PALM PRINT RECOGNITION USING VARIOUS WAVELET BASIS FUNCTIONS

Manisha H.Nikam[1] , Maithili N.Bhalerao[2] , Ravindra Pardeshi[3]

[1]*HOD, S.H.Jondhale Polytechnic, Dombivali(w),MS, (India)*

[2]*Sele. Gr.LEE Government Polytechnic, Malvan,MS, (India)*

[3]*HOD, S.H.Jondhale Polytechnic,Dombivali(w),MS, (India)*

ABSTRACT

This paper presents a system for person identification using various basis functions of wavelet transform to extract palmprint features. The palmprint image has been viewed as a texture image. The local features from the extracted region of interest (ROI) of a palmprint represent the textural information present in the palmprint image in better sense. The time-frequency representation of a signal is provided by wavelet transform. Hence in this work various discrete wavelet basis functions for textural decomposition up to third level have been used. The feature vectors of size 256×1 have been extracted from the ROI and used as the feature map. Performance of the algorithm has been tested using PolyU database. Various wavelets are compared in terms of recognition efficiency and computational complexity for personal recognition using palmprint as biometrics.

Keywords: palmprints, discrete wavelet transform, wavelet basis functions, region of interest, Euclidian distance.

I INTRODUCTION

The identity of a person based on the physiological or behavioral characteristics is provided by biometrics. Various biometric technologies have their own pros and cons. Every biometric technology finds its own application area [1]. One of the well known biometrics systems having very high accuracy is iris based system [2]. The basic shortcomings in these systems are high cost of iris acquisition system and high failure to enrolment rate andalso these systems require higher cooperation from users. Due to the simplicity, low cost and good accuracy of fingerprint recognition systems, they are most widely used in the world. Small amounts of dirt or grease on the finger may affect the performance of fingerprint based system. Hand geometry based systems suffer from low accuracy and high cost. Ear based recognition has a problem of ear being partially or fully occluded due to hair or cap [3]. Face based recognition systems are low cost, requiring only a camera mounted in a suitable position like the entrance of a physical access. In spite of such advantages, face based recognition systems are less acceptable than fingerprint or palmprintbased systems [4].

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Palmprint is the region between wrist and fingers. Palmprint has features like wrinkles, principle lines, delta point, datum points, minutiae points, singular points, ridges and textural pattern that can be considered as biometric characteristics. Palmprint based identification system in comparison with other biometric systems have advantages like stable and unique features of human hand, needs very less co-operation from users for data acquisition, non-intrusive collection of data, low cost devices for data acquisition, low resolution images provide high accuracy, palmprinthas a larger surface area for feature extraction, computation is much faster at the pre-processing and feature extraction stages, most acceptable, reliable human identifier because the print patterns are not found to be duplicated even in mono-zygotic twins [5].

Palmprint image acquisition uses offline and online methods. In offline the palm is painted with ink and put it on paper whereas in online method CCD-based palmprint scanners are used. These digital scanners [6, 7] capture high quality palmprint image which is further preprocessed to segment the centre of palmprint used for feature extraction. These features can be used for matching. Many features of a palmprint can be used to uniquely identify a person. In feature extraction low-resolution palmprint recognition approaches can be broadly classified into three categories ashybrid, holistic and featurebased methods. Holisticbased palmprint recognition approach use original palmprint image as a whole to extract the features, which can be further divided into subspace-based [8], invariant moment-based [9], and transform-based methods [10].In feature-based approaches, the local features of palmprint are extracted for efficient palmprint recognition. The hybrid approaches use both holistic and local features to improve the recognition accuracy and matching speed. Kong et al [11] used 2-D Gabor filter to obtain the textural information. Field et al [12] proposed Log-Gabor filters to overcome the bandwidth limitation in traditional Gabor filters. Zhiqiang et al [13] proposed Gabor feature-based two-directional for palmprint recognition which is effective in both recognition accuracy and speed. Meiru et al [14] proposed discriminative local binary patterns statistic for palmprint recognition. J. You et al [15] introduced a texture-based dynamic selection scheme facilitating the fast search for the best matching of the sample in the database in a hierarchical fashion. Wong et al [16] applied different Sobel operators with threshold to represent feature vector. In transform-based feature extraction methods Discrete Cosine Transform [17], Discrete Fourier Transform [18], Wavelet Transform [19], contourlet transform [20] are used.

II BLOCK DIAGRAM OF THE SYSTEM

Person identification system using palmprints operates in two modes namely enrolment phase and identification phase. In the enrolment phase, several palmprint samples of the persons are passed to the system. The samples captured by palmprint scanner are passed through pre-processing and feature extraction to produce the templates which are then stored in the database. During recognition mode, the query palmprint image is passed to the system. These query palmprints passes through pre-processing, feature extraction and comparison with the templates already stored in the database to find correct match. Block diagram of thepalmprintrecognitionsystem using Wavelet transform is as shown in Figure 1. It contains five modules such aspalmprint acquisition, preprocessing, feature extraction, storage and matching with the query imprint. Palmprint image is captured with the help of palmprint

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scanner which is then converted into a digital imprint and is transmitted to a computer for pre-processing. In pre-processing a co-ordinate system is set up on basis of the boundaries of fingers so as to extract a central part called as ROI of a palmprint for feature extraction. Various basis functions of wavelets have been applied to extract textural information from the central part. These textural features are then compared with the features stored in the database as the templates of imprints during the enrolment phase. In order to find the close match between the query palmprint and the template imprints stored in the database a distance measure is used.

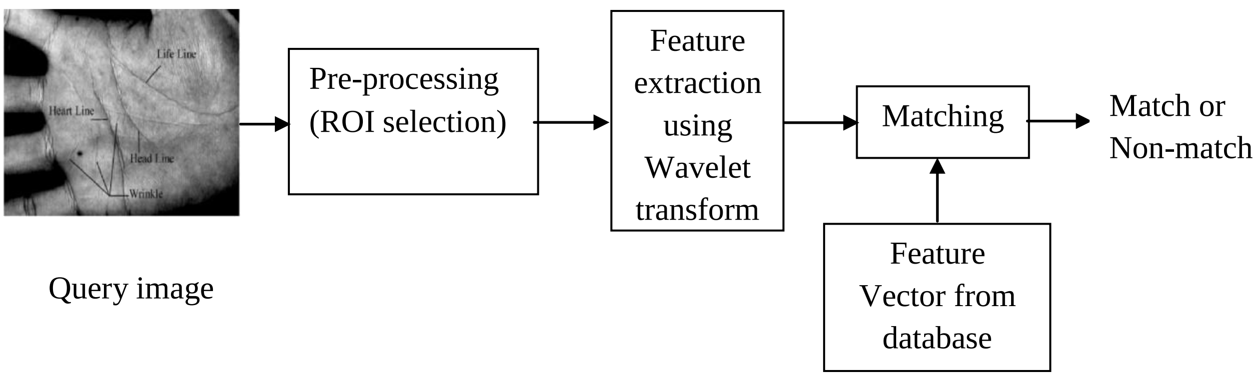

Figure 1 Block diagram of the wavelet based palmprintrecognition system

III THEORETICAL ASPECTS OF WAVELET TRANSFORM

The time-frequency representation of a signal is provided by wavelet transform. It is used to overcome the shortcomings of the short-time Fourier transform (STFT), which can be used to analyze non-stationary signals. The main limitation of the STFT is that it gives a constant resolution at all frequencies, while the wavelet transform uses a multi-resolution technique by which different frequencies are analyzed with different resolutions. The wavelet transform is generally termed mathematical microscope in which big wavelets give an approximate image of the signal, while the smaller wavelet zoom in on the small details. The basic idea of the wavelet transform is to represent the signal to be analyzed as a superposition of wavelets. Continuous and discrete wavelets with various types of basis functions have been used to do a hierarchical wavelet decomposition of the texture images by various researchers. Here we have used discrete wavelets with various basis functions for textural decomposition.

Wavelets have been used to refer to a set of orthonormal basis functions generated by dilation and translation of scaling function $\phi$and a mother wavelet ψ. The finite scale multiresolution representation of a discrete function can be called as discrete wavelets transform (DWT). DWT is a fast linear operation on a data vector, whose length is an integer power of 2. The concept of one dimensional DWT and its implementation through sub-band coding can be easily extended to two dimensional signals. Sub-band analysis of images require extraction of its approximate forms in both horizontal and vertical directions, details in horizontal direction alone (detection of horizontal edges), details in vertical direction alone (detection of vertical edges) and details in both horizontal and vertical directions (detection of diagonal edges). This analysis of 2-D signals requires the use of following two dimensional filter functions through the multiplication of separable scaling function $\emptyset$and wavelet functions ψ in x (horizontal) and y (vertical) directions defined as,

$$\emptyset(x,y) = \emptyset(x)\emptyset(y) \tag{1}$$

$$\psi^{H}(x,y) = \psi(x)\,\emptyset(y) \tag{2}$$

$$\psi^{V}(x,y) = \emptyset(x)\psi(y) \tag{3}$$

$$\psi^{D}(x,y) = \psi(x)\psi(y) \tag{4}$$

where,

$\emptyset(x,y)$ represents the approximate signal,

$\psi^{H}(x,y)$represents signal with horizontal details,

$\psi^{V}(x,y)$represents signal with vertical details, and

$\psi^{D}(x,y)$ represents signal with diagonal details.

The 2-D analysis filter implemented through separable scaling and wavelet functions is shown in Figure 2. Sub-sampling by a factor of two is followed by filtering in each direction in such a way that each sub-bands corresponding to the filter outputs include one-fourth of the number of samples compared to the original 2-D signal. The output of the analysis filter banks is the Discrete Wavelet Transformed Coefficients.

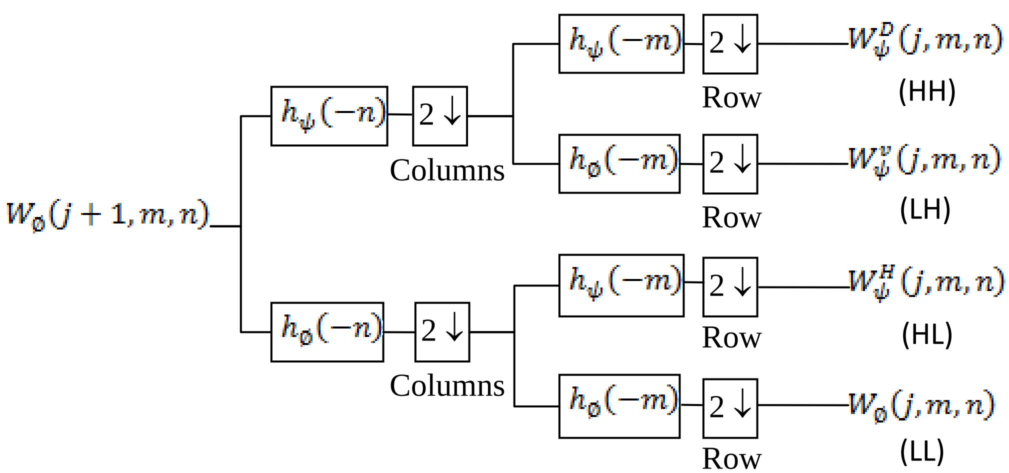

Figure 2 2-D filtering analysis through separable scaling and wavelet functions.analysis filter.

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Figure 3 shows the decomposed sub-bands of the DWT. The bands $\emptyset(x,y)$, $\psi^H(x,y)$, $\psi^V(x,y)$ and $\psi^D(x,y)$ are also referred to as LL, LH, HL and HH respectively, where the first letter represents whether it is low-pass (L) or high-pass (H) filtered along the columns and the second letter represents whether the low-pass (L) or high-pass (H) filtering is applied along the rows. Iterative application of the 2-D sub-band decompositions is possible on any of the sub-bands. Commonly, it is the LL sub-band (the approximated signal) that requires analysis for further details. If the LL sub-band is iteratively decomposed for analysis, the resulting sub-band partitioning is called the dyadic partitioning. Every level of decomposition sub-samples the newly created sub-bands by a factor of two along the rows and columns (that is, by a factor of four) as compared to the previous level of decomposition. However, the total number of DWT coefficients considering all the sub-bands always remains same as that of the total number ofpixels in the image. If one goes further up in the levels of decomposition, suffers a loss of resolution in the newly created sub-bands. Thus, the first level of decomposition extracts the finest resolution of details; the sub-bands created in the second level of decomposition extract coarser details than the first one and so on. These sub-images are shown in the Figure 3 (b). Second iterations of the filtering process produce the two-scale decomposition as shown in Figure 3(c), and the third iterations of the filtering process produce the three-scale decomposition as shown in Figure 3(d).

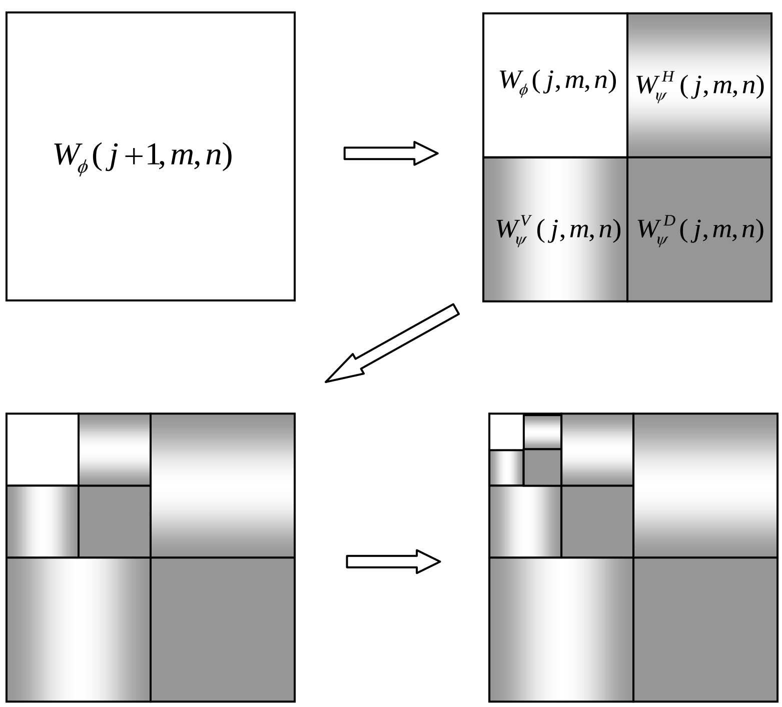

Figure 3 Image decomposition (Dyadic partitioning) by 2-D DWT (a) Original image, (b) First level, (c) Second level, (d) Third level

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It is possible to have a perfect reconstruction of the original 2-D signal (image) by a reverse process of synthesis filtering. The synthesis filter banks along the rows and columns are associated with an up sampling by a factor of two so that the reconstructed image can be shown at the original resolution. The synthesis filter banks therefore perform the inverse discrete wavelet transform (IDWT), which is also lossless, like the DWT.

Wavelet Transformation can use various basis functions as the mother wavelet, since itcan produce all wavelet functions used in the transformation through scaling and translation; it determines the characteristics of the resulting Wavelet Transform. Different wavelet families make different trade-offs between how compactly the basis functions are localized in space and how smooth they are. Also, they possess different properties of orthogonality and symmetry. The orthogonal wavelets are linearly independent, complete in $L^2(R)$ and orthogonal. A family of real orthogonal bases $\psi_{j,n}(x)$ obtained through translation and dilation of a kernel function $\psi(x)$ known as mother wavelet which is used to decompose the image is given by,

$$\psi_{j,n}(x) = 2^{-j/2}\psi(2^{-j}x - n) \quad (5)$$

where,

$j$and$n$ are integers.

To construct the mother wavelet $\psi(x)$, the scaling function $\phi(x)$ is determined which satisfies the two scale differential equation defined as,

$$\emptyset(x) = \sqrt{2}\sum_k h(k)\emptyset(2x - k) \quad (6)$$

where,

$k$is the number of coefficients in the filter.

The wavelet kernel $\psi(x)$ is related to the scaling function via,

$$\psi(x) = \sqrt{2}\sum_k g(k)\emptyset(2x - k) \quad (7)$$

where, $g(k) = (-1)^k h(1 - k)$

The coefficient $h(k)$ in (6) has to meet several conditions for the set of basis wavelet functions in (5) to be orthonormal,unique and have a certain degree of regularity. In this paper various basis functions used for extraction of palmprint features are Haar wavelet [21], Daubechies wavelets (dbN, where N is the order) [22-25], Coiflet wavelet family (coifN, where N is the order) [26], symlet wavelet, biorthogonal family, reverse biorthogonal family.

Feature extraction using wavelet basis functions

Various steps involved in Wavelet transform based palmprint feature extraction are as follows:

***Step* 1Acquire the palmprint image.**

***Step* 2Extraction of ROI from the palmprint image.**

In order to make the proposed algorithm rotation and translation invariant, it is necessary to obtain a ROI from the captured palmprint image, before extracting the feature vector. The major steps of palmprint image pre-processing to extract the ROI are performed as follows:

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Step 1: Convolve the captured palmprint image with a low-pass filter. Convert this convolved palmprint into a binary image using a threshold value.

Step 2: Extract the boundaries of the holesbetween fingers using a boundary-tracking algorithm. The start points and end points of the holes are then marked in the process.

Step 3: Compute the center of gravityof each hole. Then construct a line that passes through the center of gravity of each hole and midpoint of the holes. Based on these lines, two key pointscan easily be detected.

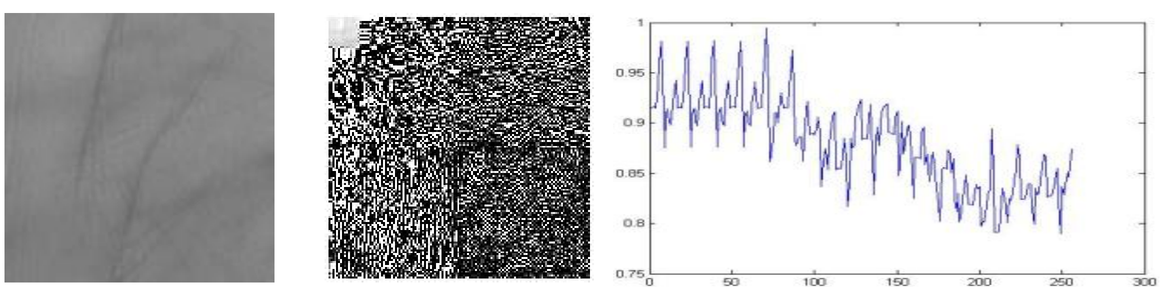
Step 4: Line up both the key points to get the *Y*-axis of the palmprint coordinate system and make a line through their midpoint which is perpendicular to the *Y*-axis in order to determine the origin of the coordinate system. Alignment of different palmprint images can be achieved with this coordinate system.

Step 5: Extraction of sub-image ofa fixed length and breadth on the basis of this coordinate system, which is located at the certain part of the palmprint for feature extraction.

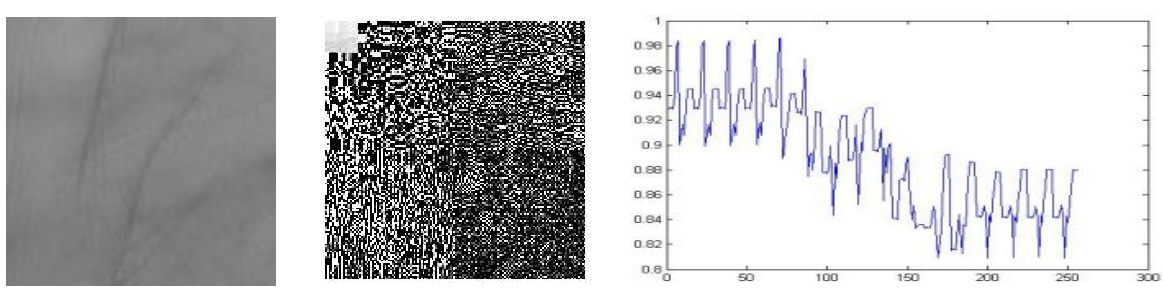
***Step* 3Compute the Wavelet Transform of ROI to generate feature vector.**

In this step, we have extracted features of palmprint using various Wavelet basis functions. The local features from the ROI of a palmprint represent the texture information present in the palmprint image in better sense. Divide the cropped image into a set of non-overlapping blocks and sample the palmprint image by set of db4 wavelet transformed images corresponding to third level of decomposition and finally the signature of the feature values are computed from the average values of LL3 used to match using Euclidian distance measure.

Thus, the signature of the palmprint image and its average values of LL3 define the global components of the palmprint and used as the feature vector. Cropped palmprint image,third level decomposition along with its signature for sample wavelet basis functions are shown in Figure 4.



(a)



(b)

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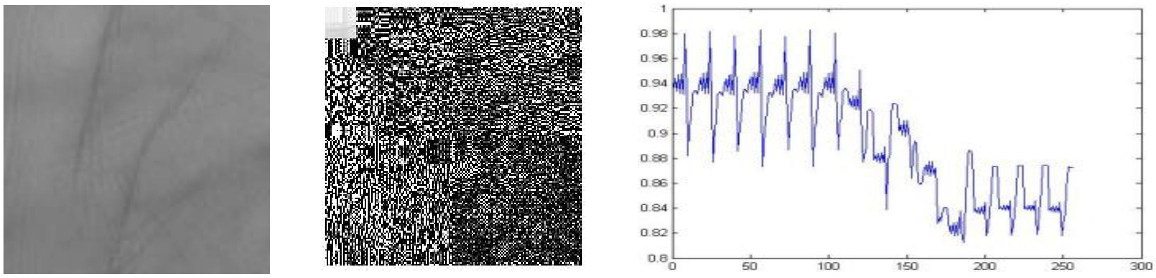
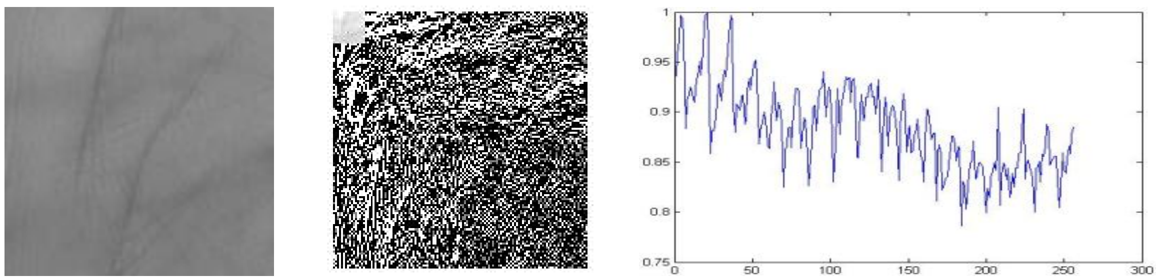
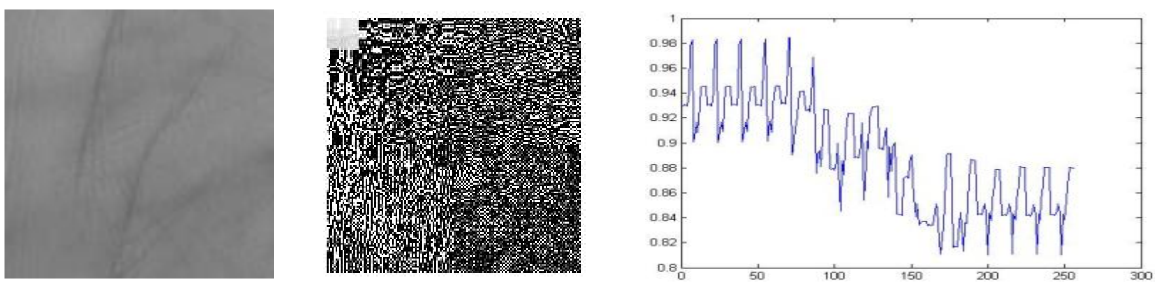


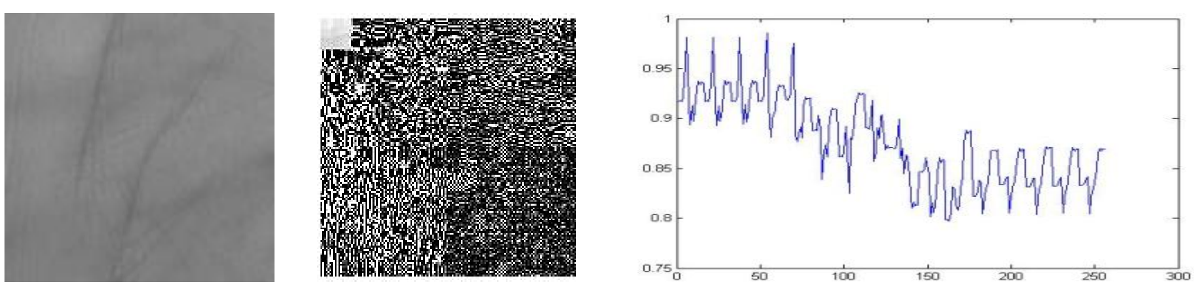
(c)



(d)



(e)



(f)

Figure 4Cropped palmprint image its third level decomposition along with signature (a) db4, (b) bior6, (c)coif5, (d) haar, (e) rbio6.8, (f) sym8.

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IV RESULTS AND DISCUSSIONS

The algorithm has been implemented and tested on Core iV processor with 3.2 GHz, 2 GB RAM under MATLAB environment. The performance analysis of the algorithm has been evaluated using the palmprint images from the standard PolyU database available on the Hongkong polytechnic university website. PolyUpalmprint is a standard Database (file size 429MB) contains 7752 grayscale images corresponding to 386 different palms in BMP image format. Two sessions were conducted to collect twenty samples from each of these palms, where 10 samples were captured in each session. Average interval between the first and the second collection was two months. The layout of the right palm images are in such a way that fingers are on the left side and thumb is up and reverse position for the left hand i.e. thumb is down. Resolution of these images is 384 × 284 with 256 grayscales.

Initially the ROI of size 128×128 is extracted from the capturedpalmprint images and images from PolyU database.Then signatures of various wavelet basis functions at third level decomposition have been obtained from these localized palmprint images. As the local features represent the texture information present in the palmprint image in better sense, the wavelet transformed palmprint image is used as the feature map. The feature maps of all the palmprint images have been stored as the database in computer hard disk. When a query palmprint image of the person is applied to the computer, initially it is preprocessed and then its feature vector is generated and matched with the feature vectors available in the database. The Euclidian distance classifier will give the minimum distance for the stored template image that best matches with the query image. For experimentation purpose we have used various wavelet basis functions like Haar, Daubechies, Biorthogonal, Symlet, Coiflet, Reverse biorthogonal wavelets, etc. to represent the multiscalepalmprint image. The palmprint image is decomposed into three level sub-bands and from LL3 the signature of feature vector is generated for each palmprintsub-band image. Thus, we have got a feature vector of size 256 × 1 from the third level of wavelet decomposition.Performance of each feature was tested independently. Here we have tested use of various basis functions for palmprint recognition. FAR and GAR for various basis functions have been computed for PolyUpalmprint databasethe corresponding FAR and GAR for various wavelets at different thresholds are shown in Figure 5.Coiflets wavelet is identified as the best wavelet basis functions for palmprint recognition. The proposed scheme using multiresolution approach is computationally and memory-wise very efficient. The computational efficiency is best using wavelet based features compared to Gabor transform. We have selected Daubechies wavelet due to the compactness and low complexity of the filter. Recognition rate for db2 wavelet was found to be 90% whereas recognition rate for Coiflets was found to be 94.33% with minimum distance classifier based on Euclidean distance.

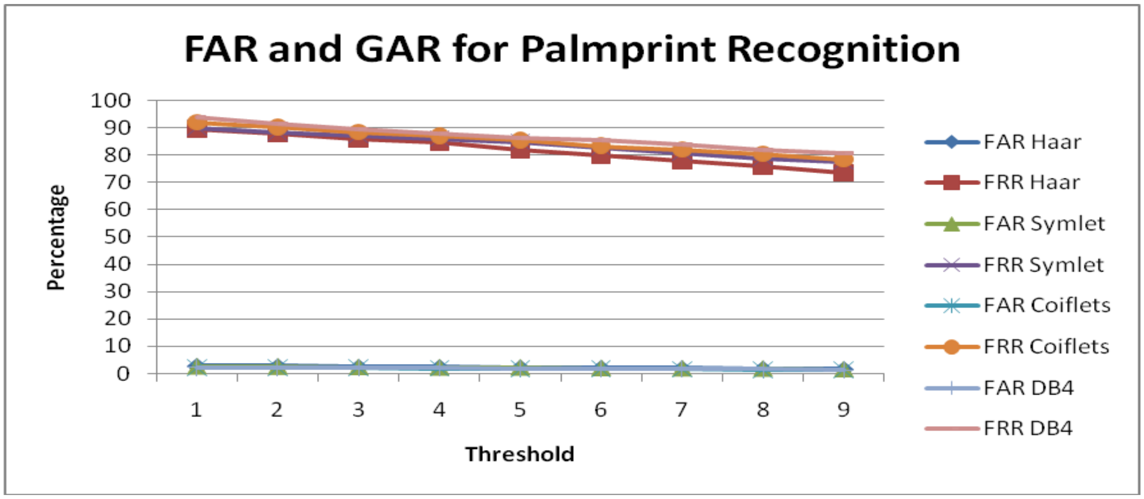

Figure 5 Percentage FAR and GAR plotted at various thresholds for different wavelets.

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