale experiment.

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