2-class, N-class Approach for Complete Multimodal Biometric Identification

Abhijit Shete, Kavita Tewari

Abstract— Multibiometric systems are expected to be more reliable than unimodal biometric systems for personal identification due to the presence of multiple, fairly independent pieces of evidence e.g. Unique Identification Project "Aadhaar" of Government of India. In this paper, we present a two step multibiometric identification system. In the first step the person is classified as an imposter or genuine, and in second step exact reorganization of a person is done. Here we have proposed PCA and Wavelet based technique to perform fusion at score level by considering two biometric modalities face and fingerprint, which handles 2-class problem and k-NN classifier to identify an individual that handles N-class problem. The results indicate that the proposed technique can lead to substantial improvement in multimodal matching performance. In this paper, score level fusion is done using two different strategies based on performance parameters, EER (Equal Error Rate) and DI (Decidability Index).

Index Terms— Wavelet, PCA, Multimodal Fusion, Decidibility Index, EER, ROC, GAR, k-NN.

1 Introduction

A number of biometric characteristics are being used in various applications. Each biometric has its pros and cons and, therefore, the choice of a biometric trait for a particular application depends on a variety of issues besides its matching performance. A reliable identity management system is a critical component in several applications that render services to only legitimately enrolled users. A biometric system is essentially a pattern recognition system that acquires biometric data from an individual, extracts a salient feature set from the data, compares this feature set against the feature set(s) stored in the database, and executes an action based on the result of the comparison. Identification occurs when a biometric system attempts to determine the identity of an individual.

The most popular approaches to face recognition are based on either (i) the location and shape of facial attributes, such as the eyes, eyebrows, nose, lips, and chin and their spatial relationships, or (ii) the overall (global) analysis of the face image that represents a face as a weighted combination of a number of canonical faces [1].

The most popular ones are based on the minutiae pattern of the fingerprint and are collectively called minutiae-based approaches. The main disadvantage of image-based approaches consists in their limited ability to track with variations in position, scale and orientation angle. Usually the variation in position between the two fingerprints is cancelled by choosing a reference point in each fingerprint. [2]

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In this paper we conclude that, if two biometrics are comparable, then performance of the automated Biometric Identification Subsystem involving two step classification improves by score level fusion techniques [3].

The paper is organized as follows. This introduction serves as the first section. The following section introduces biometric traits used and their feature extraction method. Section 3 summarizes two step classification in detail. Section 4 explains similarity measure used and score level normalization. Fusion techniques used are formulated in section 5. Weights necessary to handle 2-class problem, are calculated in section 6. Also experimental results including k-NN classification experiments are shown in the same section, and finally a brief conclusions section will summarized the paper.

2 Biometric Traits Used and Feature Extraction

2.1 Biometric Traits

Face recognition is a non-intrusive method, and facial attributes are probably the most common biometric features used by humans to recognize one another. The appearance-based approach, such as PCA based approach generally operates directly on an image-based representation (i.e., array of pixel intensities). It extracts features in a subspace derived from given images. Using PCA, a face subspace is constructed to represent "optimally" only the face object.

Fingerprint reorganization using minutiae-based approaches are different from one other, most of these methods require extensive preprocessing operations (e.g. orientation flow estimation, ridge segmentation, ridge thinning, minutiae detection) in order to reliably extract the minutia features [4]. They either match directly the fingerprint images [5], or match features extracted from the image by means of certain filtering or transform operations [6], hence their name image-based methods. In this paper we use an image-based method of fingerprint recognition. The fingerprint patterns are matched based on wavelet domain features which are directly extracted from the gray-scale fingerprint image without preprocessing.

2.2 Feature Extraction - Face

In this paper we use PCA for feature extraction and as a dimensionality reduction technique, which transforms the feature vector φ_i to a vector F_i which has a dimensionality d, where $d < M \times N$ i.e. pixel resolution of an image of person A.

Let $A_i, i = 1,2, \ldots \ldots p$ be an image from database containing p images. For each image we form a pixel vector

$\varphi_i \in \Re^k, (k = M \times N)$ and compute feature vector F_i where $F_i \in \Re^d, d \ll k$. In order to apply PCA we first form a data matrix D which contains p rows, at each row $\varphi_i's$ are stored, thus D has dimensionality of $p \times k$. Next covariance matrix of $D : C_D$ is computed. For this covariance matrix we get k eigenvalue and eigenvector pairs, where each eigenvector e_i is of dimensionality k.

The transformation matrix ψ is formed by simply putting eigenvector with biggest d eigenvalues as column of ψ. The feature vector F_i is then obtained as follows

$$F_i = \psi^T \varphi_i^T \quad (1)$$

Where ψ^T and φ_i^T are the transposes of ψ and φ respectively. Feature vector length used for face trait is 20.

2.3 Wavelet Domain Features - Fingerprint

Feature extraction is done by cropping $[90 \times 90]$ square region centered around the reference point and located inside the fingerprint pattern. Reference point is detected by the method proposed by Li Wang [7]. Central subimage is divided into 4 non-overlapping blocks of size $[45 \times 45]$.

The 2-D wavelet decomposition of J levels on each non-overlapping block represents the block in terms of $3J + 1$ wavelet sub-band images.

$$\left[A_J, \{D_j^1, D_j^2, D_j^3\}_{j=1,\ldots\ldots,J}\right] \quad (2)$$

Where A_J is a lowpass approximation of the original block, and D_j^r are the highpass details at different scales 2^j and orientations r. Wavelet coefficients of large amplitude in D_j^1, D_j^2 and D_j^3 correspond, respectively, to vertical high frequencies (horizontal edges), horizontal high frequencies (vertical edges), and high frequencies in both directions.

The normalised l_2-norm of each wavelet sub-band is computed in order to create a feature vector of length $3J$ per block as given by Eq.(3)

$$\left[\{e_j^1, e_j^2, e_j^3\}_{j=1,\ldots\ldots,J}\right] \quad (3)$$

Where

$$e_j^r = \|D_j^r\|_2 / \sum_{i=1}^{J} \sum_{l=1}^{3} \|D_i^l\|_2 \quad (4)$$

for all $j = 1 \ldots \ldots \ldots J$ and $r = 1, 2, 3$

A wavelet decomposition of each fingerprint image was performed using db10 wavelet in order to extract a feature vector of length 48.

3 Two Step Classification

Our method of two step classification is applied as follows,

Step-1, 2-class problem

1] Extract the feature vector (template) from acquired biometric sample e.g. face and finger of a person using method given in section 2.
2] Determine minimum distance for each sample, by measuring similarity of extracted template to all the templates in the respective database.
3] Determine fused score by using score normalization and one of the fusion strategy.
4] Declare a person as genuine or imposter by selecting threshold where False Match Rate (FMR) is 0.01%.
5] If genuine proceed for **Step-2**

Step-2, N-class problem

(N=40=number of individuals per trait)
5] From second procedure in **Step-1** identify class of a person i.e. identity of a person.
6] If person identified by both traits is same, identification is over, else start from the beginning.

4 Similarity Measure and Score Level Normalization

4.1 Euclidian Distance

Euclidian distance between two feature vectors is computed as

$$E(p,q) = \sqrt{\frac{1}{M}\sum_{i=1}^{M}(p_i - q_i)^2} \quad (5)$$

Where M = Dimension of feature vector. $\mathrm{E} = 0$ Indicates match condition.

4.2 Intersection Operator

The intersection operator introduced by Swain and Ballard in [8] is used as a measure of similarity between two feature vectors. If Q and T are the two feature vectors, then measure of similarity between them can be given as

$$C(Q,T) = \frac{\sum_{i=1}^{3J} min(Q_i, T_i)}{min\left(\sum_{i=1}^{3J} Q_i, \sum_{i=1}^{3J} T_i\right)} \quad (6)$$

$C = 1$ indicates match and $C = 0$ indicates non-match condition as shown in Figure 1(a) in this paper, we have examined performance of two fusion techniques, Feature Level Fusion and Match Score Level fusion with three different fusion strategies.

4.3 Score Level Normalization

The individual feature values of vectors exhibit significant differences in their range as well as form. Augmenting such diverse feature values will not be appropriate for fusion. Since all three similarity measures exhibits different range we have used "min-max" normalization technique to bring all scores in common range. Let x and x' denote a feature value before and after normalization, respectively. The min-max technique computes x' as [9]

$$x' = \frac{x - min(F_x)}{max(F_x) - min(F_x)} \quad (7)$$

where Fx is the function which generates x, and $min(Fx)$ and $max(Fx)$ represent the minimum and maximum of all possible x values that will be observed, respectively.

5 Biometric Fusion Techniques

5.1 Fusion Strategy A – Score Level Fusion *(Assignment of Weights based on EER)*

This fusion strategy assigns the weight to each characteristic e.g face and finger, based on their equal error rate (EER). Weights for more accurate characteristic are higher than those of less accurate characteristic. Thus the weights are inversely proportional to the corresponding errors. Let e_k be the EER to characteristic k, then weight w_k associated to characteristic k can be computed by,

$$w_k = \left(\sum_{k=1}^{t} \frac{1}{e_k}\right)^{-1} * \frac{1}{e_k} \quad (8)$$

5.2 Fusion Strategy B – Score Level Fusion *(Assignment of Weights based on Decidability Index)*

In strategy B, weights are assigned to individual characteristic based on their imposter and genuine scores distributions. The means of these distribution are defined by μ_k^I and μ_k^G respectively, and standard deviations by σ_k^I and σ_k^G respectively. A parameter Decidability Index d_k is used as measure of separation of these two distributions for characteristic k as

$$d_k = \frac{\sqrt{2}\left|\mu_k^G - \mu_k^I\right|}{\sqrt{\left(\sigma_k^G\right)^2 + \left(\sigma_k^I\right)^2}} \quad (9)$$

If d_k is small, overlap region of two distributions is less. Therefore, weights are assigned to each characteristic proportional to this parameter as,

$$w_k = \left(\sum_{k=1}^{t} d_k\right)^{-1} * d_k \quad (10)$$

For both fusion strategies B and C $0 \le w_k \le 1$, $(\forall k)$; $\sum_{k=1}^{t} w_k = 1$ and the fused score for user i is computed as,

$$F_m = \sum_{k=1}^{t} w_k * S_{kp}\,; \ (\forall p) \quad (11)$$

In our case $t = 3$, $k = 1, 2, 3$ indicates face, finger, iris respectively. S_{kp} indicates match score of p^{th} pair of k^{th} characteristic.

6 Performance Evaluation And Experimental Results

6.1 Performance Evaluation

We performed the experiments on Intel Core2 Duo machine using Matlab (R2010b). The performance of proposed approach is measured in terms of Receiver Operating Characteristic (ROC) curve, which plots Genuine Accept Rate (GAR) against the False Match Rate (FMR) at different thresholds. The FMR, False Non-Match Rate (FNMR) and GAR are given by Eqs. (10)-(12), respectively.

$$FMR = \frac{Imposter\ claims\ accepted}{Total\ imposter\ claims} \times 100 \quad (12)$$

$$FNMR = \frac{True\ claims\ rejected}{Total\ true\ claims} \times 100 \quad (13)$$

$$GAR = (1 - FNMR) \times 100 \quad (14)$$

Let $n =$ number of individuals and $m =$ number of images per individual, then number of genuine scores can be obtained as $nm(m-1)/2$ and imposter scores can be obtained as $n(n-1)m^2$ using the same database. For the database used $n = 40$ and $m = 8$, therefore we get 1120 genuine matching's and 99840 imposter matching's. In this paper we have used 1120 genuine and 6240 imposter pairs for each database. FMR and FNMR are obtained for all thresholds (t) by Eq.(13) Eq.(14), these equations are suitable for Color Indexing distance measure. For Euclidian and Hamming distance limits need to be changed.

$$FMR_k(t) = \frac{1}{T_k^I}\sum_{s=t}^{1} Imposter(s) \quad (15)$$

$$FNMR_k(t) = \frac{1}{T_k^G}\sum_{s=0}^{t} Genuine(s) \quad (16)$$

Where T_k^I and T_k^G are the total number of imposter and genuine matches respectively. Equal Error Rate (EER_k) is define as the rate at which $FMR_k(t) = FNMR_k(t)$. In practice the score distributions are not continuous and a crossover point might not exist. In this case, we report the interval as per FVC2000: Fingerprint Verification Competition.

6.2 Database Used

The FVC2000-Db1_a fingerprint database [10] contains a total 800 fingerprint images of size 300x300 and 500 dpi resolution from 100 individuals with 8 images per individual, which were captured with low-cost optical sensor "Secure Desktop Scanner" by KeyTronic.

The ORL standard face database [11] consists of 400 face images attained from 40 individuals. Each individual have 10 images of different expression or gesture. The resolution of the image is 112×92 and the gray scale is 256.

In this paper, we have selected 40 individuals and 8 images per individual from each database resulting 320 images per trait.

6.3 Experimental Results

The experimental results obtained are shown in Table 1. The values of EER, d_k and GAR are significantly improved in both fusion strategies A and B, than individual biometric Face and Finger. Among the fusion strategies the EER and d_k of strategy B are better than other strategy, where as GAR of strategy A is higher than strategy B.

TABLE 1
PERFORMANCE ANALYSIS BEFORE AND AFTER FUSION

Performance Parameter	Face alone	Finger alone	Fusion -A $W_1 = 0.4875$ $W_2 = 0.5125$	Fusion -B $W_1 = 0.4187$ $W_2 = 0.5813$
EER	0.1107	0.1164	0.0604	0.0603
d_k	21.09	15.19	34.88	34.94
GAR @ 0.01% FMR	64.02	60.00	85.54	84.29

The example of performance graphs of fusion strategy **B** are shown in Figure 1. Similar graphs can also be obtained for other strategies.

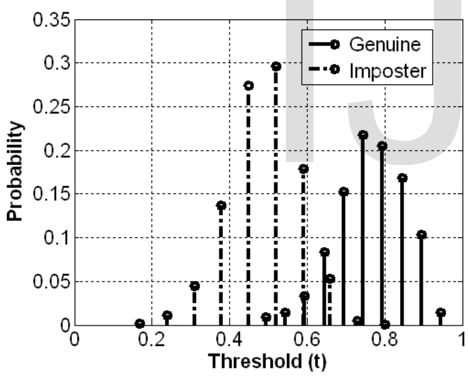

Figure 1(a) Genuine and Imposter Distribution

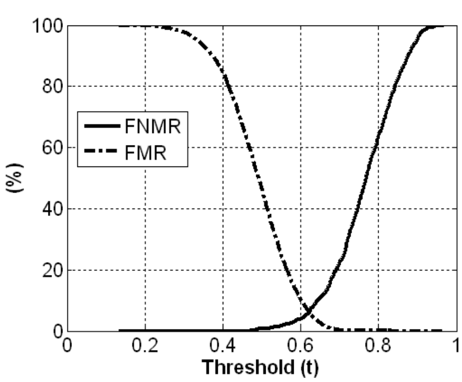

Figure 1(b) FNMR and FMR curves

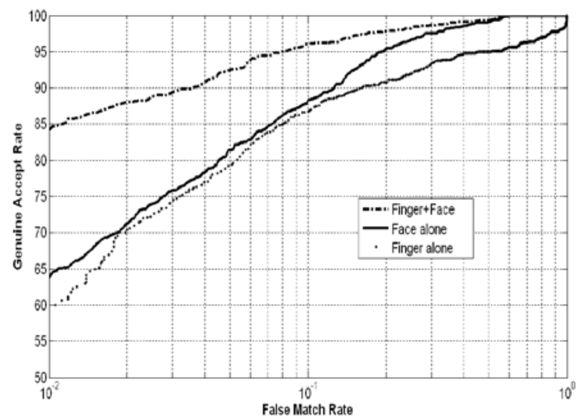

Figure 1(c) ROC curves.

The recognition performances achieved by using wavelet features for fingerprint and PCA features for face trait respectively have been evaluated using a k-NN classifier, with no rejection option a shown in TABLE 2. A number of k images from each individual (for a total of 40k images per trait) have been used as the training set, whereas the remaining 8 - k images from each individual (for a total of 40 x (8-k) images) have been used for testing.

TABLE 2
K-NN CLASSIFIER RESULTS

Biometric Trait	Recognition Rates (%)			
	1-NN	2-NN	3-NN	4-NN
Finger	75.09	87.50	90.00	94.38
Face	73.26	87.50	89.00	93.75

7. CONCLUSION

This paper deals with score level biometric fusion techniques. Among the fusion strategies the EER and d_k of strategy B are better than strategy A, where as GAR of strategy A is higher than strategy B. The high recognition rates achieved by our method as well as its low computational complexity reveal that the method can be used to efficiently solve a security problem involving a small number of fingerprint images. 2-class and N-class problems are effectively solved by using score level fusion and k-NN classifier.

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