Person Identification Using Face and Iris Multimodal Biometric System

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Abstract - Multimodal biometric systems fuse information using more than one physical and/or behavioral characteristics of a person to improve the recognition accuracy for person identification and alleviate the single biometric trait limitations. Focus of this paper is on combining the strengths of face and iris modalities to obtain better recognition accuracy for person identification by using several feature extractors, score normalization and fusion techniques. Face and iris features are extracted separately using global and local feature extractors and then the fusion of these modalities is performed. The experiments are conducted on ORL face database and CASIA iris database. Evaluation of experimental results demonstrates the enhancement of recognition for face-iris fusion compared to the individual modalities.

Keywords: Multimodal biometrics; face recognition; iris recognition; score level fusion; feature extraction

1 Introduction

Biometric recognition systems are widely used to recognize a person from his/her physical and/or behavioral characteristics. Recently, instead of using traditional methods for person identification, biometrics is used in many applications. Biometric recognition systems use physical and/or behavioral characteristics that are unique and cannot be lost or forgotten. Face, iris, fingerprint, speech, handwriting and other characteristics can be used in a unimodal or multimodal style for reliable and secure identification of human beings [1].

Lack of uniqueness, non-universality and noisy data [2] usually affect the performance of unimodal systems. In this respect, multimodality can be used to overcome aforementioned single biometric limitations. Multimodal biometrics fusion technology improves the recognition performance with extracting information from multiple biometric traits [3]. Because of many similar characteristics of face and iris, fusion of these two modalities has led to an unprecedented interest compared to other biometric technologies [4]. Generally, four different levels of information fusion can be considered: sensor level, feature level, matching score level and decision level [3]. In this study, we fuse face and iris information at matching score level because of the ease in accessing and combining the scores produced from different matchers. For this type of fusion, three major categories are available [3]: Transformation-based score fusion, Density-based score fusion and Classifier-based score fusion. In transformation based fusion, normalization of scores matched is needed before combining due to incompatibility of different modalities feature set [3]. Performance of different kinds of normalization technique such as z-score, min-max and tanh has been studied on multimodal biometric system based on face, fingerprint and hand-geometry in Jain et al. (2005). In their work, Sum Rule, Weighted Sum Rule, Mean and Product Rules have been used as combination methods. Tanh normalization has achieved the best result despite of including many parameters; in fact, this method is so good for noisy training scores.

In this study, we apply both local and global feature extraction methods to extract iris and face features. Subpattern-based Principal Component Analysis (spPCA), modular Principal Component Analysis (mPCA) and Local Binary Patterns (LBP) methods are used as local feature extractors in this study and global feature extractors such as Principal Component Analysis (PCA), and subspace LDA (ssLDA) also used to compare the performance of global feature extractors with local feature extractors on face and iris images.

We employ each feature extraction method separately on each modality to select the optimal method for iris and face biometrics. Local and global feature extractors are applied to extract face and iris features separately, and then these features are used for the fusion of these modalities. The experiments represent the effectiveness of face-iris biometrics fusion.

The organization of the paper is as follows. Section 2 presents iris recognition briefly. Face recognition is explored in section 3 and the details of multibiometric fusion and normalization techniques are described in section 4. Databases, experimental results and ROC analysis are explained in section 5, while in section 6 conclusion is drawn.
Global and local feature extraction approaches are applied to extract iris features. PCA [9] and ssLDA [10] are global methods used, while spPCA [11], mPCA [12] and LBP [13] are local approaches for feature extraction. In this study, CASIA iris image database [14] is used to measure the performance of our multimodal biometric system. Iris image preprocessing, training, testing and matching are the stages for iris recognition process.

Iris image preprocessing is performed using Libor Masek matlab open-source code [15] which is applied to detect the irises. In this system, segmentation of iris region is done by localizing the circular iris and pupil region based on Hough transform and Canny edge detection [15]. Occluded regions with eyelids, eyelashes and reflections are marked and their positions are recorded with a noise mask. Finally, detected iris region is normalized to a fixed dimension rectangular (20 x 240) form.

Illumination effects on the images are reduced using histogram equalization (HE) and mean-and-variance normalization (MVN) [16]. In training and testing steps, iris features are extracted. Finally in the last step, Manhattan distance measurement is employed between training and test iris feature vectors to compute the matching scores. Manhattan distance measurement can be represented as follows:

\[ d(X, Y) = \sum_{i=0}^{n} |X_i - Y_i| \]  

where \( X \) and \( Y \) are the feature vectors of length \( n \).

3 Face recognition

Face recognition, in the past few years, was one of the most attractive and active areas for biometric schemes. In this area, many researches and implementation of plenty of algorithms were considered. In this paper, facial features are extracted with local and global feature extraction. PCA, ssLDA, spPCA, mPCA and LBP are used for facial feature extraction in the same way as in iris feature extraction step. Face image preprocessing, training, testing and matching are the stages for face recognition process and these steps are performed in the same way as explained in iris recognition stage. In face image preprocessing step, there is not any detection for face images. As explained in the iris recognition section, the matching scores for face recognition section are also calculated using Manhattan distance measurement. ORL face database [17] is used in this study to test our multimodal biometric system.

4 Normalization techniques and fusion of multi biometrics

Normalization of matching scores is needed due to non-homogeneity of produced matching scores from face and iris images. Normalization of matching scores transforms the different matchers into a common domain and range in order to avoid degradation in fusion accuracy [18]. Focus of this study for normalization techniques is on tanh and minmax techniques to normalize the matched score to \([0, 1]\) range.

Minmax normalization is one of the simplest normalization techniques. In this method, finding the maximum and the minimum values of the scores and shifting them to 0 and 1, respectively [18], is performed straightforward. Minmax normalization is calculated as:

\[ s_k' = \frac{s_k - \min}{\max - \min} \]  

where \( s_k \) is a set of matching scores \( k=1, 2 \ldots n \).

Tanh estimator is another normalization method which is applied on matching scores in this study. This robust and efficient method was introduced by Hampel et al. [19] and works very well for noisy training scores. Tanh normalization technique also transforms the matched scores into \([0, 1]\) range. Tanh normalization is as follows [18]:

\[ s_k' = \{ \tanh(0.01(\frac{S_k - \mu_{GH}}{\sigma_{GH}})) + 1 \} \]  

where \( \mu_{GH} \) is the mean and \( \sigma_{GH} \) is the standard deviation of the genuine score distribution.

The most significant step in this study after producing the matching scores and normalization, is developing the multimodal score vector of face and iris verifiers. We apply some fusion techniques at the matching score level to develop the multimodal system.

Generally, matching score level fusion is considered as classification of the scores into one of two classes, Accept/Reject, or combination of the scores to provide an individual scalar score [4]. For this study, combination of the face and iris scores based on the Product and Sum Rules is used to fuse the normalized scores. Sum Rule is one of the simplest fusion strategies and is applied on the matching distances of individual classifiers in which equal weights for each modality are used during the fusion process [6]. Compared to Product Rule, usually Sum Rule is more efficient to meet the requirements especially under circumstances with high level of noise. The following

2 Iris recognition

Iris recognition is one of the most reliable and secure biometric recognition systems and remains stable over the human lifetime [1], [5]. Due to the valuable pattern information of iris and its invariability through a lifetime [6], [7], [8] iris recognition leads to a higher accuracy rate compared to other biometric recognition systems [6].
The formula represents the sum (s) of the scores of face (s_f) and iris (s_i) matchers:

\[ s = s_f + s_i \]  

(4)

The base of Product Rule is on the presumption of statistical independence of vectors \((X_1, X_2, \ldots, X_N)\) demonstrations [20]. The product of the scores of face \((p_f)\) and iris \((p_i)\) matchers can be represented as follows:

\[ p = p_f \times p_i \]  

(5)

Generally, different biometric traits of an individual are mutually independent and this helps us to make use of the product rule in a multimodal biometric system based on the independence assumption [18].

5 Databases, experimental results and ROC analysis

In order to validate the performance of algorithms and fusion methods in our multimodal biometric system, a multimodal biometric database using ORL face database and CASIA iris database is constructed. In ORL face data set, 10 different frontal face images for 40 different subjects are available. All 40 subjects are considered in our multimodal system and we assigned randomly 5 images per subject for training and the rest for testing. Randomly eight iris images were selected from CASIA iris images for 40 subjects, 3 for training and the remaining 5 for testing.

All local and global methods for feature extraction are used on both face and iris datasets. PCA and ssLDA as global methods are applied on the whole images of face and iris datasets. SpPCA, mPCA and LBP are local feature extractors applied by partitioning the images into subregions. Table I illustrates the performance of all the algorithms implemented using face and iris images from all databases. PCA algorithm accuracy was obtained based on the selection of maximum number of nonzero eigenvectors. On the other hand, eigenvectors corresponding to 97% of eigenvalues with \(N=81\), where \(N\) is the number of partitions, were used for subpattern-based PCA and modular PCA. In subspace LDA, eigenvectors were selected experimentally to obtain the best recognition accuracy. For Local Binary Pattern method, the number of partitions used is \(N=81\) and \((8, 2)\) is the parameter for circular neighborhood in both face and iris databases. As represented in Table I, the best accuracy for face recognition on ORL database is obtained using the local feature extractor LBP. For iris recognition, the best accuracy on CASIA dataset is achieved using ssLDA global feature extractor.

Fusion of face and iris scores lead to a higher recognition accuracy compared to the unimodal biometric systems as shown in Table II.

- TABLE I. RECOGNITION PERFORMANCE USING LOCAL AND GLOBAL METHODS ON FACE AND IRIS IMAGES

<table>
<thead>
<tr>
<th>Feature Extraction Method</th>
<th>Face Recognition ORL</th>
<th>Iris Recognition CASIA</th>
</tr>
</thead>
<tbody>
<tr>
<td>PCA</td>
<td>82.00</td>
<td>87.50</td>
</tr>
<tr>
<td>ssLDA</td>
<td>90.50</td>
<td>96.00</td>
</tr>
<tr>
<td>spPCA</td>
<td>83.50</td>
<td>90.00</td>
</tr>
<tr>
<td>mPCA</td>
<td>82.50</td>
<td>94.00</td>
</tr>
<tr>
<td>LBP</td>
<td>91.50</td>
<td>93.50</td>
</tr>
</tbody>
</table>

- TABLE II. FUSION OF FACE AND IRIS RECOGNITION SYSTEM (ORL & CASIA)

<table>
<thead>
<tr>
<th>Feature Extraction Method</th>
<th>Fusion Method</th>
<th>Sum Rule</th>
<th>Product Rule</th>
<th>Tanh Normalization</th>
<th>MinMax Normalization</th>
<th>Tanh Normalization</th>
<th>MinMax Normalization</th>
</tr>
</thead>
<tbody>
<tr>
<td>PCA</td>
<td></td>
<td>97.50</td>
<td>97.00</td>
<td>97.50</td>
<td>82.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ssLDA</td>
<td></td>
<td>99.00</td>
<td>98.50</td>
<td>97.50</td>
<td>95.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>spPCA</td>
<td></td>
<td>97.50</td>
<td>97.00</td>
<td>97.50</td>
<td>84.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>mPCA</td>
<td></td>
<td>99.00</td>
<td>97.50</td>
<td>99.00</td>
<td>88.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LBP</td>
<td></td>
<td>99.00</td>
<td>98.50</td>
<td>99.00</td>
<td>92.50</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Fusion of face and iris biometrics systems starts by applying one of the five algorithms (PCA, ssLDA, spPCA, mPCA, LBP) to extract the features of face and iris biometrics. The same feature extractor is applied on both face and iris images. The fusion of face and iris matching scores is achieved using Sum Rule and Product Rule. ORL and CASIA datasets are used for the fusion of face and iris biometrics. Comparison of the recognition performances for unimodal and multimodal systems is shown in Figure 1. The figure clearly demonstrates the performance improvement of multimodal face-iris biometrics compared to individual face and iris biometrics separately. The best recognition accuracy was achieved using LBP and ssLDA feature extractors, fusion of matching scores using Sum or Product Rule and tanh normalization for face and iris scores.

Figure 1. Face, iris and fusion of face-iris recognition accuracy on ORL and CASIA datasets
We compared our face-iris multimodal system with unimodal systems using ROC (Receiver Operator Characteristic) analysis. False Acceptance Rate (FAR) and False Rejection Rate (FRR) are used as a function of decision threshold which controls the tradeoff between these two error rates. The probability of FAR versus the probability of FRR is plotted for different values of decision threshold. The Equal Error Rate (EER) of each system, given on top of the curves in Figure 2 is obtained from the point on ROC curve where the value of FAR is equal to the value of FRR. Figure 2 demonstrates the error rates of unimodal systems and multimodal system for the fusion of face and iris biometrics. Face EER is obtained using LBP feature extractor and iris EER is calculated using ssLDA feature extractor. EER of multimodal face-iris biometrics system is calculated using LBP, tanh normalization and Sum Rule combination method. The unimodal (face and iris) methods achieve the performance of 2% EER. The multimodal face and iris method achieves a performance of 0.525% EER. The improvement of the multimodal system over the unimodal methods is clearly demonstrated on ROC curve in Figure 2.

![ROC curves of unimodal and multimodal methods on ORL and CASIA datasets.](image)

Figure 2. ROC curves of unimodal and multimodal methods on ORL and CASIA datasets.

6 Conclusion

Fusion of face and iris biometrics using local and global feature extractors, normalization techniques and fusion methods is presented in this study. Local feature extractors, namely spPCA, mPCA and LBP, and global methods such as PCA and ssLDA are used to extract face and iris features. Fusion of face and iris scores is investigated using local and global feature extractors. The fusion of the scores is conducted by using tanh normalization of face and iris scores and Sum or Product Rule fusion methods. The experiments are performed on ORL+CASIA dataset and demonstrated that the fusion of face and iris with local and global feature extractors, tanh score normalization and Sum or Product Rule achieves improved recognition accuracy compared to unimodal biometrics systems.

7 References


