A Multimodal Biometeric Integrating Palmprint and Face With Fingerprint

John Christopher† Dr.T.Jabarajan††

[1]Associate Professor, Department of Computer Science, S.T. Hindu College, Nagercoil
[2] Principal, V.V. College of Engineering, Tisayanvilai.

Abstract
This paper deals with a multimodal biometric recognition system integrating palmprint, fingerprint and face based on feature extraction fusion. The feature vectors are extracted independently from the pre-processed images of palmprint, fingerprint and face using a combined Fisher Linear Discriminant (FLD) and Gabor Wavelet responses. Gabor wavelets have properties of being more robust to image illuminations, small translations, limited rotations and having a superior feature representation in both spatial and frequency domains. On the other hand, FLD seeks those projections that are efficient for data discrimination and produces well separated classes in low-dimensional subspaces. This new combined method involves convolving a palmprint, fingerprint and face image with a series of Gabor wavelets at different scales and rotations before extracting features from the resulting Gabor filtered images. Linear discriminant analysis is then applied to the feature vectors for dimension reduction as well as class reparability. The identity established by this system is more reliable than the identity established by individual biometric systems. Integrating multiple biometric traits improves recognition performance and reduces fraudulent access. The proposed multimodal biometric system overcomes the limitations of individual biometric systems and also meets the response time as well as the accuracy requirements.

Index Terms
face recognition, Gabor wavelet, and Fisher's linear discriminator.

1. INTRODUCTION

A wide variety of systems require reliable personal recognition. The Biometric systems based on palmprint, fingerprint and face which provides rich personal information for automatic recognition of individuals based on the principal lines, wrinkles and ridges on the finger, palm and face [1]. Since the patterns of an individual's palm print fingerprint and face are stable and unique, they can be used as personal signatures for human identification. However, the similarity between the principal lines from different persons makes it difficult to discriminate different palm prints with an acceptable accuracy. Hence the texture information will add extra discriminating power since the feature extraction is a crucial step in the recognition process especially for palm print fingerprint and face images with low resolution qualities [1][2]. One of the most attractive tool to capture useful information to maximize the simultaneous localization of energy in both spatial and frequency domains is Gabor filter [3]. A Gabor filter can be applied to the whole image through a filtering process in order to break down the image content into different scales, orientations or with a combination of both with the aim of obtaining an efficient feature extraction to maximize the classification [2][4]. However, the resulting dimensionality of the feature vectors extracted is usually very high when a series of Gabor filters are used to convolve the image. A usual method for dimensionality reduction is to use a subspace projection. Two fundamental linear subspaces transform based methods: Eigenpalms, Eigenfaces and Fisher palms, Fisher face have had a significant influence for a considerable reduction of the feature vector dimensional reduction while still maintaining an acceptable discrimination [2]. Eigenpalms, Eigenfinger and Eigenfaces are a set of eigenvectors obtained when applying principal component analysis (PCA) to a set of training images in the spatial domain to approximate the original data by a linear projection onto the leading eigenvectors [2]. However, PCA computes those components that are useful for representing data and as such it does not assume that these components should be useful for discriminating between classes. In other words, PCA seeks projections that are optimal for image reconstruction from a low dimensional basis and it may not be optimal for discrimination purpose. Compared with PCA, FLD is a well-known method for feature extraction and dimensionality reduction which seeks projections that are efficient for data discrimination. It is used to determine the low-dimensional space that helps to group the images of the same class and separate images of different classes [4]. In this paper, we describe an approach that combines Gabor feature extraction and linear discriminate analysis for palmprint, and face recognition. This involves extracting discriminate features from images using a series of Gabor wavelets at different scales and orientations and projecting the resulting feature vectors into a subspace before authentication can be performed 5]. Finally, a distance measure is used to determine the similarity between a query palm print, fingerprint and the face image against images in the database in order to assess the performances achieved.

In feature extraction for fingerprint the fingerprint image is viewed as a flow pattern with a definite texture. An orientation field for the flow texture is computed [2]. The input image is divided into equal sized blocks. Each block is

Manuscript received October 5, 2010
Manuscript revised October 20, 2010

processed independently. The gray level projection along a line perpendicular to the local orientation field provides the maximum variance. Locate the ridges using the peaks and the variance in this projection. The ridges are thinned and the resulting skeleton image is enhanced using an adaptive morphological filter. The feature extraction stage applies a set of operations on to the thinned and enhanced ridge image. The post processing stage deletes noisy feature points. The overall process can be divided into following operations: First Load the image, then Orientation estimation, then Ridge Segmentation, Smoothing and Thinning. Finally Minutiae post processing.

2. PROBLEM DESCRIPTION

A general 2-D Gabor function $\psi(x, y)$ is defined as:

$$g(x,y) = \frac{1}{2\pi\sigma_x\sigma_y}\exp[-\frac{1}{2}(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}) + j2\pi Wx] \quad (1)$$

where the spatial coordinates (x, y) denote the centroid localization of an elliptical Gaussian window. The parameters σ_x and σ_y are the space constants of the Gaussian envelop along x and y axes, respectively. The Fourier transform G(u, v) of the Gabor function g(x, y) can be written as:

$$G(u,v) = \exp\{-\frac{1}{2}[\frac{(u-W)^2}{\sigma_u^2}+\frac{v^2}{\sigma_v^2}]\} \quad (2)$$

Where W represents the frequency of the sinusoidal plane along the horizontal axis and the frequency components in the x and y direction are denoted by the pair (u, v), while $\sigma_u = \frac{1}{2\pi\sigma_x}$ and $\sigma_v = \frac{1}{2\pi\sigma_y}$. By considering a non orthogonal basis set formed by Gabor functions, a localized frequency description can be obtained by expanding a signal with this basis. Self-similar class functions, known as Gabor Wavelets, can be generated by dilations and rotations of the mother wavelet ψ(x,y) through the generating function:

$$g_{mn}(x,y) = a^{-m} g(x', y'), a > 1 \quad (3)$$

by considering m = 1, ...,S and n = 1, ...,K. S and K denote the total number of dilations and orientations, respectively, and:

$$x' = a^{-m}(x\cos\theta + y\sin\theta) \quad (4)$$

$$y' = a^{-m}(-x\sin\theta + y\cos\theta) \quad (5)$$

Where θ = nπ/ K is the angle. To ensure that the energy is independent of m, a scale factor a^{-m} is introduced. By considering the redundant information presented in the filtered images due to the non-orthogonality of the Gabor wavelets, Manjunath et al designed a strategy to reduce the redundancy of the Gabor wavelet filter bank, where the half-peak magnitude of the filter responses touches each other in the frequency spectrum[2].

A. Gabor Filter Design

Let U_l and U_h denote the lower and the upper center frequencies of interest. Then the design strategy results in the following equations for computing the filter parameters σ_u and σ_v.

$$a = \left(\frac{U_h}{U_l}\right)^{\frac{-1}{s-1}} \quad (6)$$

$$\sigma_u = \frac{(a-1)U_h}{(a+1)\sqrt{2\ln 2}} \quad (7)$$

$$\sigma_v = \tan\left(\frac{\pi}{2k}\right)\left[U_h - 2\ln\left(\frac{\sigma_u^2}{U_h}\right)\right]\left[2\ln 2 - \frac{(2\ln 2)^2\sigma_u^2}{U_h^2}\right]^{-\frac{1}{2}} \quad (8)$$

In order to eliminate sensitivity of filter responses to absolute intensity values the real components of 2D Gabor filters are biased by adding a constant to make them zero mean since most of the useful information in a palmprint image is contained within a limited frequency band. Four scale and eight orientations appear to have achieved an acceptable performance in our experiments.

B. Gabor feature representation

The Gabor representation of a palmprint image x(x, y) can be obtained by convolving the image with the family of Gabor filters as follows:

$$W_{m,n}(x,y) = \iint X(x,y) g_{mn}^{*}(x-x_0, y-y_0)dx_0, dy_0 \quad (9)$$

where $W_{m,n}(x,y)$ denotes the result corresponding to the Gabor filter at scale S and orientation K and * indicate the complex conjugate. The magnitude of the convolution result of a random palmprint image with 32 Gabor filters with Ul = 0.05 and Uh = 0.4, in which four scales and eight orientations have been used to generate a series of Gabor responses involving a trade filter bandwidth against the size of the scaling factor between frequencies of the successive filters, as well as obtaining a broad and uniform coverage of the spectrum [2]. As a result, a palmprint image can be represented by a set of Gabor wavelet coefficients (Wm,n(x, y),m = 0, ..., 3; n = 0, ..., 7). The magnitude of each coefficient Wm,n(x, y) is normalized to zero mean, unit variance and at each scale level the coefficients are resampled by a factor of 1/2(s−1) giving a dimensionality that is 1/4-th of the previous level. This overcomes the dimensionality explosion relating to using a filter-bank with different scales and orientations. Finally, the coefficients are converted into a vector by concatenating the rows. A discriminative feature vector x can be derived to represent the image I(x, y) using equation (9) as follows:

$$X = \left[X_{0,0}^{T} \; X_{0,1}^{T} \ldots\ldots X_{3,7}^{T} \right] \qquad (10)$$

The dimension of the derived feature vector still too high for an efficient classification process since it requires a large memory space and a high computational effort. The palm print provides a larger surface area compared with the fingerprint, so that more features can be extracted for personal recognition. It is non intrusive and has accuracy higher than fingerprint. Therefore palm print recognition offers promising future for access control systems.
Normalization is used to standardize the intensity values in an image by adjusting the range of grey-level values so that it lies within a desired range of values. Normalization is pixel-wise operation [6]. It does not change the clarity of the ridge and furrow structures. The main purpose of normalization is to reduce the variation in gray level values along ridges and furrows, which facilitates the subsequent processing steps. Hence, a method based on variance threshold can be used to perform the segmentation.
The final step in pre-processing is thinning before the extraction of minutiae[7]. Thinning is a morphological operation that successively erodes away the foreground pixels until they are one pixel wide. A standard thinning algorithm is used, which performs the thinning operation using two sub iterations. The application of the thinning algorithm to a fingerprint image preserves the connectivity of the ridge structures while forming a skelectonized version of the binary image. This skeleton image is then used in the subsequent extraction of minutiae. The CN value is then computed, which is defined as half the sum of the differences between pairs of adjacent pixels in the eight neighborhoods. These spikes are removed using directional smoothing. Thus the three recognizers (palmprint, fingerprint, face) are combined at the matching level and final decision about the person’s identity is made.

III FEATURE EXTRACTION

A. *Palmprint Recognition*

Palmprint is one of the relatively new physiological biometrics due to its stable and unique characteristics. Biometric palmprint recognizes a person based on the principal lines, wrinkles and ridges on the surface of the palm [7]. These line structures are stable and remain unchanged throughout the life of an individual. Fig.1 shows approach can be used which transforms palmprint images into specific transformation domains to find useful image representations in compressed subspace. It computes a set of basis vector from a set of palmprint images, and the images are projected into the compressed subspace to obtain a set of coefficients [5]. New test images are matched to the coefficients by projecting them onto the basis vectors and finding the coefficients in the subspace. The basis vectors generated from a set of palmprint images are called eigenpalm.
Recognition is performed by projecting a new image into the subspace spanned by the eigenpalms and then classifying the palm by comparing its position in palm space with the positions of known coefficients .The match score (MSpalm) between two palmprint feature vectors can be calculated using the Euclidean distance.

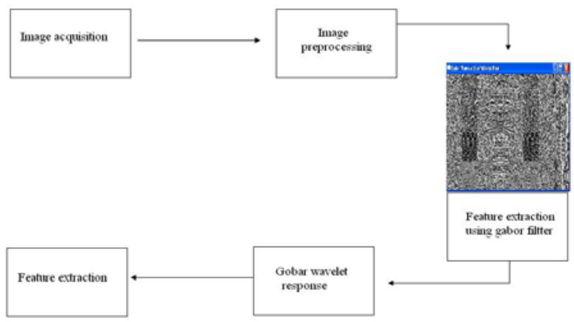

Fig.1 Steps involved in palmprint feature extraction

B. *Fingerprint Recognition.*

Fingerprint is one of the most widely used biometric trait. The fingerprint is basically the combination of ridges and valleys on the surface of the finger. The lines that create fingerprint pattern are called ridges and the spaces between the ridges are called valleys or furrows. Once a high-quality image is captured, there are several steps required to convert its distinctive features into a compact template. Fig. 2 shows the fingerprint feature extraction process and the major steps involved in fingerprint recognition using minutiae matching. The goal of fingerprint enhancement is to increase the clarity of ridge structure so that minutiae points can be easily and correctly extract then the thinning algorithm which reduces the ridge thickness to one pixel wide for precise location of endings and bifurication.

The orientation image represents an intrinsic property of the fingerprint images and defines invariant coordinates for ridges and furrows in a local neighborhood. The orientation field of a fingerprint image represents the directionality of ridges in the fingerprint image [7].

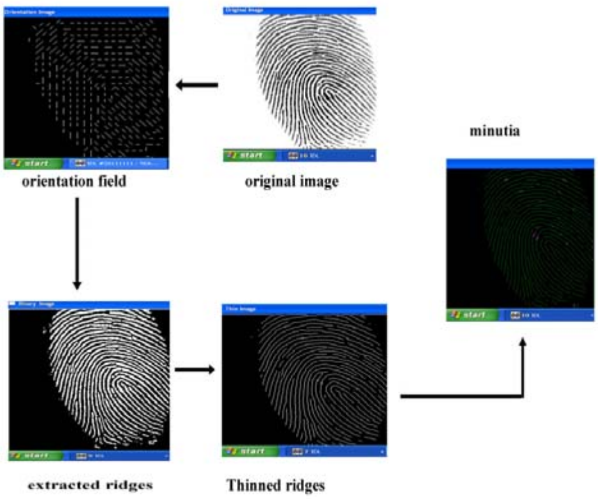

Fig.2 Steps involved in fingerprint feature extraction

The main steps for the calculation of orient direction from the normalized image are:

• Divide the image into 8x8 sized blocks.

• Compute the image gradients δx(i,j) and δy(i,j) at each pixels.

• Calculate the local orientations at each pixel by finding principle axis of variation in image gradients.

• Smooth the orientation field using Gaussian lowpass filter. The orientation image needs to be converted to continuous vector field using equation (10) and equation (11):

$$\phi_x(i,j) = \cos(2\theta(i,j)) \tag{11}$$

$$\phi_y(i,j) = \sin(2\theta(i,j)) \tag{12}$$

Where ϕ_x and ϕ_y are x and y components of vector field respectively. All possible directions should get converted into eight directions in the range of 90 degrees to -67.5 degrees [3]. We round the value of the obtained direction to the nearest values of the desired range. We are considering only this range of values for the orientation field calculation. With this, a fairly smooth orientation field estimate can be obtained.

Once the orientation field of the given fingerprint image is calculated then the frequency is rounded to reduce the number of distinct frequencies [7]. The pixel with minimum value is converted to one, while the others are converted to zero. This process is called binarization.

In the proposed algorithm for the ridge segmentation and smoothening:

1) Firstly, Angular Increment is used to divide 180 degree into equal fractions
2) Get the size of image
3) Find the valid frequency in the image .
4) Generate the array of distinct matrix .
5) Round the array to reduce the number .
6) Generate a table, given the frequency value multiplied by 100 to obtain an integer index.
7) Generate filters corresponding to these distinct frequencies and orientations in 'anglelnc' increment
8) Generate oriented versions of filters.
9) Create a function which angles +ve anticlockwise, by giving the minus sign.
10) Then convert the orientation matrix from radians to index value.
11) Finally, Find the frequency corresponding to frequency index value

The efficiency of the algorithm has been calculated in terms of the genuine acceptance rate, false acceptance rate and false rejection.

The final step in pre-processing is thinning before the extraction of minutiae. A standard thinning algorithm is used, which performs the thinning operation using two sub iterations. The application of the thinning algorithm to a fingerprint image preserves the connectivity of the ridge structures while forming a skelectonized version of the binary image [7]. This skeleton image is then used in the subsequent extraction of minutiae. After thinning there will be some spikes present in the binary image. These spikes are removed using directional smoothing.

The minutiae are extracted by scanning the local neighborhood of each ridge pixel in the image using a 3x3 window. The most commonly employed method of minutiae extraction is the Crossing Number concept [3]. The CN value is then computed, which is defined as half the sum of the differences between pairs of adjacent pixels in the eight neighborhoods [8]. For example, a ridge pixel with a CN of one corresponds to a ridge ending, and a CN of three corresponds to a bifurcation.

C. Face recognition

To recognize human faces, the prominent characteristics on the face like eyes, nose and mouth are extracted together with the shape of the face [9]. There are differences in shape, size and structure of these organs, so the faces are differ in thousand ways, and we can describe them with the shape and structure of these organs in order to recognize them. These feature points and relative distances between them make some patterns in every input signal [4][10]. These characteristic features are called eigenfaces in the facial recognition domain. Once the boundary of the face is established then the feature points are extracted.

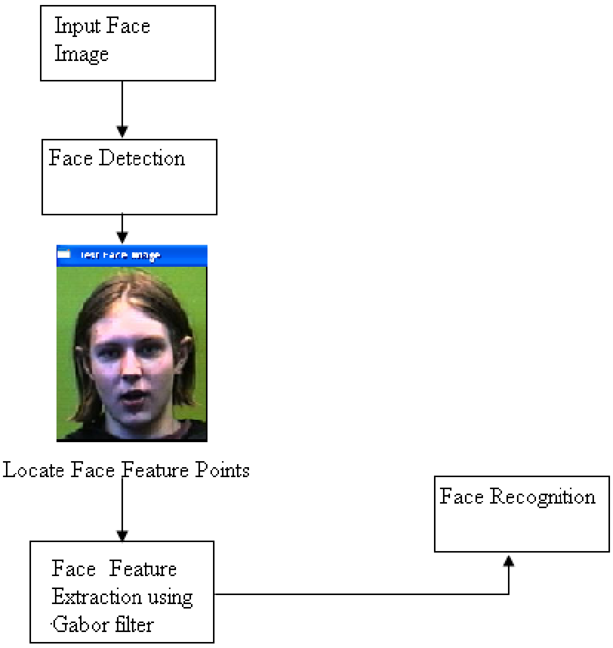

Fig. 3 Steps involved in Face Recognition

In this approach a set of images that span a lower dimensional subspace is computed using the principal component analysis (PCA) technique [2][9][10]. The feature vector of a face image in the projection of the original face image on the reduced eigenspace. The matching score (MSface) is generated by computing the Euclidean distance between the eigenface coefficients of the template and the detected face.

D. Fusion

Scores generated from individual biometric traits are combined at matching score level using sum rule. MSpalm, MSfinger and MSface are the matching scores generated by palmprint, fingerprint and face recognizers respectively [6]. Since the matching scores output by the three traits are heterogeneous because they are not on the same numerical range. The normalization of the three scores is done

$$N_{palm} = \frac{MS_{palm} - \min_{palm}}{\max_{palm} - \min_{palm}} \tag{13}$$

$$N_{finger} = \frac{MS_{finger} - \min_{finger}}{\max_{finger} - \min_{finger}} \tag{14}$$

$$N_{face} = \frac{MS_{face} - \min_{face}}{\max_{face} - \min_{face}} \tag{15}$$

Min-max normalization transforms all the scores into a common range [0, 1]. The [maxface] are the minimum and maximum scores for palmprint recognition, fingerprint recognition and face recognition, Npalm, Nfinger and Nface are the normalized matching scores of palmprint, fingerprint and face respectively. Fingerprints are represented using minutiae features, and the output of the fingerprint matcher is a similarity score [1][11]. Face images are represented using eigen-coefficients, and the output of the face matcher is a distance score. Palmprint images are also represented as eigenpalms and the matching score is generated as distance score [6]. Prior to combining the normalized scores, it is necessary that all the three normalized scores are transformed as either similarity or dissimilarity measure. In this paper, the normalized scores of face and palmprint are converted to similarity measure by subtracting them from 1 as given below:

$$N'_{palm} = 1 - N_{palm} \tag{16}$$

$$N'_{face} = 1 - N_{face} \tag{17}$$

Finally, the three normalized similarity scores N′palm , N′finger and N′face are fused using sum rule to generate final matching score as follows:

$$MS_{final} = X * N_{palm} + Y * N_{finger} + Z * N_{face} \tag{18}$$

IV Conclusion

It is well established that biometric features are unique to each individual and remain unaltered during a person's lifetime. In this paper, a multimodal biometric recognition system based on fusion of three biometric traits viz. palm print, fingerprint and face has been proposed. Fusion of these three biometric traits is carried out by feature extraction. Based on the proximity of feature vector and template, each subsystem computes its own features. These individual features are finally combined into a total matching level, which is passed to the decision module. Unimodal creates many security issues, any imposter person can be able to hack a single value of a person. In this paper it proven that the multimoadal biometric is very efficient in security purpose and all. Our future work will be focused on integrating likeness detection with multimodal biometric systems and minimizing the complexity of the system.

References

[1] Sheetal Chaudhary and Rajender Nath “A Multimodal biometric recognition system based on fusion of palm print, fingerprint and face “2009 International Conference on advanced Technology in comm.. and computing..

[2] Ramandeep karur,Parvinder S. Sandhu and Amith Kamra “A Novel Method for Fingerprint Feature Extraction” 2010 International Conference on a Networking and Information Technology.

[3] Mossadek Laadjel,Ahmed Bouridane and Faith Kurugollu,”Palm print reconition using Fisher-Gabor feature extraction” IEEE Transactions On Image Processing 1484-9 JUNE 2008.

[4] Chengjun Lin ,Member in IEEE ,and Harry Wechsler,Fellow,IEEE”A Shape and Texture- based Enchanced Fisher Classifier For Face Recognition”IEEE Transcations On Image Processing,VOL.10,NO.4,

[5] Audrey Poinsot and Fan Yang Michel paindavoine“Small Sample Biometrics Reconition Based on Palmprint and face fusion “,2009 Fourth International conference on computing in the Golbal Information.

[6] A. K. Jain, K. Nandakumar, & A. Ross, “Score Normalization in multimodal biometric systems. “ International conference pattern reorganization, Cambridge,U.K. August 2004.

[7] Manvjeet Karur, Mukhwinder Singh,AkshayGirthar,”Fingerprint verifiacatin system using minutia extraction Techniques” , International Conference , Worlds Academy of Science , Engineering and Technology 46, 2008

[8] K.Nallaperumal , A.Leninfred and Padmapriya” A Novel Techniques for Fingerprint Feature Extraction Using Fixed Size Template” IEEE Transcations On Image Processing 2005

[9] Yao Fu, Zhixing Ma, Miao Qi, Jinsong Li, Xiaolu Li and Yinhua Lu “A Novel User-Specific Face and Palmprint Feature Level Fusion”, Second International Symposium on Intelligent Information Technology Application.

[10] Mathew A. Trurk and Alex P.Pentland,”Face Reconition Ua\sing Eigenfaces”Vision and Modelling group,IEEE 1991.

[11] Girija Chetty and Michael Wagner “Audio-Visual multimodal Fusion for Biometric person Authentication and Liveness Verification”.