Multimodal Biometric Feature based Person Classification

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ABSTRACT
A Monomodal Biometric system encounters a variety of security problems and presents sometimes unacceptable error rates. Conventional biometric system tends to have larger memory footprint, slower processing speed, and higher implementations and operational costs. Multiple biometric consist in combining two or more biometric modalities in a single identification system to improve the recognition accuracy. Whereas a state of art of framework for multimodal biometric identification system which can be adapted for any type of biometrics to provide smaller memory footprints and faster implementations than the conventional multimodal biometrics systems. In these paper we extract the feature of iris and fingerprint and fuse them at feature level and utilize SVM(Support Vector Machine) classifier for matching purpose to provide a higher accuracy than unimodal system.

Keywords
Multimodal Biometric, fingerprint recognition, Iris recognition, feature level fusion, SVM Classifier.

1. INTRODUCTION
With the wide spread utilization of biometric identification systems, establishing the authenticity of biometric data itself has emerged as an important research issue. The fact that biometric data is not replaceable and is not secret, combined with the existence of several types of attacks that are possible in biometric system, make the issue of security/integrity of biometric data extremely critical Although there has been much research on combining different biometrics for variety of purposes, however, not much work has focused on the combination of fingerprint and iris, which are two of the characteristics that can reach the best recognition performance for high security application [1].

1.1 Biometric system performance
In biometric matching studies. The performance of the system is given by the accuracy of the system. False Accept Rate (FAR) and False Reject rate(FRR) are two widely used standard metrics of the accuracy of biometric systems. The FAR are the percentage of imposters that are incorrectly guaranteed the access. The FRR is the percentage of valid users who are incorrectly denied access [7]. The greatest fusion benefits typically results from uncorrected biometric characteristics. Biometric characteristics are correlated when the performance of one biometric sample on an individual predicts, to some extent, the performance of other biometric sample on same individual. The well designed multimodal biometric fusion system will take advantage of the additional information available with the second modality and will not degrade the performance below that of the more accurate modality [7].

2. RELATED WORK
Multimodal biometric authentication or multimodal biometric is the approach of using multiple biometric traits from a single user in an effort to improve the result of authentication process and to reduce error rates.

Previous work in multimodal biometric system design shows that they may be either be based on single input and multiple algorithm or multiple samples and single algorithm or they may utilize two or more different modalities, it has been empirically proven in that multimodal biometrics can improve the performance but these improvement can come at a cost [5].

2.1 Fingerprint Image Enhancement
One of the most widely cited fingerprint enhancement techniques is the method employed by Hong et al. [8], which is based on the convolution of the image with Gabor filters tuned to the local ridge orientation and ridge frequency. The main stages of this algorithm include normalization, ridge orientation estimation, ridge frequency estimation and filtering.

The first step of the fingerprint enhancement is image segmentation. Segmentation is the process of separating the foreground regions in the image from the background regions. The foreground regions correspond to the clear fingerprint area containing the ridges and valleys, which is the area of interest The background corresponds to the regions outside the borders of the fingerprint area, which do not contain any valid fingerprint information.

The next step in this approach involves the normalization of the fingerprint image so that it has a pre specified mean and variance[3]. Due to imperfections in the fingerprint image capture process such as no uniform ink intensity or non-uniform contact with the fingerprint capture device, a fingerprint image may exhibit distorted levels of variation in grey-level values along the ridges and valleys. Thus, normalization is used to reduce the effect of these variations, which facilitates the subsequent image enhancement steps.

An orientation image is then calculated, which is a matrix of direction vectors representing the ridge orientation at each location in the image. The widely employed gradient-based approach is used to calculate the gradient, which makes use of the fact that the orientation vector is orthogonal to the gradient. Firstly, the image is partitioned into square blocks and the gradient is calculated for every pixel, in the *x* and *y* directions. The orientation vector for each block can then be derived by performing an averaging operation on all the vectors orthogonal to the gradient pixels in the block. Due to the presence of noise and corrupted elements in the image, the ridge orientation may not always be correctly determined. Given that the ridge orientation varies slowly in a local neighborhood, the orientation image is then smoothed using a low-pass filter to reduce the effect of outliers.

The next step in the image enhancement process is the estimation of the ridge frequency image. The frequency image defines the local frequency of the ridges contained in the fingerprint. Firstly, the image is divided into square blocks and an oriented window is calculated for each block. For each block, an x signature signal is constructed using the ridges and valleys in the oriented window [9]. The x signature is the projection of all the grey level values in the oriented window along a direction orthogonal to the ridge orientation. Consequently, the projection forms a sinusoidal shape wave in which the centre of a ridge maps itself as a local minimum in the projected wave. The distance between consecutive peaks in the x signature can then be used to estimate the frequency of the ridges.

Fingerprint enhancement methods based on the Gabor filter have been widely used to facilitate various fingerprint applications such as fingerprint matching and fingerprint classification. Gabor filters are band pass filters that have both frequency-selective and orientation-selective properties, which mean the filters can be effectively tuned to specific frequency and orientation values. One useful characteristic of fingerprints is that they are known to have well defined local ridge orientation and ridge frequency. Therefore, the enhancement algorithm takes advantage of this regularity of spatial structure by applying Gabor filters that are tuned to match the local ridge orientation and frequency [6].

2.2 Types of Features

Since most systems only utilize limited and basic features in the fact that more complex features deduce more computational costs. Although incorporating more discriminative information available on fingerprint images into matching stages can reinforce the individuality of fingerprints and improve the system performance on large scale databases, how to find and fuse this information is still a challenging task .

Apparently, the performance of fingerprint matching algorithm greatly depends on the feature extraction and representation, so it is worthwhile to highlight several typical features as follows:

2.2.1 Minutiae feature:

Minutiae point is one of the discriminative and reliable features widely used in fingerprint matching. The matching process based on this feature first aligns two sets of minutiae points from input and template, respectively, then accumulates the minutiae pairs in a fixed or flexible bounding box, and finally estimates the matching score, where a higher score means a more credible similarity level. Although minutiae feature is necessary in most case due to its less memory expense and effectiveness in average matching, it is difficult to be extracted robustly in low quality image and easy to deduce false recognition. Moreover, a minutiae set cannot characterize the overall pattern of a fingerprint since it discards the global ridge information. So, combination with other discriminatory features can effectively strengthen the performance of this kind of feature.

2.2.2 Ridge feature:

Ridges, as well as their relationships, represent the intrinsic individuality of fingerprint. In fact, the ridges include the minutiae, and some approaches were therefore proposed to add ridge information to minutiae-based matching by means of sampling points in associated ridge of a minutiae or ridges counts among matched minutiae pairs. On the other hand, Thinned ridges can be employed to directly compare the global patterns of ridges and furrows. Generally, ridge feature can increase the difference of between-class scatter, while it is directly proportional to the quality of fingerprint enhancement and post processing, and takes more extracting and matching time, especially for totally ridge-based methods. Furthermore, the performance of this method seems not excellent in case of severe distortion.

2.2.3 Texture feature:

Textures are defined by spatial repetition of basic elements, and are characterized by properties such as scale, orientation, frequency, symmetry, isotropy, and so on. Fingerprint ridge lines are mainly described by smooth ridge orientation and frequency, except at singular regions. These singular regions are discontinuities in a basically regular pattern and include the loop(s) and the delta(s) at a coarse resolution and the minutiae points at a high resolution. Various techniques using filters are applied to extract both global and local textures.

2.2.4 Orientation feature:

Orientation is another important kind of statistical feature which utilizes line flow to represent the ridges in fingerprints. It is essential for fingerprint image enhancement, fingerprint pattern classification, synthesis fingerprint, and so forth. Hence, it is undoubtedly valuable for fingerprint matching because all the above processes must protect the ridge structure as much as possible.

2.3 Iris Recognition

The iris is the colored part of an eye behind eyelids , and in front of the lens. The function of the iris is to control the amount of light entering through the pupil by the sphincter and dilator muscles, which adjust the size of the pupil. This externally visible, yet protected organ whose unique epigenetic pattern remains stable throughout the life[5].

The algorithm consists of 2 steps: Iris preprocessing, feature extraction.

2.3.1 Iris preprocessing

The important preprocessing steps are localization and normalization.

2.3.1.1 Localization

It is used to isolate the actual iris region in a digital eye image by detecting the inner and outer boundary of the iris. The segmentation step consists in applying Canny edge detection to generate an edge map, then using circular Hough transform to detect the iris and pupil boundaries and deduce their radius and center coordinates.

To increase efficiency of the circle detection process, we apply the Hough transform for the iris/scalera boundary first, then for the iris/pupil boundary within the iris region, instead of the whole eye region. As a result six parameters are stored: the radius and (x,y) center coordinates for both the circles[5].

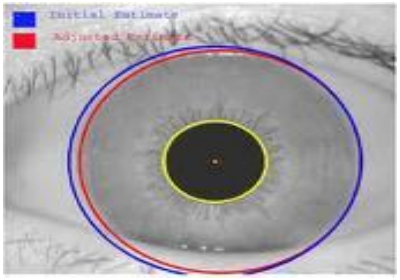

Fig 1: Localized image

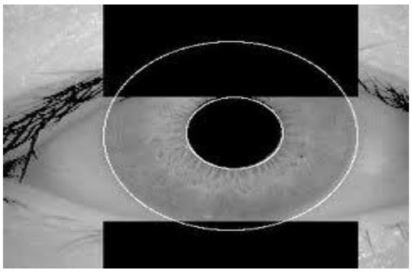

Fig 2: Segmented image

2.3.1.2 Normalization

Once the iris region is segmented, the next stage is to normalize this part so as to enable the generation o the iris code and their comparisons. Since the variation in the eye like size of iris, position of pupil in the iris, and the iris orientation vary from person to person, so it is required to normalize iris image so that representation is common to all.

The unwrapping of iris and converting it into normalized non-concentric polar coordinates from Cartesian representation is modeled using Daugman's Rubber sheet model. The center of the pupil is considered as the reference point and a remapping formula is used to convert the points on the Cartesian scale to the polar scale.

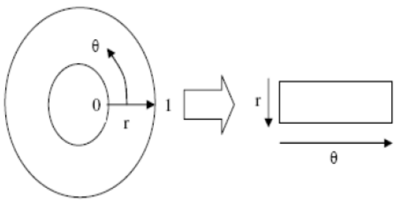

Fig 3: Daugman's Rubber Sheet Model

Fig 4: Normalized Image

2.3.2 Types of features:

2.3.2.1 Texture based:

The information lying between the pupilary and outer iris boundary is extracted and some texture analysis algorithm is applied to extract unique feature. This gives amplitude information of an image.

2.3.2.2 Phase based

Phase angle are assigned to iris pattern by finding the subpixel image translation.

2.3.2.3 Zero crossing

Zero crossing of wavelet transform at various resolution levels are calculated over concentric circles on iris, and the resulting 1-D signals are compared with model features using different dissimilarities functions.

2.3.2.4 Intensity Variation

Thesetechnique takes into consideration the shape information of the iris by analyzing local intensity variation of an iris image.

2.4 Fusion Strategies

2.4.1 Decision level

Each sensor can capture multiple biometric data and the resulting feature vector individually classified into the two classes: accept or reject. A majority vote scheme, such as that employed in can be used to make the final decision.

2.4.2 Match Score level

Each system provides a matching score indicating the proximity of the feature vector with the template vector. These scores can be combined to assert the veracity of the claimed identity.

2.4.3 Feature level

The data obtained from each sensor is used to compare the feature vector as the feature extracted from one biometric trait are independent of those extracted from the other, it is reasonable to concatenate the two vectors into a single new vector[4].

3. PROPOSED WORK

3.1 Preprocessing

The preprocessing gives an insight into the process that has been followed for the enhancement of the input fingerprint image. In preprocessing stage, normalization of the finger print image so that it has prespecified mean and variance. Due to imperfection in the fingerprint image capture process such as non-uniform contact with the fingerprint capture devices, a fingerprint image may exhibit distorted levels of variation in grey-level values along the ridges and valleys. Thus, normalization is used to reduce the effect of this variations, which facilate the subsequent image enhancement steps. An orientation image is then calculated, which is a matrix of direction vectors representing the ridge orientation at each location in the image. Then the image enhancement is done by Gabor, histogram equalization, followed by Binarization. The next step deals with the extraction of minutia. Here first thinning is done and then nearest neighborhood operation is performed by feature extraction.

3.2 Feature Extraction

We are using two algorithms for feature extraction

3.2.1 Fingerprint Recognition

3.2.1.1 Minutiae Based

Minutiae points are one of the discriminative and reliable features widely used in fingerprint matching. Minutiae based technique first locates the minutiae points then this technique match the relative placement of minutiae points in a given fingerprint image. This approach depends heavily on preprocessing and post-processing operations in order to extract the reliable minutiae features from the fingerprint image.

3.2.1.2 Wavelet

Wavelet transform is a mathematical tool based on many-layer function decomposition. After WT, a signal can be described by many wavelet coefficients which represent the characteristics of the signal. So, WT has been widely used in signal processing, image processing, pattern recognition and texture recognition.

One-dimension WT is defined as Equ.1

$$w_T(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(x)\overline{\psi(\frac{x-b}{a})}dx$$

(1)

where, $\Psi(x)$ is basic wavelet function, b is the location shift, a is the size and a >0, f(x) is the analyzed signal [9].

On the basis of Equ.1, if the WT of direction-y is introduced, one-dimension WT can be changed into two-dimension WT. Suppose b and c is x-direction and y direction shift parameters, respectively, a is the size parameters, $\psi(\frac{x-b}{a})dx$ is the wavelet function of x-direction, $\psi(\frac{y-b}{a})dy$ is the wavelet function of y-direction, f (x, y) is the two-dimension function to be analyzed, the two-dimension WT can be expressed by Equ.2,

$$w_T(a,b,c) = \frac{1}{\sqrt{a}} \int_R \int_R f(x,y)\overline{\psi_x(\frac{x-b}{a})\psi_y(\frac{y-c}{a})}dxdy \quad \textbf{(2)}$$

Binary WT is usually used in image processing. Suppose a = 20, 21, 22,_ , 2j, j= 1, 2, .., N. If j changes little, a will changes much. So, Binary WT has effectively changes the focus in signal analysis [15]. If (x, y) represents an image signal, its binary WT is equal to two one-dimension filters (x-direction and y-direction), as shown in Figure3(a), where LL represents low-frequency vectors, HL represents high frequency vectors in horizontal direction, LH represents high-frequency vectors in vertical direction, HH represents diagonal high-frequency vectors .

If low-frequency vector LL is decomposed, two level decomposition can be attained, as shown in Figure3. After WT, if the image has distinct features in some frequency and direction, the corresponding sub-images have larger energies. So, image information focused on the less wavelet coefficients.

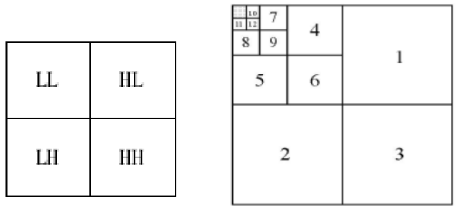

Fig 5(a): Wavelet Decomposition

5(b): Image of Four-level wavelet decomposition.

A vector of 4xl is attained by four levels WT decomposition on the basis of satisfying image resolution. Fingerprint recognition is accomplished by comparing the vector with the stored vector previously. One portion of the "central sub-image" results in 12 features.

3.2.2 Iris recognition:

The main problem regarding the iris recognition is that the recognition accuracy is decreased when the eyelids and eyelashes corrupts the iris image partially. To overcome these problems preprocessing steps are required i.e, Localization, Segmentation and Normalization.

We are using two techniques for feature extraction from iris :

1) HAAR transform
2) Block sum

3.2.2.1 HAAR Wavelet

HAAR transform decomposition operates by calculating the sums and differences of intensity values. The iris strips is taken as input to the process and at each level the algorithm finds four coefficients i.e. approximation, vertical, horizontal and diagonal. The process is again repeated for the generated approximation coefficients. This is again iterated for four levels and last level coefficients (horizontal, vertical and diagonal) forms the feature set. The pictorial representation of feature extraction using HAAR Wavelet is given in figure 6.

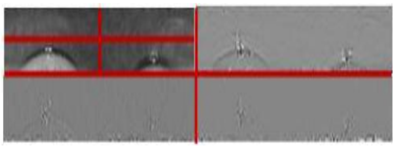

Fig 6: Feature Extraction using HAAR Wavelet

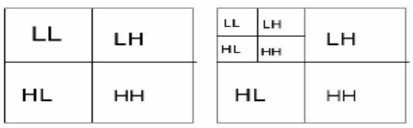

Fig 7: HAAR Transform

3.2.2.2 Block Sum

In this section a Block Sums based analysis method for feature extraction is explained. Block sums are calculated simply and do not need much processing burden.

Step 1. We are using block sum method to divide normalized iris image into some cell regions .

Step 2. Each cell region is represented by its entropy of gray scale image, which is used for calculating the block sum.

Step 3. Basic cell regions are grouped in horizontally directions and vertical directions. As shown in figure.

Step 4. Calculate block sums over each group.

Step 5. Generate iris feature codes.

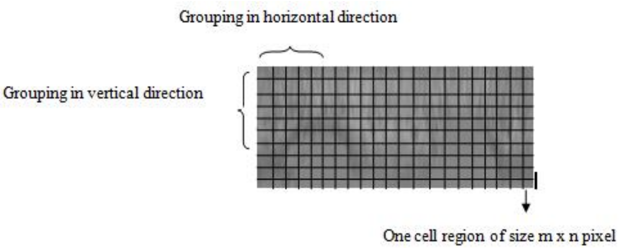

Fig 8: Feature Extraction using Block Sum

3.3 Fusion

Fusion is the technique for combining multiple feature vectors into a single vector. In this case, we have at hand four sets of feature vectors namely- two from fingerprint and two from iris. The next step is to fuse the four sets of features at the feature level to obtain a multi-modal biometric template.

Concatenation

- Let we call the iris feature vectors as I1 & I2 for HAAR & Block sum and fingerprint feature vectors as F1 & F2 for Minutia & Wavelet respectively.
  F_1= [x_1, x_2, x_3,…..x_n]; $|F_1|$=m

  F_2= [y_1, y_2, y_3,…..y_n]; $|F_2|$=n

  I_1= [a_1, a_2, a_3,…....a_n]; $|I_1|$ =p

  I_2= [b_1, b_2, b_3,…...b_n]; $|I_2|$ =q
- For fusion we were used the traditional technique i.e. serial fusion, in which we are combining vectors I1 & F2 into single vector in M1 & vectors I2 & F1 into vector M2.
- Here M1 obtained is the triplet of M2. Now we combined these two vectors M1 and M2 by parallel fusion. In which, we combine the vectors in such a way that three elements from vector M1 and one element of vector M2, and we obtained the fused vector M.

3.4 Reduction

As we are using feature level fusion, the high dimension feature vector is get as result, to increase recognition speed , reduction is necessary.

For reduction on the obtained fused feature vector, we apply following steps:

1) Firstly, we convert the fused feature vector of iris and fingerprint into three different matrices m1, m2, m3 of size 12*17 each.

2) The co-occurrence of these three matrices with offset one pixel and angles 0, 45, 90 degree is created and name this matrix: CO1, CO2 and CO3. In this case for each image 3 co-occurrence matrixes with 5*8 dimensions are created. Now we add these three co-occurrence matrices and create a single matrix of size 5*8.

3) According to the Haralick‘s theory the co-occurrence matrix has 14 properties, of which in our multi- biometric system we used 5 properties which are used for the matrix obtained [9], so the feature vector is as follow:

F = [E H AC D I]. In other word, the feature matrix in our method has only 200 elements of size 40*5 where each vector consists of 40 elements.

Properties used for reduction:

i)

$$\text{Energy} = \sum_i \sum_j p(i,j)^2$$

ii)

$$\text{Homogeneity} = \sum_i \sum_j \frac{1}{1+(i-j)^2} P(i,j)$$

iii)

$$\text{Autocorrelation} = \sum_i \sum_j (ij) P(i,j)$$

iv)

$$\text{Dissimilarity} = \sum_i \sum_j |i-j| . P(i,j)$$

v)

$$\text{Inertia} = \sum_i \sum_j (i-j)^2 P(i,j)$$

3.5 SVM

Support Vector Machine (SVM) is a well accepted approach for pattern classification due to its attractive features and promising performance. Support Vector Machine classifiers devise a computationally efficient way of learning good separating hyperplane in high dimensional feature space[6].

In this multimodal biometric system, we are using the simplest form of a prediction problem is binary classification:

trying to discriminate between objects that belong to one of two categories — genuine (+1) or imposter (-1).

In SVM, a few important points called support vectors(SV) are selected on which decision boundary is exclusively dependent[6]. The parameter selection of SVM plays a very important role to improve the overall generalization performance in order to make SVM more feasible, the parameters of SVM are tuned carefully.

For classification purpose, we are given some training data, a set of points of the form

$$\mathcal{D} = \{(\mathbf{x}_i, c_i) | \mathbf{x}_i \in \mathbb{R}^p, c_i \in \{-1, 1\}\}_{i=1}^{n}$$

where the c_i is either 1 or −1, indicating the class to which the point $\mathbf{x}_i$ belongs. Each $\mathbf{x}_i$ is a p-dimensional real vector. We want to give the maximum-margin hyperplane which divides the points having $c_i = 1$ from those having $c_i = -1$. Any hyperplane can be written as the set of points $\mathbf{x}$ satisfying

$$\mathbf{w} \cdot \mathbf{x} - b = 0,$$

where . denotes the dot product. The vector $\mathbf{w}$ is a normal vector: it is perpendicular to the hyperplane. The parameter $\frac{b}{\|\mathbf{w}\|}$ determines the offset of the hyperplane from the origin along the normal vector $\mathbf{w}$.

We want to choose the $\mathbf{w}$ and b to maximize the margin, or distance between the parallel hyperplanes that are as far apart as possible while still separating the data. These hyperplanes can be described by the equations

$$\mathbf{w} \cdot \mathbf{x} - b = 1$$

and $$\mathbf{w} \cdot \mathbf{x} - b = -1.$$

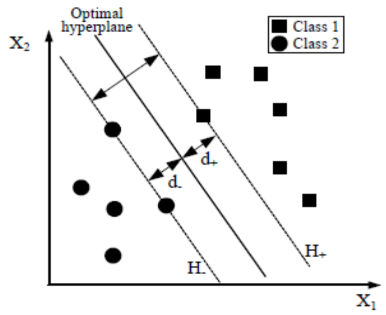

Fig 9: Illustration of two-class classification process using SVM

4. EXPERIMENTAL RESULTS

We use database of CASIA which is standard data taken in very controlled environment and best suited for iris recognition. Although, the database consists of fingerprint and iris images. Fingerprint samples are taken in college, five to six samples of each 50 users. Although, to check performance of system on noisy images we are using upol phonex database.

To evaluate the genuine vs. imposter decision, one iris and one fingerprint image is selected from same subject, and their features are fused using fusion technique and finally it is decided by SVM classifier. Although the fusion has improved the overall performance of the system. The approximate percent of system is 96%.

5. CONCLUSION

This paper has presented a novel approach of combining fingerprint and iris at the feature level using two different algorithms for each modality to build multimodal biometric system, to improve recognition speed and accuracy.

Finally we trained our CASIA database, phonex database, and real fingerprint images (taken from our colleague) using the SVM classifier and results are in experimental results. Nobody can be accepted as genuine unless both modalities don't accept him as genuine.

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