Multibiometric Systems: A Comparative Study of Multi-algorithmic and Multimodal Approaches

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Abstract

In this paper, we present a comparative analysis of Multi-algorithmic and Multimodal approaches. We have used palmprint and face as biometric traits and other popular subspace algorithms (PCA, FLD, and ICA). Subsequently, the different combinations of algorithms are also evaluated in our experiment. The multi-algorithmic approach achieves incremental results where as multimodal approach yields far improved results. Hence Complimentary information available through multimodal approach always performs better than multi-algorithmic approach which mainly builds on supplementary information.

Keywords: Biometric, Multi-algorithmic, Multimodal, Score level Fusion, Weighted Sum rule;

1. Introduction

The world is becoming increasingly security conscious; people are looking for new approaches to security which are more reliable and authentic [2, 6]. Reliable person authentication techniques play a critical role in our everyday activities. In access control to secure systems, authorized users should be allowed for access with higher accuracy while unauthorized users should be denied. Examples of such applications include physical access control to a secure facility, e-commerce, access to computer networks and welfare distribution [3]. The primary task in any identity management system is the determination of an individual's identity [5]. Biometrics refers to an automatic recognition of a person based on behavioral and/or physiological characteristics [6]. Many business applications rely on biometrics since using biometrics is the only way to guarantee the presence of the owner when a transaction is made. However, sometimes a single biometric system fails to authenticate the identity of a person due to insufficient information or by spoofing. By combining multiple algorithms and multiple modalities we can achieve higher performance. Due to its promising applications as well as the theoretical challenges, multibiometrics has drawn increased attention in recent years.

Mehrotra et al.[9] proposed a multi-algorithmic approach for iris, using texture and phase features. Texture features were extracted using Haar wavelets while phase features were obtained using Log-gabor wavelets. These features (texture and phase) were concatenated. Fierrez et al. [10] investigated the effect of image quality on the performance of fingerprint. In this case, they employed the minutia and ridge based fingerprint matcher and also they proposed quality-based weighted sum for different quality groups. Kumar et al. [7] proposed a method of person authentication using palmprint. In this, the comparative performance is between three different approaches namely texture based, line based and appearance based. Fusion is performed at match score level and decision level using sum, max, min and product rule. Prabhakar et al. [12] presented a scheme for combining multiple matchers at decision level. They developed four different fingerprint verification systems using three minutiae based and one filter based algorithm. Roli et al. [13] proposed an experimental comparison between fixed and trained fusion rules for multimodal person verification. In this case, different experiments are performed and fusion was carried out for

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fixed and trained fusion rules. From the experimental results, fixed rules performed well under all circumstances. Many of these results fail to provide effective comparison between choices of multi-algorithmic or multimodal approaches.

Thus in this paper, we are evaluating the performance of multi-algorithmic and multimodal approaches by fusing the data at match score level using weighted sum rule[10]. Palmprint and face are the two modalities which we use in our experiments due to their universality, acceptability and non-invasive characteristics. We have obtained a sub palmprint images by selecting Region of Interest(ROI) for feature extraction and to eliminate the variation caused by the rotation and translation [8][2]. The rest of the paper is organized as follows: Section 2 discusses about subspace algorithms and multibiometrics approaches. Detailed experimental results are given in Section 3. Conclusion is mentioned in Section 4.

2. Multibiometric System

The multibiometric systems are those that utilize more than one physiological or behavioral characteristic [3] and rely on the evidence presented by multiple sources of biometric information. Based on the nature of these sources multibiometric system can be classified into one of the following five approaches: **Multi-sensor systems:** which employs multiple sensors to capture a single biometric trait of an individual. **Multi-algorithmic systems:** which employs multiple feature extraction and/or multiple matching algorithms on the same biometric to improve the performance **Multi-Instance systems:** which uses multiple instances of the same body trait one example is the use of multiple fingers in fingerprint verification. **Multi-sample systems:** where uses single sensor may be used to acquire multiple samples of the same biometric trait in order to account for the variations that can occur in the trait [1, 9]. **Multimodal systems:** these establish identity based on the evidence of multiple biometric traits. The multibiometric systems offers several advantages over the traditional biometric systems, it can offer substantial improvement in the matching accuracy of a biometric system since information is combined, it addresses the issue of non-universality and it is more difficult to spoof. Some of multibiometric approaches are elaborated with their block diagram in Figure-1 and Figure-2.

2.1. Multi-algorithmic Approach

The basic aim of any biometric system is to improve the performance; this is normally achieved by comparing different existing algorithms on the specific problem and selecting best of them. But selecting the best algorithm is not an easy task. Hence, we choose more than one algorithm. In multi-algorithmic approach we employ multiple feature extraction and/or multiple matching algorithms on the same biometric to improve the performance [4]. In other words, the supplementary information which we are getting by more than one algorithm helps to improve the performance. So, utilization of new sensor is not required and hence it is cost effective. Even though there are many algorithms, we explore well known subspace algorithms (PCA, FLD, and ICA) for multi-algorithmic approach.

2.1.1. Principal Component Analysis (PCA)

The PCA [14] technique considers each image as a feature vector in a high dimensional space by concatenating the rows of the image and using the intensity of each pixel as a single feature vector. Let there be N images (A_1, A_2...A_N) constituting the training set denoted by $m \times n$ matrices. Now the average matrix $\bar{A}$ of all training samples has to be calculated then subtracted from the original image Ai and the result is stored in ϕ_i

$$\bar{A} = \frac{1}{N} \sum_{i=0}^{N} A_i \tag{1}$$

$$\phi = A_i - \bar{A} \tag{2}$$

In the next step, the covariance matrix C is calculated according to $C = (1/N) \sum_{i=0}^{N} \phi_i \varphi_i^T$ Now the eigenvectors U_i(i=1...N) and corresponding eigenvalues λ_i (i=1...N) are calculated. From the above N eigenvectors, only k $(k << N)$ should be chosen corresponding to k largest eigenvalues. The higher the eigenvalues, the more characteristic features of an image are described in the particular eigenvector. Using the k eigenvectors U_k, feature extraction is done by PCA as follows:

$$F_i = U_k^T (A_i - \bar{A}) \qquad i = 1.....k \tag{3}$$

The first principal component is the linear combination of the original dimensions that has the maximum variance: the kth principal component is the linear combination with the highest variance, subject to it being orthogonal to the k-1 previous principal components. The basic idea corresponds to selecting the direction of maximum variance and is chosen as the first principal component. In a two-dimensional case, the second principal component is then determined uniquely by the orthogonality constraints. In a higher-dimensional space, the variances of the projection guide the selection process of dimension of feature matrices.

2.1.2. Fisher Linear Discriminant (FLD)

Fisher Linear Discriminant (FLD) [11] finds the vectors in the underlying space that best discriminate among classes. For all samples of all classes, the between-class scatter matrix S_b and the within class scatter matrix S_w are defined by:

$$S_w = \sum_{i=0}^{C} \sum_{x_k \in C_i} (x_k - \overline{m_i})(x_k - \overline{m_i})^T \tag{4}$$

$$S_b = \sum_{i=0}^{C} n_i (\overline{m_i} - \overline{m})(\overline{m_i} - \overline{m})^T \tag{5}$$

Where n_i is the number of training samples in class i, C is the number of distinct classes, m_i is the mean vector of samples belonging to class i and x_k being the k-th image of that class. The FLD subspace is spanned by set of vectors, W satisfying the following:

$$W = \arg_w \max \frac{|W^T S_b W|}{|W^T S_w W|} \tag{6}$$

The W is composed of eigenvectors corresponding to 'l' largest eigenvectors of matrix: $S_w^{-1} S_b$.

2.1.3. Independent Component Analysis (ICA)

ICA accounts for higher order statistics and it identifies the independent source components from their linear mixtures (the observables) [11]. ICA thus provides a more powerful data representation than PCA [14] as its goal is that of providing independent rather than uncorrelated image decomposition and presentation. ICA of a random vector searches for a linear transformation which minimizes the statistical dependence between its components.
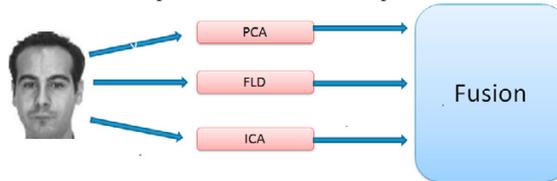

Figure 1: Multi-algorithmic Approach

2.2. Multimodal Approach

The multimodal approach has attracted much attention in the last years. Here, we combine more than one evidence presented by different traits for establishing identity and to improve the performance of the system [3]. Hence, the cost of this system is substantially more due to the requirement of new sensors and, consequently the performance can be significantly improved by utilizing more than one trait. Here we are getting the complimentary information from the different traits. Ultimately this approach improves the performance of system. Hence this method is dependent on fusion strategies [6]. Multimodal biometric systems are divided into four categories based on fusion methods: a) Sensor level fusion- combination of the raw data from the biometric sensor, b) Feature level fusion- combination of different feature vectors c) Score level fusion- combination of matching score provided by different biometric systems d) Decision level fusion- combination of decisions already taken by individual system [4]. In our experiment we have considered the palm and face modalities and adopted the score level fusion since it offer best trade-off between the information and it is also easy to implement.
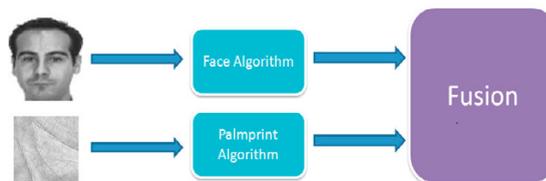

Figure 2: Multimodal Approach

3. Results and Discussion

In order to compare multi-algorithmic and multimodal approaches we use publicly available large databases viz., the PolyU Palmprint database, AR Face database [1][2]. The performance evaluation of all our experiments is measured by Genuine Acceptance Rate (GAR) at 0.1% of False Acceptance Rate (FAR). First we have evaluated the results for each modality by implementing different subspace algorithms namely PCA, FLD, ICA and results are tabulated in Table-1.

From the Table-1 we can observe that the ICA algorithm performs well for both individual modalities. The performance of PCA is low when compared to FLD and ICA, later we also estimate the results for multi-algorithmic and multimodal approaches. Table-2 and Table-3 shows the multi-algorithmic and multimodal performance results respectively.

Table 1: Performance in GRA at 0.1% of FAR

Method	PCA	FLD	ICA
Face	22.18	42.83	46.89
Palm	38.91	61.14	62.17

3.1. Results on Multi-algorithmic Approach

In this section, the experimental results obtained from multi-algorithmic approach for face and palmprint biometrics are discussed in detail.

In the Table-2, we have evaluated all the combinations of algorithms. The combination of PCA and ICA algorithms outperforms and the combination of FLD and ICA underperforms for multi-algorithmic approach of palmprint. But in multi-algorithmic approach for face, the combination of PCA and ICA underperforms and the combination of FLD and ICA outperforms. Thus, Figure-3 shows the Receiver Operating Characteristic (ROC) curve for multi-algorithmic approach for face and palmprint. Even though we have fused three algorithms, there is no significant improvement in the performance rather than the other multi-algorithmic approaches. In multi-algorithmic approach, the combinations of algorithms play a major role rather than the fusion of number of algorithms. The degree of supplementary information available from each algorithm is matters more than individual high scores. This aspect needs further investigation into qualitatively or quantitatively explaining this degree of supplementary information based on both modality and algorithms.

Table 2: Multi-algorithmic Approach for Face and Palm

Method	Face-GAR at 0.1% of FAR	Palm-GAR at 0.1% of FAR
PCA + FLD	42.31	67.81
FLD + ICA	51.20	65.53
PCA + ICA	40.13	69.87
PCA + FLD + ICA	50.03	68.44

3.2. Results on Multimodal Approach

In this section, the experimental results of multimodal approach for two modalities viz., face and palmprint are discussed in detail.

From the table-3, one can learn that there are nine different combinations of the two modalities considered with respect to three algorithms. The performance of fusion of face with ICA and palm with ICA outperforms the other combinations of the modalities considered with different algorithms where as the performance of fusion of face with PCA and palm with FLD is significantly low among the other combinations as shown in the ROC curve in the Figure- 4.

Table 3: Multimodal Approach for Face and Palm

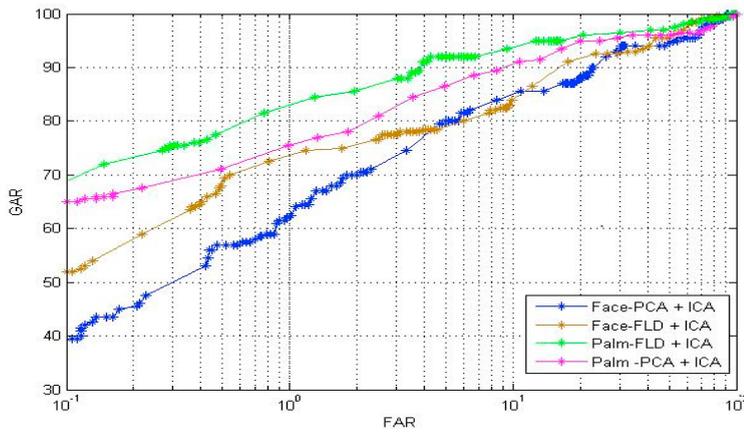| Method	GAR at 0.1% of FAR
Face-PCA + Palm-PCA	66.60
Face-FLD + Palm-FLD	73.69
Face-ICA + Palm ICA	80.03
Face-PCA + Palm-FLD	65.10
Face-FLD + Palm-ICA	79.88
Face-PCA + Palm-ICA	71.13
Face-ICA + Palm-PCA	75.52
Face-FLD + Palm-PCA	70.23
Face-ICA + Palm-FLD	73.22

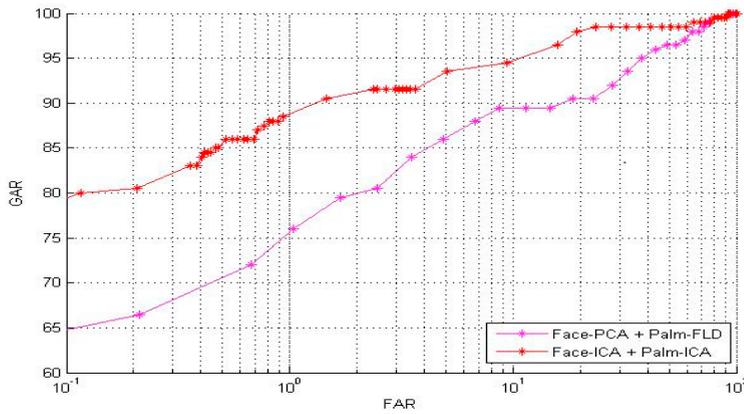Figure 3: Performance of Multi-algorithmic Approach

Figure 4: Performance of Multimodal Approach

4. Conclusion

This paper presents an independent and comparative analysis of multi-algorithmic and multimodal approaches. From the experimental results of both approaches, we claim that the performance of multimodal approach always gives better results than the multi-algorithmic approach. Subsequently, from the results obtained from our experiment we arrive at the following inference: a) Complimentary information always yields better results than supplementary information. b) Fusion of best combination of algorithms play a major role in multi-algorithmic approach, rather than the number of algorithms fused. c) Performance of algorithms is always dependent on modality. d) In general multimodal always yields better results than multi-algorithmic versions of same modality/algorithm.

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