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A Statistical Model Using Contourlet Transform Coefficients Based Feature Extraction Algorithm for Palm-print Recognition

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Abstract: *Human palm prints have been used as a trusted form of individual identification because palm-prints have both uniqueness and permanence. In this paper, the Contourlet coefficient dependencies in terms of coefficient correlations in the gray-scale palm-print image (ROI, 150 x 150 in size) between all bands and all sub-bands are expressed. Then statistical model for contourlet transform coefficients is proposed for the execution of a feature extraction methodology. For each sub-band of a contourlet-based transform, eight statistical features are calculated in two groups. The first group is directly calculated from the coefficients themselves and the first four higher order statistics (mean, variance, skewness, and kurtosis) of the coefficients are calculated. The second group is calculated over prediction error between the coefficients themselves and the prediction of the coefficients by using the statistical model proposed. In this group, the first four higher order statistics of these log prediction errors are calculated. After obtaining feature vector of eight statistical features for palm-print images stored in IIT Delhi Touchless Palm-print database, the distance based classifier is used for matching purpose. The Genuine Acceptance Rate (GAR) is used for the evaluation of accuracy. The results are better as compared to Hybrid DWT-DCT based algorithm.*

Keywords: *Palm-print recognition, Contourlet Transform, feature extraction, Laplacian Pyramid, Directional Filter Bank, Genuine Acceptance Rate.*

1. INTRODUCTION

A biometric system is a personal identification system which plays a significant role in daily life. There are two approaches of the personal identification: the first method is token-based such as a passport, a physical key and a Unique ID (Aadhaar card in India), and the second method is based on Knowledge such as a password [1]. However, these approaches have few limitations such as in token-based method, token can be stolen or lost easily and in a knowledge-based method, password can be forgotten or guessed.

Automatic palm-print recognition has extensive applications in surveillance, security, authentication, and criminal identification. The popular Conventional ID card and password based identification methods are no more reliable because of the utilization of the advanced forgery and password hacking techniques. Therefore, biometric is being used for identity access as an alternative [2, 3]. The main advantage of biometric features is that these are not prone to theft and loss, and do not rely on the memory of their users. Moreover, biometrics, such as palm-print, finger-print, face and iris, does not change significantly over time and it is difficult for a person to alter own physiological biometric or imitate that of other persons. Among different biometrics, in security applications with a scope of collecting digital identity, the palm-prints are recently getting more attention among researchers. Low resolution images of palm-print could be used for extracting the features.

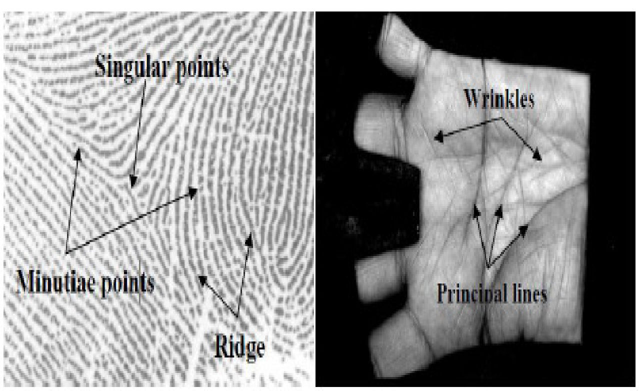
It has been analyzed for discriminating features like principal lines [4], [5], appearance based [6], and texture based [7-18]. The tools employed for the texture analysis of palm-print are DFT [7], DCT [18], 2-D Gabor filter [17], wavelet transform [10-16, 19] and Hybrid DWT-DCT Transform [20-23]. In [10]-[16] and [19], the feature extraction algorithm has been proposed based on the segmentation of the palm-print image into narrow-width bands in spatial domain and then transforms have been applied on each modules to extract the dominant feature coefficients. In [20-23], the segmentation of LL band followed by DCT has been done. In order to reduce the computational cost, this paper proposes a new approach for palm-print recognition based on Contourlet Transform [8, 9].

The objective of this paper is to develop an efficient algorithm using Contourlet Transform for feature extraction from the palm-print. Higher order statistics are calculated from the contourlet coefficients and coefficients of proposed model to form a feature vector. The average sum-squares distance classifier is used to determine the palm-print classification. Section II deals with the feature extraction method and higher order statistics calculation. Section III deals with the algorithm for palm-print recognition using Contourlet Transform. Section IV deals with the Results and discussions and Section V deals with the conclusion.

2. PALM-PRINT RECOGNITION

The inner surface of the palm normally contains three flexion creases, known as principal lines, wrinkles and ridges. These complex line patterns are very useful in personal identification. Nevertheless, palm-print recognition is a complicated visual task for humans. The primary difficulty arises when different palm-print images of a particular person may vary largely, while those of different persons may not necessarily vary significantly. Moreover, some aspects of palm-prints, such as variations in illumination, position, and scale, make the recognition task more complicated [1, 4].

There are two types of Palm-print features with reference to the field at which palm-print systems are used. The first type of features are the principal lines and wrinkles which could be extracted from low resolution images (<100 dpi) and it is used for identification in the commercial applications. The second type of features are the singular point, ridges and minutiae point which could be extracted from high resolution images (>100dpi) and it is used for forensic applications such as law enforcement application [4]. Both high and low resolution image Features in palm-print are shown in Fig. 1. Palm-print recognition methods are based on extracting unique major and minor line structures that remain stable throughout the lifetime of a person.



(a) High Resolution Image (b) Low Resolution Image

Fig. 1. Palm-print Features

2.1 PROPOSED METHOD FOR PALM-PRINT RECOGNITION

A palm-print recognition system consists of some major steps; input palm-print image collection, pre-processing, feature extraction using Contourlet Transform, template storage or database and classification, as illustrated in the block diagram in Fig. 2.

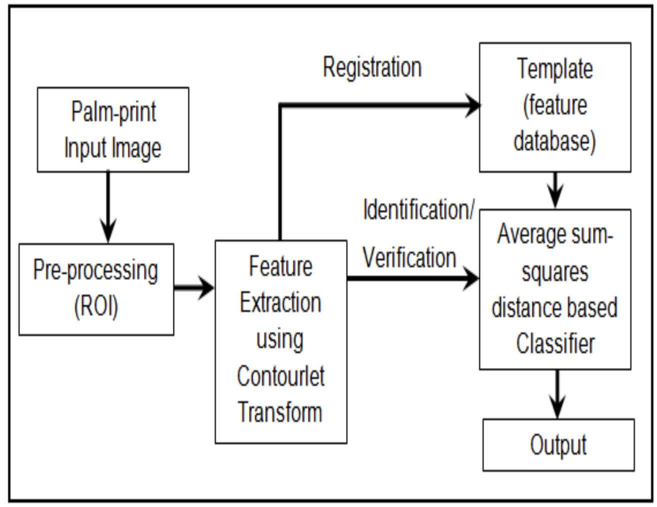


Fig. 2. Block diagram of the palm-print recognition method.

The input palm-print image can be collected by using a palm-print scanner. In the process of capturing palm images, distortions including rotation, shift and translation may be present in the palm images, which make it difficult to locate at the correct position. Pre- processing sets up a coordinate system to align palm-print images and to segment a part of palm-print image i.e. Region of Interest (ROI) for feature extraction. For the purpose of classification, an image database is needed to be prepared consisting of template palm-images of different persons. The recognition task is based on comparing a test palm-print image with template data through a distance based classifier. It is obvious that considering images themselves would require extensive computations for the purpose of comparison [5, 6]. Thus, instead of utilizing the raw palm-print images, some characteristic features are extracted for preparing the template. It is to be noted that the recognition accuracy strongly depends upon the quality of the extracted features. Therefore, the main focus of this research is to develop an efficient algorithm for feature extraction.

2.1.1 CONTOURLET TRANSFORM

Contourlet Transform is obtained by combining the Laplacian pyramid (LP) with a directional filter bank (DFB). It provides a flexible multi-resolution, local and directional expansion for images. LPs provide a multi-resolution system while DFBs give a directional nature to the Contourlet Transform. The LP decomposition at each level generates a down-sampled low-pass version of the original and the difference between the original and the prediction resulting in a band-pass image. Band-pass images from the LP are fed into a DFB so that the directional information can be captured. This is illustrated in Fig. 3. Thus, LP is first used to capture the point discontinuities, which is then followed by a DFB to link point discontinuities into linear structures. The result is an image expansion using elementary images like contour segments.

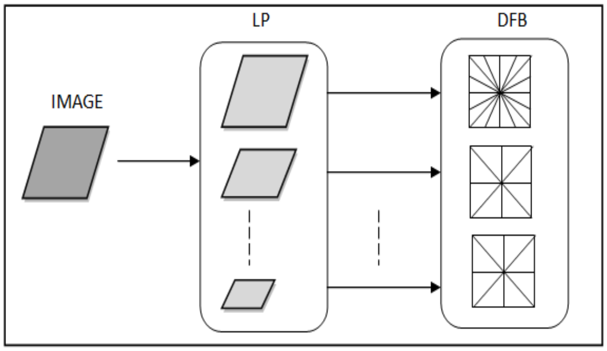


Fig. 3. Contourlet Transform of the input image

The LP decomposition only produces one bandpass image in a multidimensional signal processing, that can avoid frequency scrambling and DFB is fit for high frequency as it removes the low frequency of signals in its directional sub-bands. This is the reason to combine DFB with LP [9]. Therefore, image signals pass through LP sub-bands to get bandpass signals and pass those signals through DFB to capture the directional information of image. This double filter bank structure of combination of LP and DFB is also called as pyramid directional filter bank (PDFB), and this transform is approximate the original image by using basic contour, so it is also called Contourlet Transform.

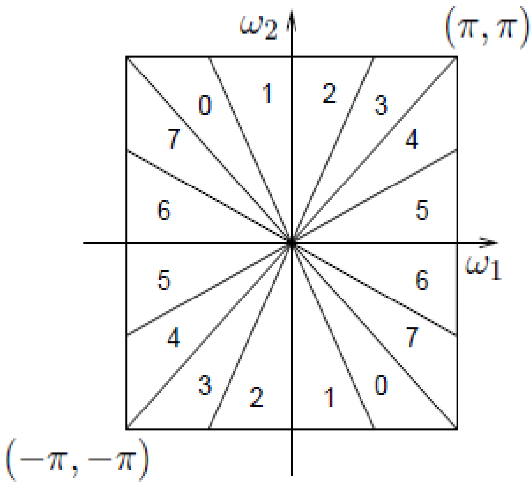


Fig. 4. Frequency partitioning of DFB where l = 3 and there are 2^3 = 8 real wedge-shaped frequency bands. Subbands 0–3 correspond to the mostly horizontal directions, while subbands 4–7 correspond to the mostly vertical directions.

The frequency partitioning of the DFB is shown in Fig. 4. The DFB realizes a division of 2D spectrum into 2^n wedge-shaped slices using an n-level iterated tree-structured filter bank [10]. The flow of operation for Contourlet Transform is illustrated in Fig. 5.a, where the LP iteratively decomposes a 2-D image into low-pass and high-pass sub-bands, and the DFB are applied to the high-pass sub-bands to further decompose the frequency spectrum. Using ideal filters, the contourlet transform will decompose the 2-D frequency spectrum into trapezoid-shaped regions as shown in Fig. 5.b.

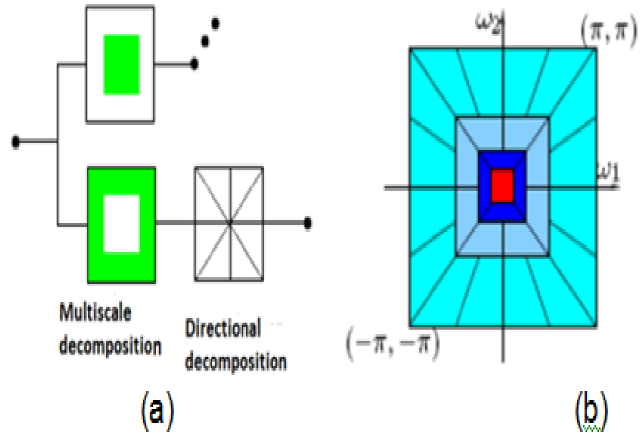


Fig. 5. Original contourlet transform

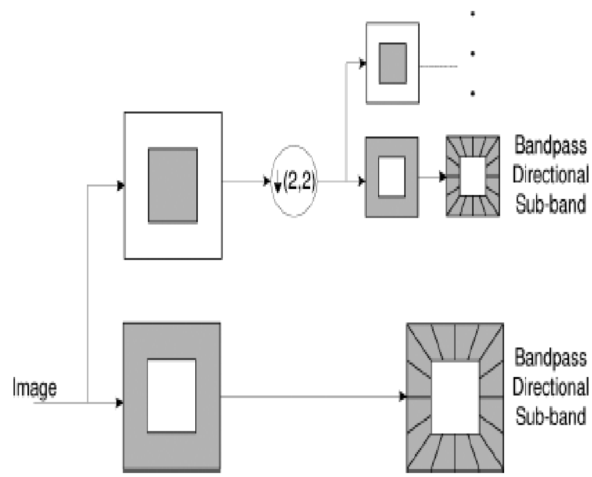


Fig. 6. The contourlet filter bank

Fig. 6 shows a multiscale and directional decomposition using a combination of a LP and a DFB. Bandpass images from the LP are fed into a DFB so that directional information can be captured. The scheme can be iterated on the coarse image. The combined result is a double iterated filter bank structure, named contourlet filter bank, which decomposes images into directional sub-bands at multiple scales [9].

2.1.2 STATISTICAL MODEL FOR CONTOURLET COEFFICIENTS

A statistical model for Contourlet Transform coefficients is proposed as shown in Fig. 7 by considering the reference paper [8]. In this study, the new statistical model is applied for contourlet coefficients. In Fig. 7, a basic feature extraction process is given.

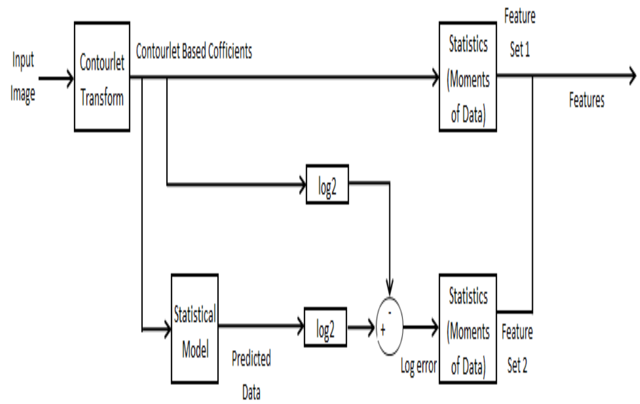


Fig. 7. Feature extraction process using Contourlet Transform

The following notation is adopted for a contourlet coefficientX_c, (Fig. 8):

1) $N_{i,j}^{c}$ for $i, j \in \{-4, -3, -2, -1, 0, 1, 2, 3, 4\}$ are neighbor contourlet coefficients in the same sub-band at the same band and $N_{0,0}^{c}$ corresponds to X_c. Here, i and j denote the distance in the x- and y-directions from the coefficientX_c, respectively.

2) C_k^c is a cousin contourlet coefficient at the same position as X_c in a different subband at the same band, where k denotes the sub-band number.

3) P^c is a parent contourlet coefficient located at the corresponding position to X_c in the same subband but in the coarser band.

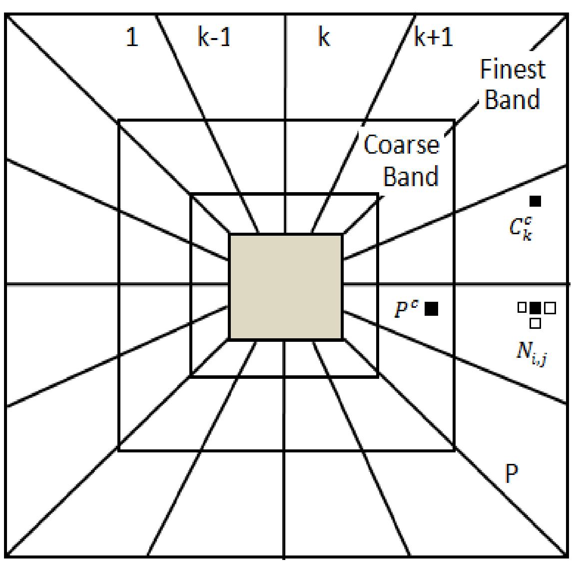


Fig. 8. Contourlet Transform Data Structure

In order to obtain the predicted data, a linear prediction formula for the first sub-band in gray-level (one channel) palm-print image is expressed as follows:

$$
\begin{aligned}
\left|C_1^i(x,y)\right| = {} & \left|C_1^i(x-4,y)\right| + \left|C_1^i(x-3,y)\right| + \left|C_1^i(x-2,y)\right| \\
& + \left|C_1^i(x-1,y)\right| + \left|C_1^i(x+1,y)\right| \\
& + \left|C_1^i(x+2,y)\right| + \left|C_1^i(x+3,y)\right| \\
& + \left|C_1^i(x+4,y)\right| + \left|C_1^i(x,y-2)\right| \\
& + \left|C_1^i(x,y-1)\right| + \left|C_1^i(x,y+1)\right| \\
& + \left|C_1^i(x,y+2)\right| \\
& + \left|C_1^{i+1}\left(\frac{x}{2},\frac{y}{2}\right)\right| \qquad (1)
\end{aligned}
$$

where C_1 represents 1st sub-band of contourlets. Similarly, C_2 represents 2nd sub-band and so on, and i is the band number (Here, i = 1)

In simulations, 8 sub-bands at third resolution level are used. Therefore, there are 7 other representations for each sub-band of a contourlet band.

2.1.3 FEATURE COEFFICIENTS FOR CONTOURLET TRANSFORM

For each sub-band of a contourlet transform, eight statistical features are calculated in two groups [8].

Feature Set 1: The first group is directly calculated from the contourlet coefficients themselves. In this, the first four higher order statistics (mean, variance, skewness, and kurtosis) of the coefficients are calculated.

$$M(j,k) = \frac{1}{N_1 N_2} \sum_{x=1}^{N_1} \sum_{y=1}^{N_2} W_{j,k}(x,y) \qquad (2)$$

$$V(j,k) = \frac{1}{N_1 N_2} \sum_{x=1}^{N_1} \sum_{y=1}^{N_2} \left|W_{j,k}(x,y) - M(j,k)\right| \qquad (3)$$

$$S(j,k) = \frac{1}{N_1 N_2} \sum_{x=1}^{N_1} \sum_{y=1}^{N_2} \frac{\left[W_{j,k}(x,y) - M(j,k)\right]^3}{V(j,k)^{3/2}} \qquad (4)$$

$$K(j,k) = \frac{1}{N_1 N_2} \sum_{x=1}^{N_1} \sum_{y=1}^{N_2} \frac{\left[W_{j,k}(x,y) - M(j,k)\right]^4}{V(j,k)^{3/2}} \qquad (5)$$

where M(j, k) is Mean, V(j, k) is Variance, S(j, k) is Skewness, K(j, k) is Kurtosis, N_1 and N_2 denote the number of rows and columns of the sub-band image, j and k denote the index of scale and direction, W is the coefficient of row N_1 and column N_2 in sub-band indexed by j and k.

Feature Set 2: The coefficients are predicted by using the proposed statistical model and each of them can be formed as a matrix equation-

$$x_{est}^{m} = A(A^T A)^{-1} A^T x \qquad (6)$$

Where x is the column-wise lined-up version of the coefficient itself

A is the column-wise lined-up versions of the coefficients determined in

the statistical models

x_{est} is the prediction for the original coefficient

It has been observed that the conditional probabilities between coefficients become fuzzy when the magnitude of a contourlet coefficient is less than 1. Therefore, the coefficients with a magnitude less than 1 are ignored.

The second group is calculated over prediction error between the coefficients themselves and the prediction of the coefficients by using the statistical models proposed. In this group, the first four higher order statistics (mean, variance, skewness, and kurtosis) of these log prediction errors are calculated. The log error between the prediction and the original coefficient is calculated by

$$E_{est} = \log_2(x) - \log_2(x_{est}^{m}) \qquad (7)$$

2.1.4 DISTANCE BASED MATCHING CLASSIFIER

The features once extracted from the palm-print image are stored in the form of feature vectors for every sample images (training) of different individuals in the system or database. The recognition task is carried out based on the distances of the feature vectors of the training palm-images from the feature vector of the test palm-image.

Given the m-dimensional feature vector for the k-th sample image of the j-th person be $\{\gamma_{jk}(1), \gamma_{jk}(2), \ldots, \gamma_{jk}(m)\}$ and a test sample image f with a feature vector $\{q_f(1), q_f(2), \ldots, q_f(m)\}$, a similarity measure between the test image f of the unknown person and the sample images of the j-th person, namely average sum-squares distance, Δ, is defined as

$$\Delta_j^f = \frac{1}{n}\sum_{k=1}^{n}\sum_{i=1}^{m}\left|\gamma_{jk}(i)-q_f(i)\right|^2 \qquad (8)$$

where a particular class represents a person with n number of sample palm-print images. Therefore, according to (3.7), given the test sample image f, the unknown person is classified as the person j among the p number of classes when

$$\Delta_j^f \le \Delta_g^f,\ \forall\, j \ne g \text{ and } \forall\, g \in \{1, 2, \ldots, p\} \qquad (9)$$

3. ALGORITHM: PALM-PRINT RECOGNITION USING CONTOURLET TRANSFORM

Step 1: Input the palm-print image (ROI) of size 150 x 150.

Step 2: Laplacian pyramid is applied on the palm-print image for its decomposition into four and eight sub-bands and then a 3-level DFB is applied to analyze each detail image from eight directional sub-bands. The Contourlet coefficients are obtained.

Step 3: Proposed statistical model is applied for computing the predicted contourlet coefficients by using the equation (1) for eight sub-bands.

Step 4: For each sub-band, four statistical features (i.e. mean, variance, skewness, kurtosis) are computed from the contourlet coefficients obtained in step 2 to form Feature Set 1 and four statistical features (i.e. mean, variance, skewness, kurtosis) are computed from the predicted contourlet coefficients obtained in step 3 to form Feature Set 2.

Step 5: Combine the Feature Set 1 and Feature Set 2 obtained in step 4 to form a feature vector for the input palm-print image.

Step 6: The features once extracted from the palm-print image are stored in the form of feature vectors for every sample images (training) of different individuals in the system or database. The recognition task is carried through average sum-squares distance given by equation (8) between the feature vectors of the training palm-images and the feature vector of the test palm-image.

4. RESULTS

The palm-print recognition has been performed on the IITD Touchless Palm-print database available online [25]. The simulations have been performed using MATLAB R2014b on an Intel CORE i5 1.60 GHz machine with Windows 8.1, 64 bit operating system and 4 GB of RAM. The performance of the palm-print recognition system can be determined by computing the Genuine Acceptance Rate (GAR) [24]. The accuracy of the authentication system is given by:

$$\mathrm{GAR} = 100 - \frac{(\mathrm{FAR}\% + \mathrm{FRR}\%)}{2} \qquad (10)$$

where, FAR is False Acceptance Rate

FRR is False Rejection Rate

The accuracy of the system increases if the value of FAR and FRR decreases.

TABLE 1: Performance Comparison for IITD Touchless Palm-print Database

	Hybrid (DWT-DCT)	**Contourlet Transform**
GAR	94.44 %	98.71 %

After performing the simulations and analysis, it is observed that the recognition accuracy using the feature extraction algorithm based on proposed statistical model for Contourlet Coefficients is better than the recognition accuracy using the feature extraction algorithm based on narrow-width modules for hybrid DWT-DCT [23]. The

GAR for Contourlet Transform based feature extraction algorithm is found to be 98.71%.

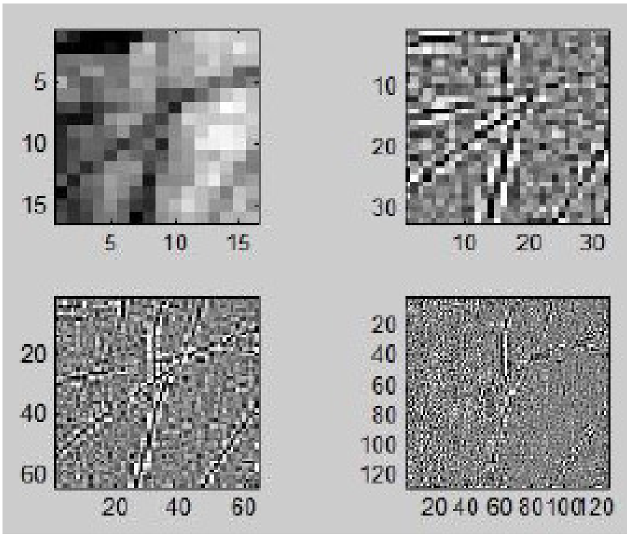


Fig. 9. Decomposition of image using Laplacian Pyramid

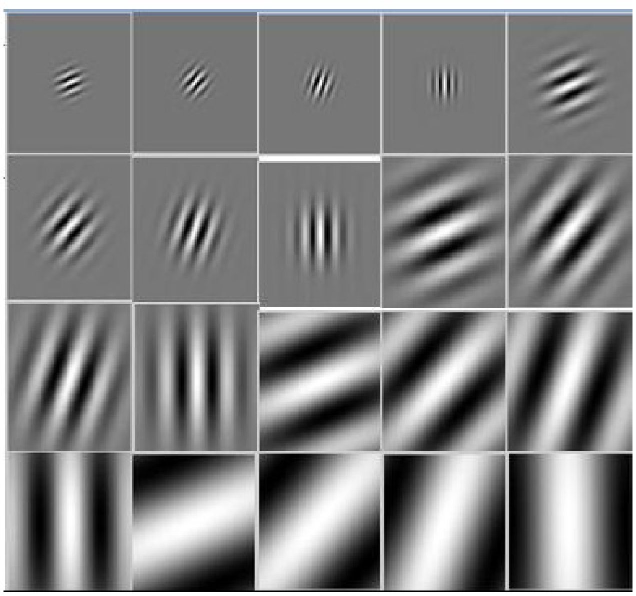


Fig. 10. Detail of image analyzed by DFB

5. CONCLUSIONS

Two-dimensional DWT is good at catching point discontinuities and Hybrid DWT-DCT reduces blocking artifacts and false contouring but both transforms lack directionality and anisotropy. Contourlet Transform is utilized as an improvement over wavelets in terms of mentioned inefficiencies. The Contourlet Transform provides a flexible multiscale decomposition by using LP and directional decomposition by using DFB for palm-print images. The Contourlet Transform includes the property of capturing the smooth contours from the image.

In the paper, two feature sets are considered. First feature set includes first four higher order statistics of the contourlet coefficients and second feature set includes the first four higher order statistics of the log prediction errors between the coefficients themselves and the prediction of the coefficients by using the proposed statistical model. The combination of both feature sets is considered as a feature vector consisting of eight statistical features for each palm-print image.

The recognition accuracy is computed by setting reference threshold to obtain FAR and FRR. The results revealed that the proposed statistical model of contourlet coefficients have performed better than Hybrid DWT-DCT based method. The accuracy is 98.71% which shows the proposed statistical model of contourlet coefficients improves in terms of high accuracy and lower computation cost.

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