

# Palmprint Verification By Proficient Filtering Using Wavelet

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**Abstract**—Among the various palm print recognition techniques, coding technique is very effective and gives efficient results. In this coding method, gabor filters of four different orientation are convolved with the palm print image to extract the orientation information from the image. The imaginary part of each orientation is added pixel by pixel and then each imaginary palm code is coded into 3 bits. Different wavelet filters are used to improve the accuracy of the system. This scheme is applied in the approximate band. Two different palm prints are matched using angular distance matrices, and db7 wavelet filter gives the equal error rate of 1.1739%, accuracy of 98.84%.

**Keywords**-Discrete wavelet transform, Region of interest, Gabor filter, Euclidean Distance, Equal Error Rate, TSR etc.

## I. INTRODUCTION

Biometric is the science of recognizing a person based on one or more intrinsic physical or behavioral characteristics. Some different biometric techniques are being used in different purposes. Fingerprints can easily be steal because of its small size features. Iris is another reliable characteristic, but its attainment device is comparatively expensive and has low accessibility. Other features, such as the face, voice, and hand geometry are not yet sufficiently accurate. Each biometric has its own strength and weakness depending on the particular application and requirements. As compared to the other biometrics, palm print has several advantages such as stable line features, low-resolution image, low cost acquisition device, very difficult to fake, and easy to user acceptance etc. [1].

Palm print has features like texture, wrinkles, principal lines, ridges, and minutiae points that can be used for its representation. In the precedent decade, the researchers have devoted to develop a robust and very accurate palm print recognition system. Researchers have applied five different classes of extraction algorithms for palm print feature extraction. These extraction algorithms are Subspaced based, Texture-based coding, Line-like features, Statistical based and Fusion with the other biometrics [2].

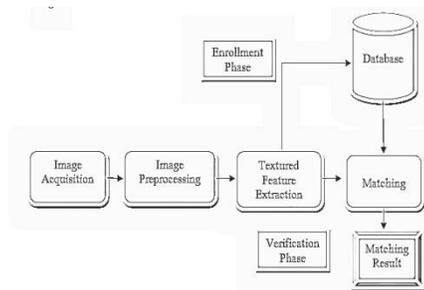
Subspace-based approaches are principal Component Analysis (PCA) [3], Fisher Discriminant analysis [4], Locality Preserving Projections (LPP) [5] and independent component analysis (ICA) [6]. In adding up, PCA, LDA and ICA are directly applied to palm print images, researchers also employ wavelets, Gabor, Discrete Cosine Transform [2]. The common tasks in texture-based approach algorithms are to extract

palm line orientation and match up the similarity between different images. A number of coding methods have been developed using Gabor filter such as Competitive code [7] [8], Fusion code [9] and palm code [10]. Four orientations of Gabor filters are applied to each palm print ROI (Region of Interest) for generating the corresponding orientation map. In this work, angular distance metrics is used to match two palm print images. The work proposes a Gabor filters based palm code method in which four Gabor filters of different orientation are applied to each ROI and the index of filtered image which has minimum value corresponding to each pixel is selected.

Rest of the paper is organized as follows; Section 2 describes a Palm print recognition system, Section 3 explain the preprocessing for extraction of the region of the interest. Section 4 describes the feature extraction using DWT and competitive index method followed by principal component analysis. Matching of the two palm image describe in the Section 5. Section 6 explains the experimental results. Last section is the conclusion of the work.

## II. SYSTEM OVERVIEW

As illustrated in fig. 1, a typical palm print verification system consists of five parts: palm print acquisition, preprocessing, feature extraction, database and matcher.



**Figure 1 Overview of palm print recognition system**

The palm print scanner gather round palm print images. Preprocessing sets up a coordinate system to side with palm print images and to segment the center part of palm print image for feature extraction and it also improves the quality of the image. Feature extraction obtains effective features from the preprocessed palm prints. A matcher matches up two palm print features and a database stores registered templates. If the score of the matcher is less than threshold, the two palm print image are matched, else they are not matched.

### III. PREPROCESSING

Before the feature extraction, palm print should be aligned to a predefined coordinate to make possible consistent extraction. The size of the original palm print images in the IIT Delhi palm print database under study is  $150 \times 150$  pixels. Then the resizing of the image is being done, and the size of the extracted images are  $128 \times 128$  pixels. ROI is decomposed into lower resolution representation by using DWT. Most of the potential information of the palm print is also removed by the down sampling process of ROI. Observing this, the work steps forwarded to the AROI by applying different filters of DWT on the ROI image.

A complete localization of the time-frequency features of an image is provided by the Wavelet Transform. The features present in the palm print, such as principal lines, wrinkles, and ridges, have different resolutions. The image is splitted into details coefficients and approximation coefficients in the wavelet decomposition. The higher energy compaction is there in approximation coefficients as compared to detail coefficients. The principal lines are sufficient to verify a person and the principal lines information are contained in an approximation image, and the detail coefficients are discarded because they are associated with non significant features of palm print. After the two-level DWT decomposition of ROI image, the AROI so obtained is used for feature extraction. Without losing the information of the principal lines, the size of the ROI is reduced by using the decomposition up to 2 levels. The high-frequency components are neglected by the approximation image, it makes the system durable to high frequency noise. By using DWT, the ROI size of palm print scales down approximately by a factor of 16 i.e. they are in the ratio of 16:1 which leads to the increase in accuracy and increase in speed of palm print verification.

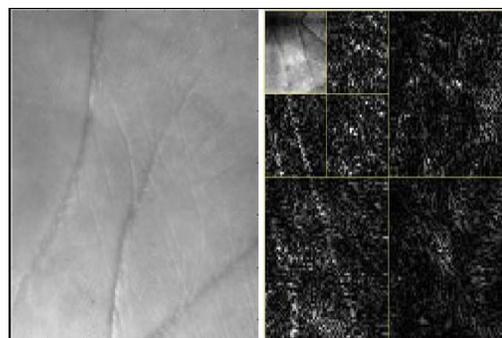
**Table 1 Optimal parameters of Gabor Filter [12]**

Size	F	$\Sigma$	$\Theta$	P
$31 \times 31$	0.0916	5.791	$P*\pi/N$	0,1,2..N-1

### IV. PROPOSED SCHEME

#### A. Discrete wavelet transform

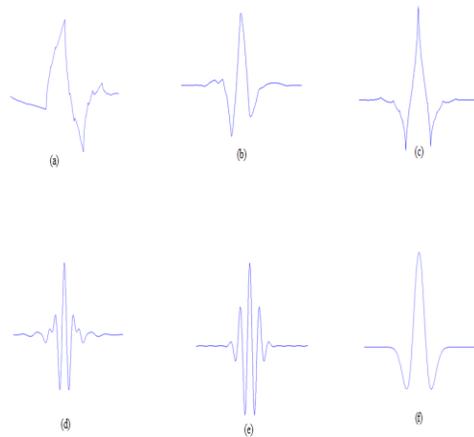
With the use of digital computing, existence of all signals is in digital form therefore we need a discrete transform for such signals. When input signal  $f(t)$  as well as dilation and translation parameter ( $s$  and  $\tau$  respectively) are in discrete form the wavelet transform is called as Discrete Wavelet Transform (DWT). Discrete Wavelet Transform representation of any signal is done by using filter banks, which is a key to multiresolution analysis of signal. The wavelet transform, as compared with the traditional Fourier analysis, has better space-frequency localization. Therefore, it is suited for analyzing images where most of the information content are represented by components localized in space, such as, edges and borders and by information at different scales or resolutions, with large and small features.



**Figure 2 Decomposition the image into 2 levels using DWT**

Different frequencies, together with approximation coefficients and detailed coefficients (horizontal, vertical and diagonal) can be attained by Wavelet Decomposition. Since horizontal, vertical and diagonal, all represent the high frequency of the image, so we should retain the approximate coefficient which is decomposed by wavelet and consider it as the final feature of palm print. In fig 2, an example (palm image) of two level wavelets decomposition is reported. The low frequency information on the wavelet transform is the most useful feature set for verification problem.

The wavelet basis used in decomposition, will govern the wavelet transform of any signal. There are different types of basis function that can be used as the mother wavelet. The type of mother wavelet which we have to use is dependent on the application where wavelet transform is used. For an effective wavelet transform, an appropriate mother wavelet should be chosen. The commonly wavelet basis function includes Haar, Daubechies, Symlet, Meyer, Coiflet, Morlet, Mexican Hat, etc. Following figure shows these wavelet functions.



**Figure 3** Various wavelets (a) Daubechies, (b) Symlet, (c) Meyer, (d) Coiflet, (e) Morlet, (f) Mexican Hat

### B. Gabor Filter

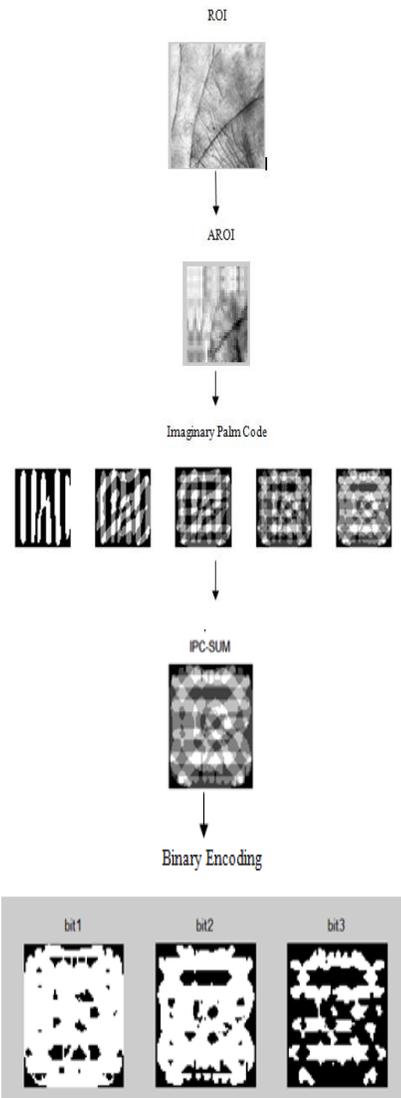
A 2D Gabor function can be viewed as a sinusoidal plane modulated by a Gaussian envelope. A 2D Gabor filter can characteristically optimize the space and frequency domain locally, is used to extract texture information of palmprint[13].

$$G(x, y, \theta, f, \sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} \left\{ - \left( \frac{x^2 + y^2}{\sigma^2} \right) \right\} e^{[2\pi i f (x \cos \theta + y \sin \theta)]}$$

where  $i = \sqrt{-1}$ ;  $f$  is the frequency of the sinusoidal wave;  $\theta$  controls the orientation of function and  $\sigma$  is the standard deviation of the Gaussian envelope. It provides robustness against varying brightness and contrast of the images. The filters can model the receptive fields of a simple cell in the primary visual cortex. Gabor filter is applied for finding the line information of the palmprint image [12]. Parameters for the gabor filter are selected according to table 1.

### C. DIRECT-SUM Code Method

The imaginary parts of Gabor filtered image contains equally potential information as of the real part. The bank imaginary parts of the response of a Gabor filter for different orientations  $N$ , is convolved with the AROI of palm print image. For each corresponding orientation, every imaginary Palm Code is binarized with a threshold. To get the line features, the binarized palm print images of all the orientations are added together. The resulting image is then coded into  $\lfloor (N + 1)/2 \rfloor$  bits [14]. The following basic steps of the DIRECT-SUM Code method are: –



**Figure 4** (a) ROI, (b) AROI, (c) Imaginary Palm Code, (d) Imaginary Palm Code-Sum, (e) Binary Encoding(DIRECT-SUM Code)

Let  $I$  is the preprocessed image,  $im\_g$  are the imaginary parts of Gabor filter respectively, with fixed optimum values of  $\sigma$ ,  $f$ , and different number of orientations  $p * \pi/N$  as shown in Table 1. Then the convolution of the image  $I$  with the imaginary parts of Gabor filter is done and then binarization of the filtered image as shown in Eqs. 2:

$$Pip(x,y) = \begin{cases} 1 & \text{if } I(x,y) * im\_g(x,y,\sigma,f,\theta) \geq 0 \\ 0 & \text{otherwise} \end{cases} \quad ..(2)$$

$Pip(x,y)$  is the imaginary Palm Code of the pre-processed image  $I(x,y)$ .

– Add each corresponding pixel of all the imaginary Palm Code images. Value of each pixel of the added image  $S(x, y)$  varies from 0 to  $N$ .

$$S(x, y) = \sum_{p=0}^{N-1} Pip(x, y) \dots\dots\dots(3)$$

$S(x, y)$ , the DIRECT-SUM feature of the palm print, can be coded into bits as follows [15]:

$$DSC(x, y, b) = \begin{cases} 1 & \text{if } b \leq S(x, y) < b + \frac{N+1}{2} \\ 0 & \text{otherwise} \end{cases} \dots(4)$$

where  $b = 1, 2, \dots, [(N + 1)/2]$  bits is defined to compactly encode each DIRECT-SUM feature. For  $N$  orientations, DIRECT-SUM code features are coded into  $[(N + 1)/2]$  binary bits.

**V. DISTANCE MATCHING**

The accuracy of verification depends on the kind of distance metrics for comparison of palm print templates. Here, angular distance Dang is used to measure the likeness among the DIRECT-SUM Codes of two palm prints [31].

$$Dang(P, Q) = \frac{\sum_{y=1}^M \sum_{x=1}^N \sum_{i=1}^b Pi(x, y) \otimes Qi(x, y)}{b \times M \times N}$$

where P and Q are two XOR-SUM Codes of size  $M \times N$ ,  $P_i$  and  $Q_i$  are  $i$ th bit plane of P and Q, and  $\otimes$  is bit wise XOR operation

**VI. EXPERIMENTAL RESULTS AND DISCUSSIONS**

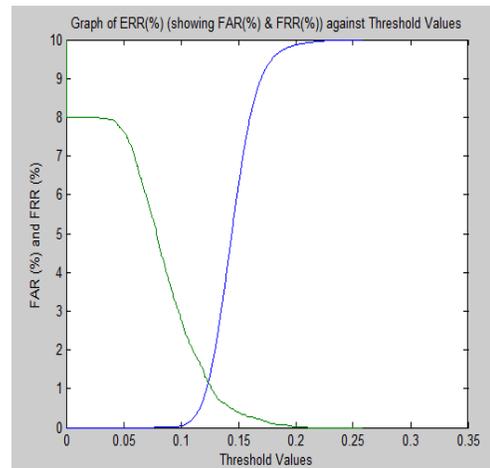
The proposed technique is tested on the IIT Delhi Palm print Image Database version 1.0, this database consists of segmented 1150 images of right hand from 230 different palms. The size of the segmented images present in the database is  $150 \times 150$ . After the resizing, the size of the extracted ROIs from the palm prints is  $128 \times 128$ , and after applying DWT up to 2 levels, the size of the AROI is reduced to approx.  $32 \times 32$ .

Wavelet Filter	GAR(%)	EER(%)
Haar	98.78	1.22
Db3	98.74	1.26
Db4	98.76	1.24
<b>Db7</b>	<b>98.84</b>	<b>1.17</b>
Db10	98.75	1.24
Bior2.2	98.70	1.31
Bior4.4	98.63	1.37
Coif4	98.77	1.23
Sym4	98.67	1.32

**Table 4 Comparison of different Wavelet Filter’s**

Each palm print in the database is compared with the rest of the palm prints. The matching of different palmprints is regarded as an imposter matching, while the matching of the same palmprint is regarded as a genuine matching. The number of genuine and imposter matching is 2300 and 658375 respectively.

In experiments, the legality of the verification is measured by EER value. The False Acceptation Rate (FAR) and False Rejection Rate are plot together for different threshold. The point where the FAR and FRR curve intersect is known as the equal error rate. The result is shown in the table 4 which shows that the db7 filter gives the best accuracy and Equal Error rate(TSR) as compared with the other wavelet filter used for the coding technique.



**Figure 5 FAR and FRR for different threshold**

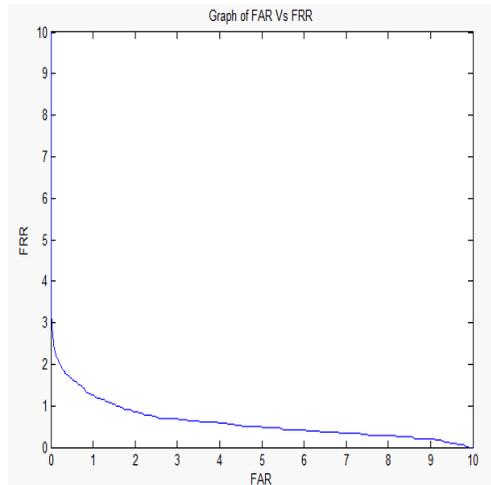


Figure 6 FAR Vs FRR

## VII. CONCLUSION

This paper presents the use of different wavelet filters to extract features of palm print in an efficient manner, which gives the accuracy and EER of 98.84% and 1.17% respectively. Approximation band of discrete wavelet transform of the image is used to compress image which has important information and makes the system invariant to illumination and also invariant to translation.

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