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# A Feature Extraction Algorithm for Palm-Print Recognition using Hybrid RDWT-DCT Method

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***Abstract:*** *Palm-print Recognition is one of the emerging fields for human identification which is based on the differences of extracted features from the palm-print image. In this paper, hybrid Redundant Discrete Wavelet Transform – Discrete Cosine Transform (RDWT-DCT) technique is proposed for the feature extraction in palm-print image. The Region of Interest (150 x 150 in size) of a palm-print image is segmented into hundred bands (15 x 15 each) in spatial-domain followed by a frequency-domain transformation on each band to create the dominant feature set containing high energy coefficients. In the paper, a comparison of the palm-print recognition accuracy is demonstrated using two transformation techniques – hybrid (DWT-DCT) and hybrid (RDWT-DCT). The Euclidean Distance is applied as a matching classifier against the images stored in IIT Delhi Touchless Palm-print database and PolyU Palm-print database. The Genuine Acceptance Rate (GAR) is used for the evaluation of accuracy. The result shows that the proposed hybrid method provides better palm-print recognition accuracy compared with hybrid (DWT-DCT).*

***Keywords:*** *Palm-print, Hybrid DWT-DCT, Hybrid RDWT-DCT Transform, feature extraction, Genuine Acceptance Rate*

## 1. INTRODUCTION

A wide variety of systems requires reliable personal recognition schemes to either confirm or determine the identity of an individual requesting their services. Biometric recognition refers to the automatic recognition of individuals based on their physiological and/or behavioral characteristics. A biometric system is essentially a pattern recognition system that operates by acquiring biometric data from an individual, extracting a feature set from the acquired data, and comparing this feature set against the template set in the database [1, 2]. Depending on the application context, a biometric system may operate either in verification mode or identification mode.Recently, biometric features recognition systems have been widely used in many personal authentication applications because they have some advantages such as universality, uniqueness, permanence, collectability, performance, acceptability, and circumvention.

Among different biometrics, palm-print recognition has shown several advantages over other physical characteristics: (a) low-resolution requirement; (b) low intrusiveness; (c) stable feature; (d) be easy to be collected and (e) has comparatively high recognition accuracy [3, 4].There are many unique features in a palm-print image that can be used for personal identification. Principal lines, wrinkles, ridges, singular points and texture are regarded as useful features for palm-print representation [6]. These characteristics of human hand are relatively stable and the hand image from which they are extracted can be acquired relatively easily. For identification tasks, the features of principal lines and wrinkles can be exploited and derived from a low-resolution palm-print image.

Various methods of feature extraction have been studied and analyzed in order to obtain the efficient algorithm for palm-print recognition. But these methods have their limitations in terms of accuracy and computational cost. The tools employed for the texture analysis of palm-print are DCT [7, 8], DWT [10, 11] and Hybrid DWT-DCT Transform [12, 14, 15]. In [8] and[11], 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 has been applied on each modules to extract the dominant feature coefficients. In [12], first the DWT is applied to obtain the approximate details (LL band) and then LL band is segmented into small modules followed by the implementation of DCT. In order to reduce the computational cost and for better accuracy, this paper proposes a new approach for palm-print recognition based on Hybrid RDWT-DCT Transform [8, 9].

The objective of this paper is to develop an efficient algorithm using Hybrid RDWT-DCT Transform for feature extraction from the palm-print. Dominant feature coefficients from each module are considered to form a feature vector. The Euclidean distance classifier is used to determine the palm-print classification. Section II deals with the palm-print recognition system and the techniques have been used. Section III deals with the algorithm for palm-print recognition using Hybrid DWT-DCT AND RDWT-DCT Transforms. Section IV deals with the Results and discussions and Section V deals with the conclusion.

## 2. PALM-PRINT RECOGNITION SYSTEM

A palm-print recognition system consists of some major steps, namely, input palm-print image collection, pre-processing, feature extraction, classification and template storage or database, as illustrated in Fig. 1. 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 for feature extraction. For the purpose of classification, an image database is needed to be prepared consisting template palm-images of different persons.

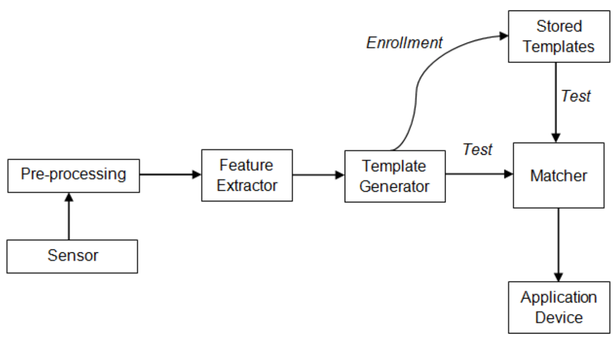



**Fig. 1. General Block Diagram of a Palm-print Recognition System**

The recognition task is based on comparing a test palm-print image with template data. It is obvious that considering images themselves would require extensive computations for the purpose of comparison. 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 depends upon the quality of the extracted features. Therefore, the main focus of this research is to develop an efficient feature extraction algorithm.

### 2.1 DISCRETE COSINE TRANSFORM (DCT)

A discrete cosine transform (DCT) expresses a finite sequence of data points in terms of a sum of cosine functions oscillating at different frequencies [7, 8]. In this paper, we deal with lower frequency DCT coefficients having maximum compaction energy for the purpose of feature extraction. For an input image function f(x, y) with dimension of M × N, the 2D-DCT F(u,v) is computed by equation (1) as:

$$F(u,v)=\alpha_u\alpha_v\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y)\cos\frac{(2x+1)u\pi}{2M}\cos\frac{(2y+1)v\pi}{2N} \quad (1)$$

where,

$$\alpha_u=\begin{cases}\sqrt{\dfrac{1}{M}}, & \text{if } u=0\\ \sqrt{\dfrac{2}{M}}, & \text{if } 1\le u\le N\text{-}1\end{cases} \quad \text{and} \quad \alpha_v=\begin{cases}\sqrt{\dfrac{1}{N}}, & \text{if } v=0\\ \sqrt{\dfrac{2}{N}}, & \text{if } 1\le v\le N\text{-}1\end{cases}$$

### 2.2 DISCRETE WAVELET TRANSFORM (DWT)

In case of sub-band analysis of images, we 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) [10]. This analysis of 2-D signals require the use of following two-dimensional filter functions through the multiplication of separable scaling and wavelet functions in (horizontal) and (vertical) directions, as defined below:

$$\varphi(n_1,n_2)=\varphi(n_1)\varphi(n_2) \quad (2)$$

$$\psi^H(n_1,n_2)=\psi(n_1)\varphi(n_2) \quad (3)$$

$$\psi^V(n_1,n_2)=\varphi(n_1)\psi(n_2) \quad (4)$$

$$\psi^D(n_1,n_2)=\psi(n_1)\psi(n_2) \quad (5)$$

In the equations (2), (3), (4) and (5), $\varphi(n_1,n_2)$, $\psi^H(n_1,n_2)$, $\psi^V(n_1,n_2)$ and $\psi^D(n_1,n_2)$ represent the approximated signal, signal with horizontal details, signal with vertical details and signals with diagonal details respectively. The 2-D analysis filter implemented through separable scaling and wavelet functions is shown in Fig. 2.

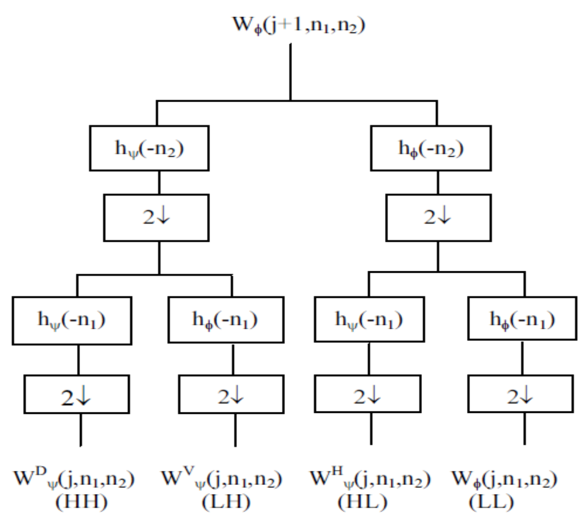



**Fig. 2. Block diagram of 2-D analysis filtering through separable scaling and wavelet functions.**

The filtering in each direction follows sub-sampling by a factor of two, so that each of the sub-bands corresponding to the filter outputs contain one-fourth of the number of samples, as compared to the original 2-D signal. The output of the analysis filter banks is the Discrete Wavelet Transformed (DWT) coefficients. The bands $\phi(n_1,n_2)$, $\psi^H(n_1,n_2)$, $\psi^V(n_1,n_2)$ and $\psi^D(n_1,n_2)$ 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 (vertical direction) and the second letter represents whether the low-pass or high-pass filtering is applied along the rows (horizontal direction). It is possible to iteratively apply the 2-D sub-band decompositions as above on any of the sub-bands. Commonly, it is the LL sub-band (the approximated signal) that requires analysis for further details. Like this, if the LL sub-band is iteratively decomposed for analysis, the resulting sub-band partitioning is called the dyadic partitioning [11, 12].

The two-dimensional DWT of an image function $s(n_1, n_2)$ of size $N_1 \times N_2$ may be expressed by equation (6) and (7) as:

$$W_\varphi(j_0,k_1,k_2)=\frac{1}{\sqrt{N_1N_2}}\sum_{n_1=0}^{N_1-1}\sum_{n_2=0}^{N_2-1}s(n_1,n_2)\varphi_{j_0,k_1,k_2}(n_1,n_2) \quad (6)$$

$$W_\psi^i(j_0,k_1,k_2)=\frac{1}{\sqrt{N_1N_2}}\sum_{n_1=0}^{N_1-1}\sum_{n_2=0}^{N_2-1}s(n_1,n_2)\psi^i_{j_0,k_1,k_2}(n_1,n_2) \quad (7)$$

where i = {H, V, D} indicate the directional index of the wavelet function. As in one-dimensional case, $j_0$ represents any starting scale, which may be treated as $j_0 = 0$.

It is to be noted that the LL, LH, HL and HH sub-band partitions indicate the approximated image and the images with horizontal edges, vertical edges and diagonal edges respectively. The main advantage of DWT over DCT is that DWT allows good localization both in time and spatial frequency domain [9, 11].

### 2.3 HYBRID DWT-DCT TRANSFORM

Firstly, DWT is applied with level 1decomposition and then DCT is applied on LL band to obtain hybrid (DWT-DCT) transform. The hybrid DWT-DCT algorithm for image compression is to exploit the properties of both the DWT and the DCT. Hybrid (DWT-DCT) transformation gives more compression ratio, preserving most of the image information and creates good quality of reconstructed image. Hybrid (DWT-DCT) Transform reduces blocking artifacts, false contouring and ringing effect [10].

### 2.4 REDUNDANT DISCRETE WAVELET TRANSFORM (RDWT)

DWT is very useful to determine areas in the original image where a watermark can be imperceptibly inserted because of its excellent spatio-frequency localization properties. So, it is commonly used for watermarking [5]. On the other hand, DWT has a lot of disadvantages. The major disadvantage is the shift variant. This occurs due to the down-sampling process after each level of filtering, which causes a significant change in the wavelet coefficients of the image even for minor shifts in it. This leads to inaccurate extraction of the watermark data and the cover image. RDWT is established to overcome that problem because it is shift invariant. RDWT has been independently discovered a number of times and was given a number of different names, including the algorithm a´ a trous, the over complete DWT (ODWT), the un-decimated DWT (UDWT), the discrete wavelet frames (DWF) and the shift-invariant DWT (SIDWT) [13, 15]. There are multiple methods to implement the RDWT, and multiple methods to represent the resulting over complete set of coefficients. The original implementation was in a form of the algorithm a´ a trous, which, in its core, eliminates the down-sampling operator from the usual implementation of the DWT [15].

For any image, important textures in it will be at the same spatial location in each sub-band, if each sub-band maintains the same size as the original image. In DWT, the size of each sub-band is decreased when the decomposition level is increased. This can be seen in Fig. 3. Thus, for DWT as decomposition level increases, it should consider increasingly larger spatial regions. But this cannot be achieved in DWT technique.

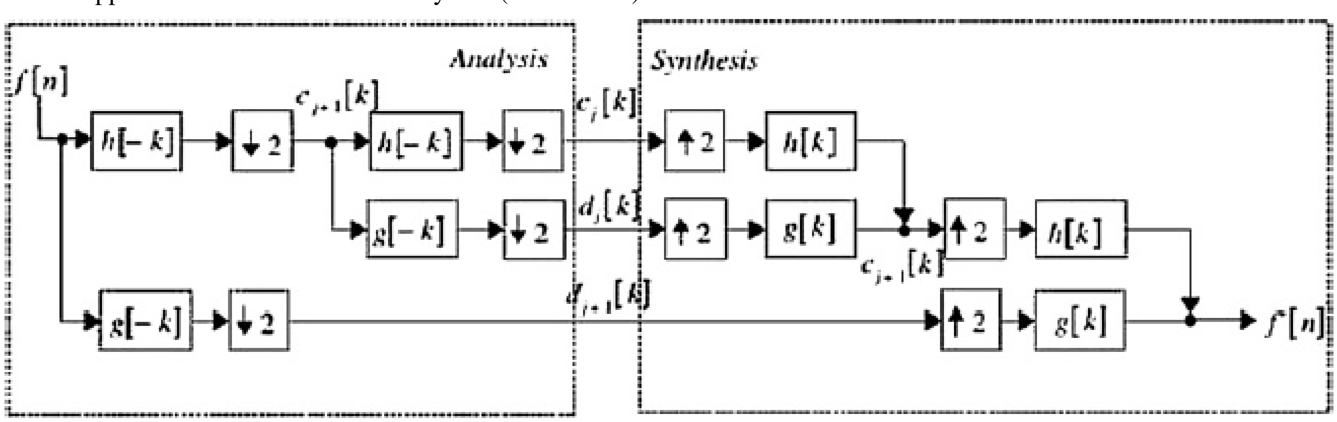



**Fig. 3. Two level 1D-DWT analysis and synthesis filter banks**

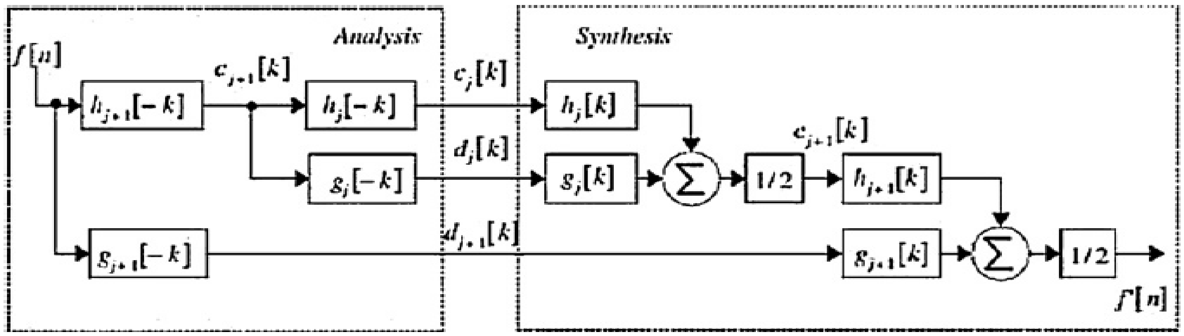



**Fig. 4. Two level 1D-RDWT analysis and synthesis filter banks**

Based on the observations, more accurate capturing of the local texture within RDWT domain can be done [13]. So, the exact measure of local texture can be used. It is used to steer the watermark casting, and increase the watermark capacity into those areas with advanced texture where the human visual system (HVS) is less sensitive to embedded watermark. A 1D DWT and its inverse are shown in Fig. 4 [15] (f[n] represents the 1D input signal and f[n] represents the reconstructed signal). The low-pass and high-pass analysis filters are h[−k] and g[−k] and the corresponding low-pass and high-pass synthesis filters are h[k] and g[k]. $c_j$ and $d_j$ are the low-band and high-band output coefficients at the level j.

### 2.5 HYBRID RDWT- DCT TRANSFORM

In order to obtain hybrid RDWT-DCT transform, RDWT is applied with level 1 decomposition and then DCT is applied on LL band obtained from RDWT.Based on the observations, more accurate capturing of the local texture within RDWT domain can be achieved. So, the exact measure of local texture can be utilized.

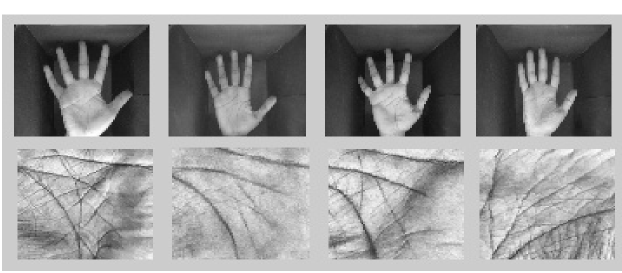
## 3. PALM-PRINT DATABASE AND CLASSIFICATION

### 3.1 PALM-PRINT DATABASE USED IN SIMULATION

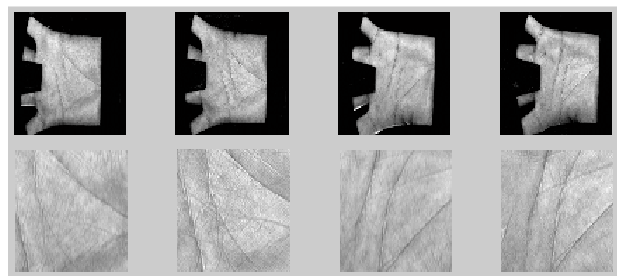
The performance of the palm-print recognition scheme has been tested upon the following two databases:

i) IIT Delhi Touchless Palm-print database [17]

ii) PolyU Palm-print Database (2nd Version) [18].



**(a) IITD database**



**(b) PolyU Palmprint Database**

**Fig. 5. Sample palm print images along with ROI**

Fig. 5 shows sample palm-print images along with ROI from the IIT Delhi Touchless Palm-print database PolyU Palmprint Database. The IITD database consists of total 2791 images of 235 persons, each person having 5 to 6 different sample palm-print images for both left hand and right hand. For our simulation purpose, only 800 images of 100 persons, each having 4 sample palm-print images for both left and right hand are considered.The PolyU database consists of total 7752 images of 386 persons, each person having 9 to 10 different sample palm- print images for both left hand and right hand. For our simulation purpose, only 800 images of 100 persons, each having 4 sample palm-print images for both left and right hand areconsidered.

### 3.2 MATCHING CLASSIFIER

In this paper, for the purpose of palm print recognition, the recognition task is based on the Euclidean distances of the feature vectors of the training palm-images from the feature vector of the query palm-image.

Given the n-dimensional feature vector for the j-th sample image of the i-th person be $\{\Upsilon_{ij}(1), \Upsilon_{ij}(2), ..., \Upsilon_{ij}(n)\}$ and a f-th test sample image with a feature vector $\{ \upsilon_f(1), \upsilon_f(2), ..., \upsilon_f(n) \}$, a similarity measure between the test image f of the unknown person and the sample images of the j-th person is defined by equation (8) as -

$$D_i^f = \sum_{j=1}^{m} \sum_{k=1}^{n} \left| \gamma_{ij}(k) - v_f(k) \right|^2 \qquad (8)$$

where a particular class represents a person with 'm' number of sample palm-print images [5]. Therefore, according to above equation, given the f-th test sample image, the unknown person is classified as the person among the 's' number of classes when

$$D_i^f \leq D_g^f\ ,\ \forall\ i \neq g \text{ and } \forall\ g \in \{1, 2, \ldots, s\} \quad (9)$$

### 3.3 FEATURE EXTRACTION ALGORITHM USING HYBRID DWT-DCT TRANSFORM

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

Step 2: Apply 2D-DWT (Duabechies 4 wavelet 'db4') on the input image to obtain LL band.

Step 3: Divide the LL band into 100 narrow-width bands each of size 15 × 15.

Step 4: Apply 2D-DCT on each band to obtain the fewer number of DCT coefficients with high compaction energy at low frequency.

Step 5**:** Dominant magnitudes are obtained by arranging them in descending order in each band of the image.

Step 6: All hybrid DWT-DCT coefficients pertaining to first dominant magnitudes in each band of image are considered as the feature vector. This feature vector is utilized in matching classifier.

### 3.4 FEATURE EXTRACTION ALGORITHM USING HYBRID RDWT-DCT TRANSFORM

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

Step 2: Apply 2D-RDWT (Duabechies 4 wavelet 'db4') on the input image to obtain LL band.

Step 3: Divide the LL band into 100 narrow-width bands each of size 15 × 15.

Step 4: Apply 2D-DCT on each band to obtain the fewer number of DCT coefficients with high compaction energy at low frequency.

Step 5: Dominant magnitudes are obtained by arranging them in descending order in each band of the image.

Step 6: All hybrid RDWT-DCT coefficients pertaining to first dominant magnitudes in each band of image are considered as the feature vector. This feature vector is utilized in matching classifier.

## 4. RESULTS

The palm-print recognition has been performed on the IITD Touchless Palm-print database [17] and PolyU Palm-print Database (2nd Version) available online [18]. 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) [16]. The accuracy of the authentication system is given by -:

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

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.

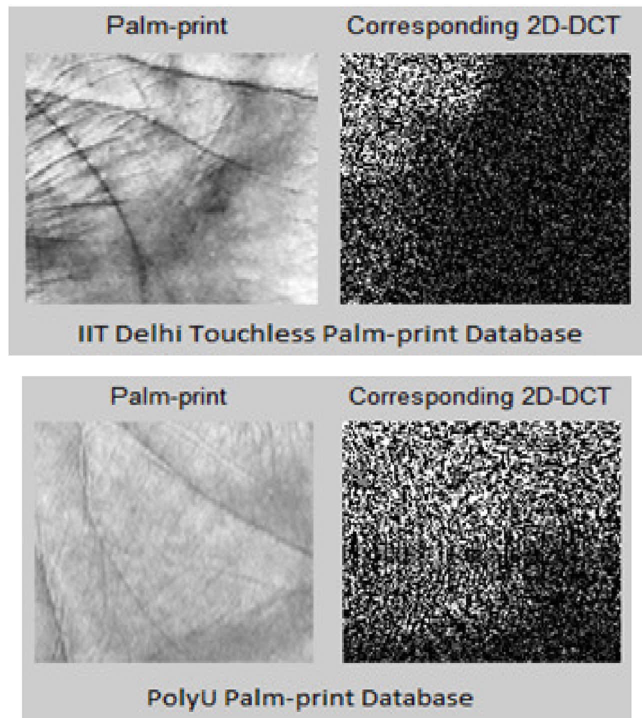
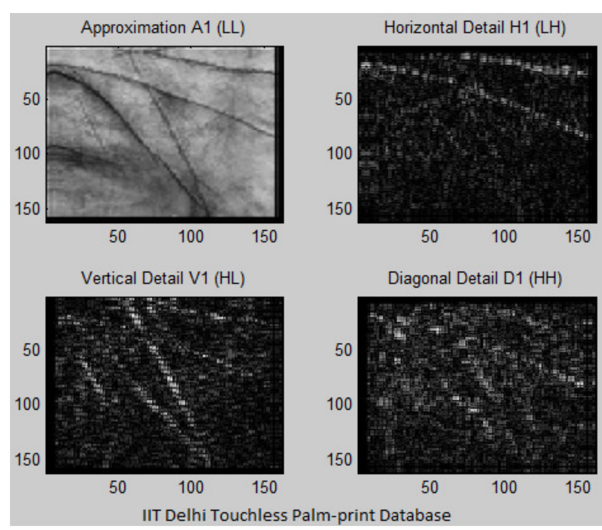



**Fig. 6.A sample palm-print image along with corresponding 2D-DCT**



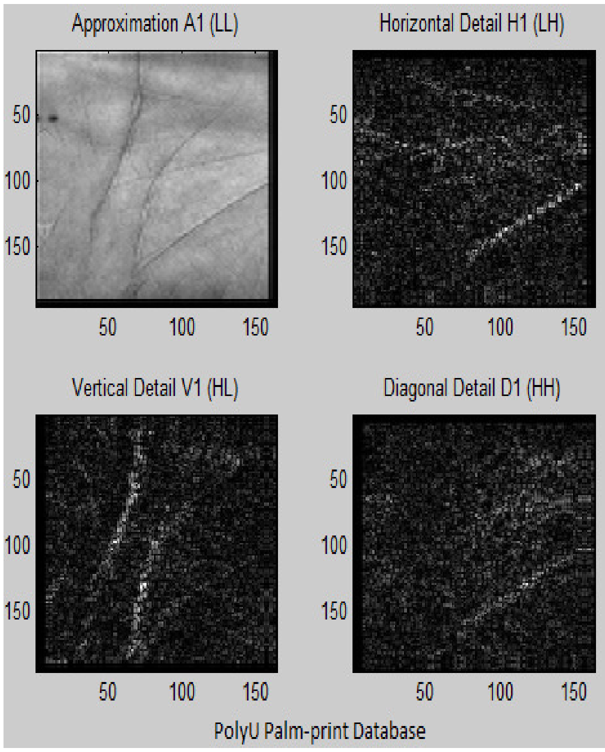



**Fig. 7. A Sample Palm-print image along with corresponding 2D-DWT after level 1 decomposition**

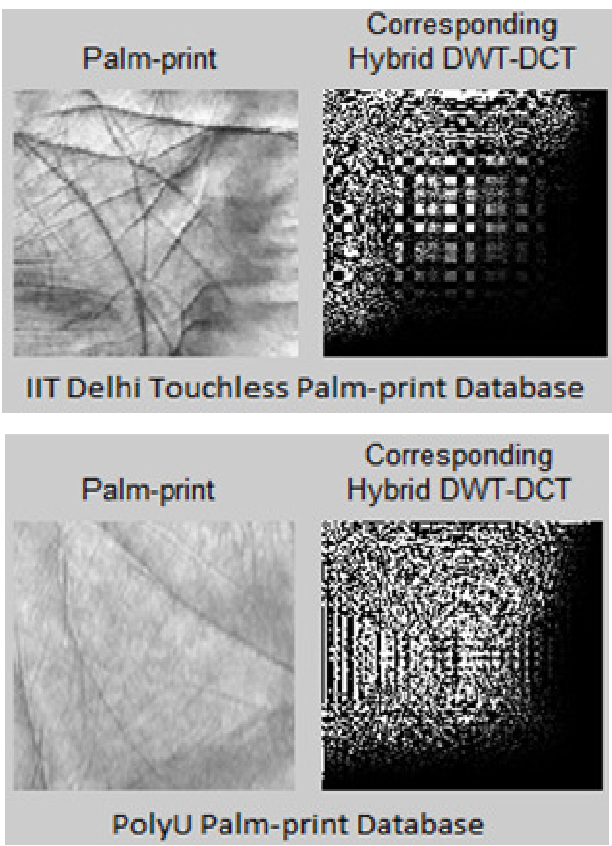



**Fig. 8. A Sample palm-print image along with Corresponding Hybrid DWT-DCT**

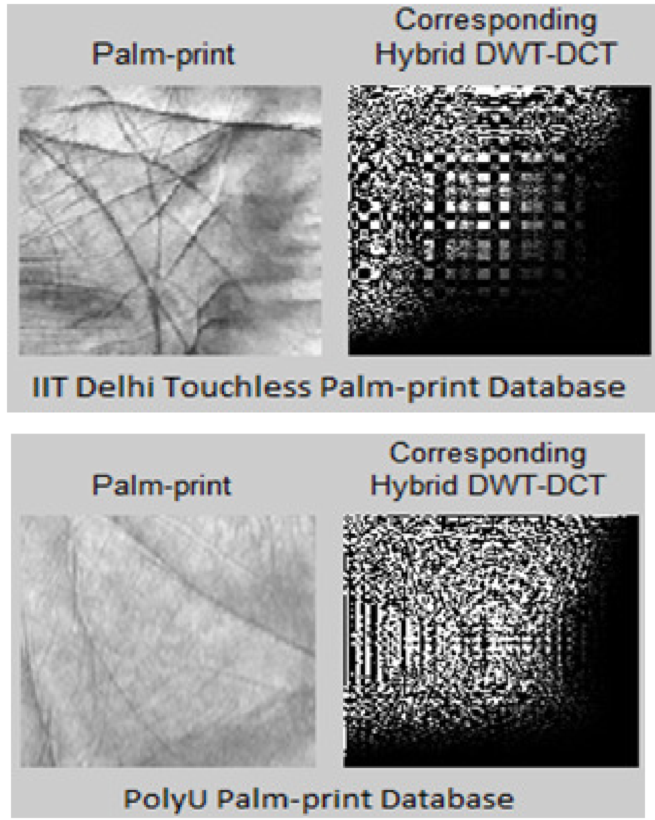



**Fig. 9. A Sample palm-print image along with corresponding Hybrid RDWT-DCT**

**TABLE 1. Performance Comparison**

| Genuine Acceptance Rate (GAR) | Hybrid (DWT-DCT) | Hybrid (RDWT-DCT) |
|---|---|---|
| GAR (IITD Toucless Palm-print Database) | 94.44 % | 97.16 % |
| GAR (PolyU Palm-print Database) | 95.65 % | 97.83 % |

After performing the simulations, the GAR for palm-print recognition are tabulated in Table 1 for both databases. It is observed that the recognition accuracy in the case of hybrid RDWT-DCTtransform is better than the hybrid DWT-DCT transform.

## 5. CONCLUSIONS

In the paper, the Hybrid RDWT-DCT Transform is proposed for palm-print recognition and performance comparison is done with Hybrid DWT-DCT Transform.In Hybrid DWT-DCT Transform, DWT is applied on the palm-print image and then feature extraction is done by segmenting the approximate band into several narrow-width bands followed by DCT on each segment. The DCT is applied in order to obtain the low frequency component having high compaction energy in each band, which in turn forms the feature vector by considering the dominant magnitudes.

In Hybrid RDWT-DCT Transform, the RDWT is applied on the palm-print image and then feature extraction is done in the same way as for Hybrid DWT-DCT Transform.The test features are compared with the features of each image in the IIT Delhi Touchless Palm print database and PolyU Palm-print Database using Euclidean Distance. From the result analysis and comparison, it is observed that the proposed Hybrid RDWT-DCT method gives better palm-print accuracy with reduced computational cost in comparison to Hybrid DWT-DCT.

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