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Palmprint Recognition System By Using Contourlets Transform And Artificial Neural Network

By

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تمييز بصمة اليد باستخدام التحويل الكنترولي والشبكات العصبية

PalmPrint Recognition System by Using Contourlets transform and artificial Neural Network

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واللجنة إذ تمنحه هذه الدرجة فإنها توصيه بتقوى الله ولزوم طاعته وأن يسخر علمه في خدمة دينه ووطنه.

والله ولي التوفيق ،،،

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ABSTRACT

Palmprint recognition is a promising biometric system for forensic and commercial applications. Palmprint recognition has been investigated over ten years. Many different problems related to palmprint have been addressed. The proposed work provides a novel technique from the combination between multiscale transforms: 2D discrete wavelet, Ridgelet, Curvelet, and Contourlet for features extraction phase, 2D principal component analysis (2D PCA) and 2D linear discriminant analysis (2D LDA) are used for dimensionality reduction. Feed forward back-propagation neural network used for recognition phase. The algorithms have been tested by using PolyU hyperspectral palmprint database. Finally, a comparative analysis of the proposed approach has been taken. The recognition accuracy of the proposed approach with some existing approaches are taken. The simulation results show that the proposed approach gives good and comparable results with some other approaches.

DEDICATION

To all my family members, colleagues, and friends who have been constant source of motivations, inspiration, and support

Mohanad A. M. Abukmeil

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CHAPTER ONE INTRODUCTION

1.1 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 an ID card, and the second method is based on Knowledge such as a password. However, these approaches have some limitations [1]. In token-based, “token” can be stolen or lost easily and in a knowledge-base in a certain degree knowledge can be forgotten or guessed.

The biometric personal identification systems concern with identifying persons by either physiological characteristics such as fingerprints, palmprint, iris, face or by using some aspects such as the signature or the voice [1]. Fingerprint-based personal identification has drawn considerable attention over the last 25 years [2]. However, workers and old people may not provide clear fingerprints because of their problematic skin caused by physical work. Recently, voice, face, and iris-based verifications have been studied extensively [3]. Palmprint recognition system is a promising technology which received considerable interest. Among various Biometric identifications technologies palmprint recognition system has been successful due to its simplicity, feature extraction, matching feature, small size, high precision, real time computation, and the resolution of used images.

Palmprint identification has emerged as one of the popular and promising biometric modalities for forensic and commercial applications [4]. Palmprint features are considered promising in identify people. There are two types of

Palmprint features with reference to the field at which palmprint 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 palmprint are shown in Figure (1.1) [4].

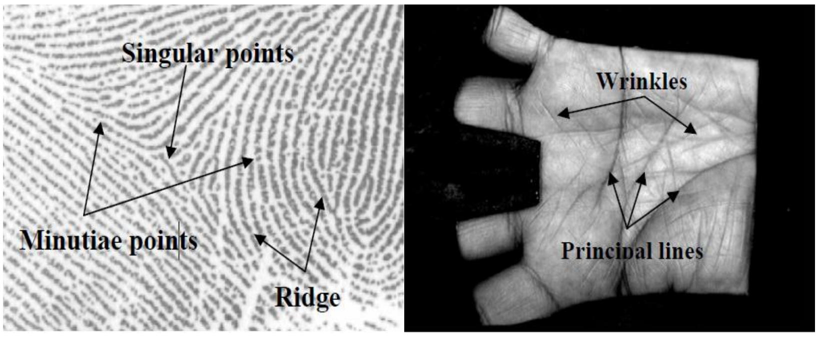

Figure (1.1) Palmprint features

This thesis introduces a new proposed method to extract effectively features for palmprint recognition and it implements many feature extraction technique which projected to reduce the dimensions and feed to neural network classifier.

1.2 BACKGROUND AND LITERATURE REVIEW

Valuable researches have been presented in literature for the identification of people using palmprint features. Recently, a lot of techniques used to extract features from palmprint images have been attracting much research interest.

Jiwen, et.al. (2006), [5], proposed a novel method using wavelet decomposition and 2D principal component analysis (2DPCA) for palmprint recognition. 2D wavelet transform was adopted to obtain different level of wavelet coefficients of the original palmprint image; secondly 2DPCA was applied on the low-frequency. The algorithm was tested on the Poly palmprint image database and the experimental result was encouraging and achieved comparatively high recognition independent component analysis. The major limitation of this paper in database which consist of only 100 palmprints and six samples for each palm. In addition, the number of training and testing palms where inconsistent. Another limitation in comparison with other projection techniques, the comparison was done with PCA and ICA while the better working with image require 2-D domain. 10 projection vectors where used as a classifier input so it is important limitation because it make the time complexity when making the prediction.

Masood, et.al. (2009), [6], suggested a novel palmprint based identification approach drew on the textural information available on the palmprint by utilizing a combination of Contourlet and Non-Subsampled Contourlet transforms. Algorithm was tested on a total of 500 palm images of GPDS Hand database. Different measures of effectiveness of the proposed algorithm were computed and compared with reported results in literature the proposed algorithm outperforms reported methods of palmprint matching in Equal Error Rate (EER). ROI were 256×256 pixels which may increase the complexity in some phases and the comparison with other sophisticated techniques was not clear. The features may be inadequate to distinguish the different classes, features could be highly correlated and features space may simply be too complex which were the limitations of Euclidean distance classifier that used in Masood, et.al search.

Sharkas, et.al. (2010), [7], suggested and compared two techniques for palmprint recognition. The first technique extracted the edges from the palm images, then performed the CT or the Discrete Wavelet Transform (DWT) on the edge extracted images. The second technique employed the principal component analysis PCA. Features extracted from both techniques were tested and compared where it was found that the best achieved recognition rate was about 94%. ROI in this paper is not clear, the minimum distance classifier was used this means that insensitive to differences in variance among categories problem might have occurred. Five palmprint images were trained and the recognition depend on the number of eigenvectors are insufficient in sharkas,et.al. paper.

Kekre, et.al. (2012), [8], suggested the use of a hybrid wavelet, generated by using Kronecker product of two existing orthogonal transforms, Walsh and DCT to identify multi-spectral palmprints. One-to-many identification on a large database containing 3 sets of 6000 multi-spectral palmprint images from 500 different palms was used to validate the performance. The matching accuracy of the proposed method terms of genuine acceptance ratio of 99.979% using score level fusion has been obtained. Selection feature vectors was depend on highly energy components was insufficient to select the most discriminative feature. Algorithm that started from transformed domain toward recognition phase were complex and time consuming because kronecker and hybrid wavelets have been applied.

The major disadvantages of existing works are high implementation complexity, execution time, cost, etc. The existing methods depend on some approaches which gives accuracy less when it compared with our work. The classifier type in some researches may time consuming and reliableless when it compared with neural network classifier which is the faster classifier in testing phase, number of vectors that used as a classifier input in some researchers are more than one vector meaning that recognition may consume more time. The projection technique may not supports 2D domain and the combination between the classifier and image transform technique may be inconsistent are additional problems addressed in recent researches. In order to overcome the disadvantages of existing techniques a new palmprint recognition based on the combinations between multiscale image transforms, dimensionality reduction by 2D PCA and 2D LDA and back-propagations neural networks that require less formal statistical training for recogntion.

1.3 PROBLEM STATEMENT

There is a need for modern technology to use systems that recognize or verify the identity of people when performing task or transactions. Passwords or token suffer from loss or stolen problems. Thus, there is a need to develop more usable and secure system. The answer to this is using biometric systems.

The biometric systems that are used for commercial applications or forensic applications depend on many factors such as, real-time processing, high accuracy, low complexity, low cost and design simplicity. Real-time processing is one of the important factors which affect features extraction and matching phases in biometric systems. In addition, low computational time is affected by features type which is extracted from palm images. The palmprint recognition systems which are used for commercial applications require features such as principal lines and wrinkles which extracted from low resolution images.

workers and old people may not provide a clear physiological features such as fingerprints or voice because of their problematic skin caused by physical work. Recently, voice, face, and iris-based verifications have been studied extensively. The development of maltiscale image transforms provides the biometric systems with transformations which deal with low resolution images to identifies the individuals from their palmprints. The combination between multiscale image transform together with 2D projection technique and back-propagation neural network will be used in our research.

1.4 THESIS OBJECTIVES

- To build a recognition system based on palmprint features.
- To apply multiscale transform for palmprint images in order to extract features.
- To apply dimensionality reduction technique to extract fine features and reduce features size.
- To model the recognition of the extracted features by using feed-forward back-propagation neural network.

1.5 THESIS MOTIVATION

During my study, I have studied several topics in digital signal processing, artificial intelligent and pattern recognition which provided me with suitable and relative subjects to do my research in recognition systems. palmprint recognition system achieves high accuracy and low cost so it could be used in vast areas.

1.6 THESIS CONTRIBUTION

A novel palmprint recognition system was designed based on multiscale transform for feature extraction from low resolution palmprint images which less than 100 dots per inch. 2D discrete wavelets, Ridgelets, Curvelets and Contourlets transforms have applied applied to extract features. The features size is reduced by using projection techniques and to Neural network was applied to train and test those features to achieve high accuracy in real-time processing.

1.7 METHODOLOGY

The main objective of our proposed work is to use palmprint features to build a biometric recognition system based on features which are extracted from low resolution palmprint images to achieve simplicity and real-time processing. In recognition phase, all the palmprints will be divided into two sets: the first images are token as training set while the left as the test set. The features for all data sets will be extracted by applying multiscale image transforms: 2D discrete wavelets, ridgelets, curvelets, and contourlets transform. The feature measurements such as length, lightness, width are passing to neural network classifier then, matching score by comparing feature vector of test palmprint image with the feature vector of the palm images available on database.

1.8 THESIS ORGANIZATION

The remaining chapters of this thesis are organized as follows:

Chapter two covers palmprint recognition system components and multiscale transforms: 2D discrete wavelet, Ridgelet, Curvelet and Contourlet. Dimensionality reduction by 2D PCA and 2D LDA in addition to feed-forward back-propagation neural network are highlighted in Chapter three. Chapter four reports features extraction and recognition phase for each multiscale image transform. Finally, the conclusion and future work are presented

CHAPTER TWO SYSTEM COMPONENTS

A typical palmprint recognition system consists of five parts: palmprint scanner, pre-processing, feature extraction, matcher and database illustrated in Figure (2.1). The palmprint scanner collects palmprint images. Pre-processing sets up a coordinate system to align palmprint images and to segment a part of palmprint image for feature extraction. Feature extraction obtains effective features from the pre-processed palmprints. A matcher compares two palmprint features and a database stores registered templates. [4]

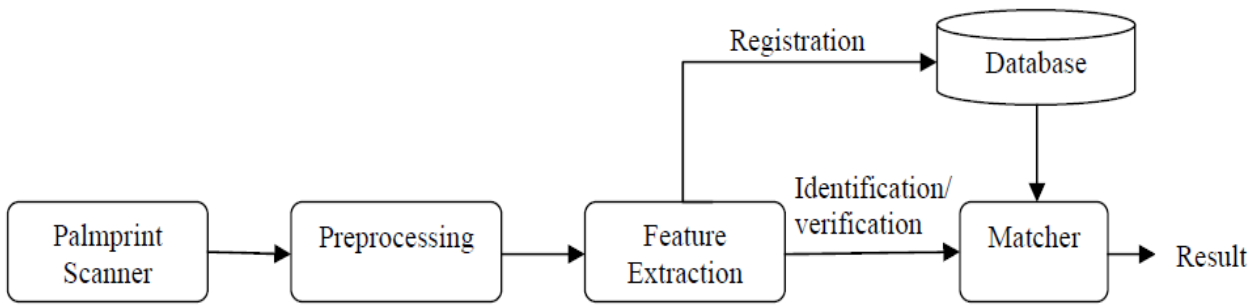

Figure (2.1) palmprint recognition system

2.1 PALMPRINT SCANNER

Researchers utilize several types of sensors, capture couple devise CCD-based palmprint scanners, digital cameras, digital scanners and video cameras to collect palmprint images [4]. Figure (2.2) shows a CCD-based palmprint scanner.

Figure (2.2) palmprint scanner

Palmprint scanners capture high quality palmprint images and align palmprints accurately because the scanners have pegs for guiding the placement of hands [1,9].These scanners simplify the development of recognition algorithms because the images are captured in a controlled environment. Collection approaches based on digital scanners, digital cameras and video cameras require less effort for system design and it could be found in office environments. These approaches do not use pegs for the placement of hands, some researchers believe these increases user acceptance [4].

Digital cameras and video cameras could be used to collect palmprint images without contradiction [10]. However, these images might cause recognition problem as their quality is low because they collect it in an uncontrolled environment with illumination variations and distortions due to hand movement. Digital scanners are not suitable for real-time applications because of the scanning time [4].

2.2 PRE-PROCESSING

Pre-processing is used to align different palmprint images and to segment the centre of palmprint for features extraction [4]. Pre-processing involves five common steps:

- Binarize the palmprint images.
- Extract the contour of hand and/or fingers.
- Detect the key points between fingers.
- Establish a coordination system
- Extract the central parts.

Figure (2.3) illustrates the key points and Figure (2.4) illustrate pre-processed image.

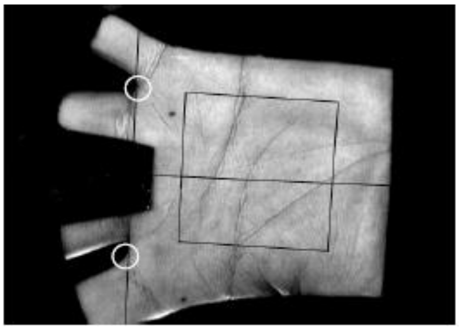

Figure (2.3) Palmprint key points

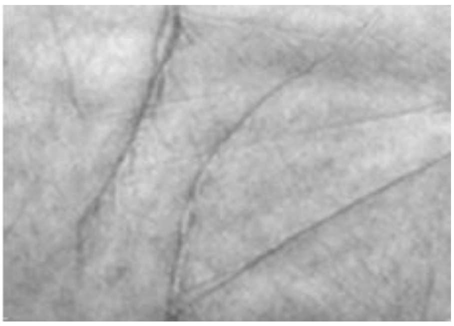

Figure (2.4) Pre-processed palmprint image

The first and second steps in all the pre-processing algorithms are similar [4]. However, the third step has several different implementations including tangent-based, bisector based and finger-based to detect the key points between fingers [4].

The tangent-based approach considers the two boundaries one from point finger and middle finger and the other from ring finger and last finger as two convex curves and computes the tangent of these two curves. The two intersections are considered as two key points for establishing the coordinate system.

Bisector-based approach constructs a line using two points, the center of gravity of a finger boundary and the midpoint of its start and end points. The intersection of the line and the finger boundary is considered a key point. The multiple finger approach uses a wavelet and a set of pre-defined boundary points on the three fingers to construct three lines in the middle of the three fingers. The two lines from point and ring fingers are used to set the orientation of the coordinate system and the line from the middle finger is used to set its position.

After obtaining the coordinate systems, the central parts of palmprints are segmented. Most of the pre-processing algorithms segment square regions for features extraction but some of them segment are circular [11] and half elliptical regions [12]. The square region is easier for handling translation variation, while the circular and half elliptical regions may be easier for handling rotation variation [4].

2.3 FEATURES EXTRACTION

A palmprint could be represented by some line features from low resolution image. Algorithms such as the stack filter are able to extract the principal lines. However, these principal lines are not sufficient to represent the uniqueness of each individual's palmprint because different people may have similar principal lines in their palmprints [1]. In addition, some palmprint images do not have clear wrinkles.

Several techniques have been implemented to extract features from palmprint image such as wavelet, and other but these methods are unable to detect clear edges and smooth curves which result from the conjunctions of principal lines and wrinkles.

We will extract features from low-resolution palmprint images by using PolyU hyperspectral palmprint database, multiscale image transform; 2D wavelet, Ridgelet, Curvelet and contourlet transform which are significant methods in curves and edge detection. The wavelets transform are effective technique in representing the palmprint images with isolated points singularities meaning that's the features which will be extracted from palmprints images when the transformation take place are edges and other isolated points of principal lines and wrinkles.

Ridgelets are very effective in representing the palmprint images with singularities along lines so the transformation will capture lines which constitute the principal lines and wrinkles more effective than wavelets.

In curvelets smooth curvelets will be captured so it's effective in capturing curves that constitute the wrinkles and principal lines, the curvelets relies on features that are different in discrete domain while the contourlets are staring from discrete domain towards into continuous domain. The contourlets can capture most discriminative features from wrinkles, principal lines, and singular points so resulted features will be smooth curves with singular points in palmprints.

The features size is reduced by using powerful projection technique in order to get a vector containing the most discriminative features. Feed-forward back-propagation neural network which is a perfect classifications technique in testing phase has been used as a classifier to recognize palmprint images of individuals. The Matlab was the software that used in our work.

2.4 MATCHER

Once the central part is segmented, features can be extracted for matching. There are two types of recognition algorithms, verification and identification [4]. A matching algorithm determines the degree of similarity between two data sets [1]. To describe the matching process clearly, we will use a feature vector to represent image data that consists of two feature matrices, real and imaginary.

The proposed approach highlights the feature extraction and matching phases in order to develop a novel technique to extract features by using a combination between multiscale transform for features extraction phase and artificial neural network for matching phase.

The proposed approach aims to reduce the execution time in palmprint recognition system. The major advantage of the proposed work is using multuiscale transform which can capture geometrical regularity in images.

CHAPTER THREE MULTISCALE TRANSFORMS AND CLASSIFIER

The term multiscale is intended to describe a system with a passband whose spatial scale is controlled by a single parameter. For example, in the context of linear filters the parameter is the wavelength. Here, the wavelength is closely related to resolution as short wavelengths are needed to describe small sized objects associated with fine resolution [13].

3.1 2D Discrete Wavelet

The 2D DWT [14 , 15] is a very modern mathematical tool. It is used in compression (JPEG 2000), denoising and watermarking applications. It is built with separable orthogonal mother wavelets (ψ), having a given regularity. At every iteration of the DWT, the lines of the input image (obtained at the end of the previous iteration) are low-pass filtered with a filter having the impulse response m_0 and high-pass filtered with the filter m_1. Then the lines of the two images obtained at the output of the two filters are decimated with a factor of 2. Next, the columns of the two images obtained are low- pass filtered with m_0 and high-pass filtered with m_1. The columns of those four images are also decimated with a factor of 2.

Four new sub-images (representing the result of the current iteration) are generated. The first one is obtained after two low-pass filtering; it is named approximation sub-image (or LL image), the others three are named detail sub-images: LH, HL and HH. The LL image represents the input for the next iteration. In the following, the coefficients of the DWT will be noted with xD_m^k where x represents the image who’s DWT is computed, m represents

the iteration index (the resolution level) and k =1, for the HH image, k = 2, for the HL image, k = 3, for LH image and k = 4 for the LL image.
These coefficients are computed using the following relation:

$$xD_m^k[n,p] = \langle x(\tau_1\tau_2), \psi_{m,n,p}^k(\tau_1,\tau_2)\rangle \tag{1}$$

Where the wavelets can be factorized:

$$\psi_{m,n,p}^k(\tau_1,\tau_2) = \alpha_{m,n,p}^k(\tau_1) \,.\, \beta_{m,n,p}^k(\tau_2) \tag{2}$$

And the two factors can be computed using the scale function $\varphi(\tau)$ and the mother wavelets $\psi\ (\tau)$with the aid of the following relations:

$$\alpha_{m,n,p}^k(\tau) = \begin{cases} \varphi_{m,n}(\tau), k = 1\,,4 \\ \psi_{m,n}(\tau), k = 2\,,3 \end{cases} \tag{3}$$

$$\beta_{m,n,p}^k(\tau) = \begin{cases} \varphi_{m,n}(\tau), k = 2\,,4 \\ \psi_{m,n}(\tau), k = 1\,,3 \end{cases} \tag{4}$$

Where:

$$\varphi_{m,n}(\tau) = 2^{\frac{-m}{2}}\,\varphi\,(2^{-m}\,\tau - n\,) \tag{5}$$

$$\psi_{m,n}(\tau) = 2^{\frac{-m}{2}}\ \psi\,(2^{-m}\,\tau - n\,) \tag{6}$$

Despite the huge success of wavelets in the domain of image compression, the failure of two-dimensional multiresolution wavelets when dealing with images of the cartoon class, i.e., images consisting of domains of smoothly varying grey values, separated by smooth boundaries, have been noted repeatedly.

3.2 Continuous Ridgelet Transform

Given an integrable bivariate function $f(x)$, its Continuous *Ridgelet Transform* (CRT) in$\mathbb{R}^2$ is defined by [16 , 17]

$$CRT_f(a,b,\theta) = \int_{\mathbb{R}^2} \psi_{a,b,\theta}(x) f(x) dx, \tag{7}$$

where the ridgelets, $\psi_{a,b,\theta}(x)$ in 2-D are defined from a wavelet type function in 1-D $\psi(x)$as

$$\psi_{a,b,\theta}(x) = a^{-\frac{1}{2}}\psi((x_1\cos\theta + x_2\sin\theta - b)/a) \tag{8}$$

Figure (3.1) shows an example of ridgelet function, which is oriented at an angle θ and is constant along the lines

$x_1\cos\theta + x_2\sin\theta = const$

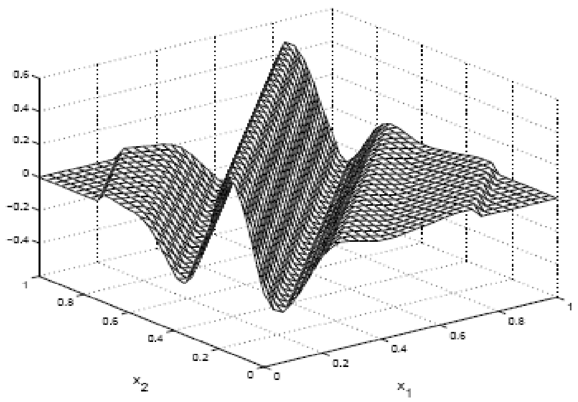

Figure (3.1) An example of ridgelet function

As can be seen, the CRT is similar to the 2-D continuous wavelet transform except that the point parameters (b_1, b_2) are replaced by the line parameters (b, θ). In other words, these 2-D multiscale transform are related by:

Wavelet: $\rightarrow\ \psi_{Scale,point\_position,}$

Ridgelets: $\rightarrow\ \psi_{Scale,line\_position,}$

As a consequence, wavelets are very effective in representing objects with isolated point singularities, while ridgelets are very effective in representing objects with singularities along lines. In fact, one can think of ridgelets as a way of concatenating 1-D wavelets along lines. Hence, the motivation for using ridgelets in image processing tasks is appealing since singularities are often joined together along edges or contours in images.

In 2-D, points and lines are related via the Radon transform; thus, the wavelet and ridgelet transforms are linked via the Radon transform. More precisely, denote the Radon transform as

$$R_f(\theta, t) = \int_{\mathbb{R}^2} f(x)\, \delta(x_1 cos\theta + x_2 sin\theta - t)dt, \tag{9}$$

Then, the ridgelet transform is the application of a 1-D wavelet transform to the slices (also referred to as projections) of the Radon transform,

$$CRT_f(a, b, \theta) = \int_{\mathbb{Z}} \ \psi_{a,b}\, (t) R_f(\theta, t)dt \tag{10}$$

It is instructive to note that if in (10) instead of taking a 1-D wavelet transform, the application of a 1-D Fourier transform along t would result in the 2-D Fourier transform. More specifically, let $F_f(\omega)$ be the 2-D Fourier transform of $f(x)$, then we have

$$F_f(\xi \cos\theta, \xi \sin\theta) = \int_{\mathbb{R}} e^{-j\xi t} R_f(\theta, t)dt \quad (11)$$

This is the famous projection-slice theorem and is commonly used in image reconstruction from projection methods [18 , 19] The relations between the various transforms are depicted in Figure (3.2).

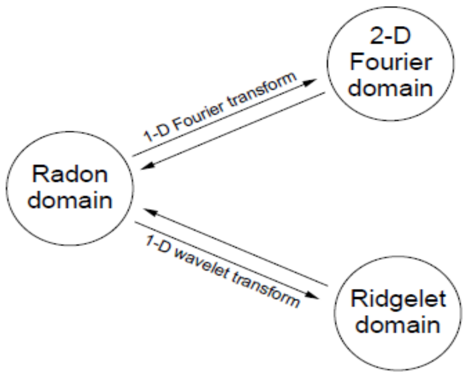

Figure (3.2) Relations between transforms

The ridgelet transform is the application of 1-D wavelet transform to the slices of the Radon transform, while the 2-D Fourier transform is the application of 1-D Fourier transform to those Radon slices.

3.3 Curvelet

Curvelet [20] approximation is based on the decomposition of the image into a fixed system of components, prescribed without prior knowledge of the image. The curvelet system is a family of functions $\gamma_{j,l,k}$ indexed by a scale parameter j, an orientation parameter l and a position parameter k ∈ ℝ, yielding a normalized tight frame of the image space. The latter property amounts to postulating for all $f \in L^2(\mathbb{R}^2)$

$$\|f\|_2^2 = \sum_{j,k,l} \left| < f, \gamma_{j,k,l} > \right|^2 \quad (12)$$

In the curvelet setting, image approximation is performed by expanding the input in the curvelet frame and quantizing the coefficients, just as in the wavelet setting. However, the effectiveness of the approximation scheme critically depends on the type of scaling, and the sampling of the various parameters. A comparison of the two types of curvelets is contained in [21].

Both curvelets constructions are different realisations of a core idea which may be summarized by the catchphrase that the curvelet system corresponds to a critically sampled, multiscale directional filterbank, with angular resolution behaving like$1/\sqrt{\mathrm{Scale}}$.

As the filterbank view suggests, curvelets are most conveniently constructed on the frequency side. The basic idea is to cut the frequency plane into subsets that are cylinders in polar coordinates. The cutting needs to be done in a smooth way; however, in order to ensure that the resulting curvelets are rapidly decreasing.

For this purpose, two window functions have been fixed

$v: [-\pi, \pi] \to \mathbb{C}$, $w: \mathbb{R}^+ \to \mathbb{C}$

Both v and w are assumed smooth in addition, for v we require that its 2π periodic extension v_{per} is smooth as well. In addition, w picked to be compactly supported. v act as angular window; in order to guarantee that the functions constructed from v are even.

To obtain estimates for the scalar products $\langle f, \gamma_{j,k,l} \rangle$ depending on the position of the curvelet relative to the boundary. Recall that $\gamma_{j,k,l}$ is a function that has elongated essential support of size $2^{-|j/2|} \times 2^{-j}$. In the appropriately rotated coordinate system, and oscillates in the "short" direction. Then there are basically three cases to consider, sketched in Figure (3.3):

1- Tangential: The essential support of $\gamma_{j,k,l}$ is close in position and orientation to one of the covering boxes, i.e., it is tangent to the boundary.
2- Transversal: The essential support is close in position to one of the covering boxes, but not in orientation. Put differently, the support intersects the boundary at a significant angle.
3- Disjoint: The essential support does not intersect the boundary.

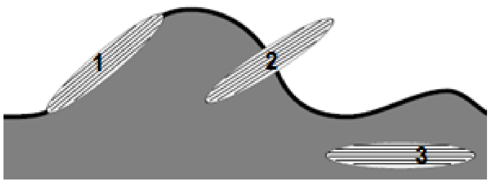

Figure (3.3) An illustration of the three types of curvelet coefficients

The essential supports of the curvelets are shown as ellipses, with indicated oscillatory behaviour. From left to right tangential, transversal and disjoint case.

3.4 Digital Curvelets: Contourlets

The curvelet construction [20] relies on features that are hard to transfer to the discrete setting, such as polar coordinates and rotation. Several approaches to digital implementation have been developed since the first inception of curvelets, see e.g. [22 , 23 , 24]. The approach introduced by Do and Vetterli [24], which the most promising among the currently available implementations, for several reasons: It is based on fast filterbank algorithms with perfect reconstruction; i.e., the tight frame property of curvelets is fully retained, in an algorithmically efficient manner.

Contourlet transform is an efficient directional multi-resolution expansion that is digital friendly. Contourlets are constructed via filter banks and can be viewed as an extension of wavelets with directionality [24].The main idea when constructing a discrete domain with reference to filter banks is to get multiscale and directional steps. Multiscale step is to capture point discontinuities and directional step is to link point discontinuities into linear structure. Figure (3.4) illustrate discrete time- construction using filter banks.

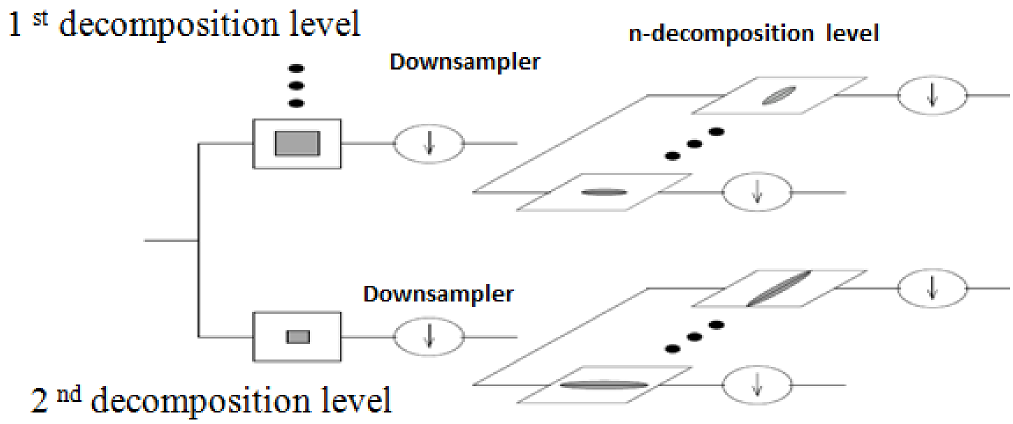

Figure (3.4) Discrete Time- Construction using Filter banks

The contourlet transform [24,25] is constructed as a combination of the Laplacian pyramid and the directional filter banks (DFB), the flow of operation is illustrated in Figure (3.5A), where the Laplacian pyramid iteratively decomposes a 2-D image into lowpass and highpass subbands, and the DFB are applied to the highpass subbands 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 Figure(3.5B).

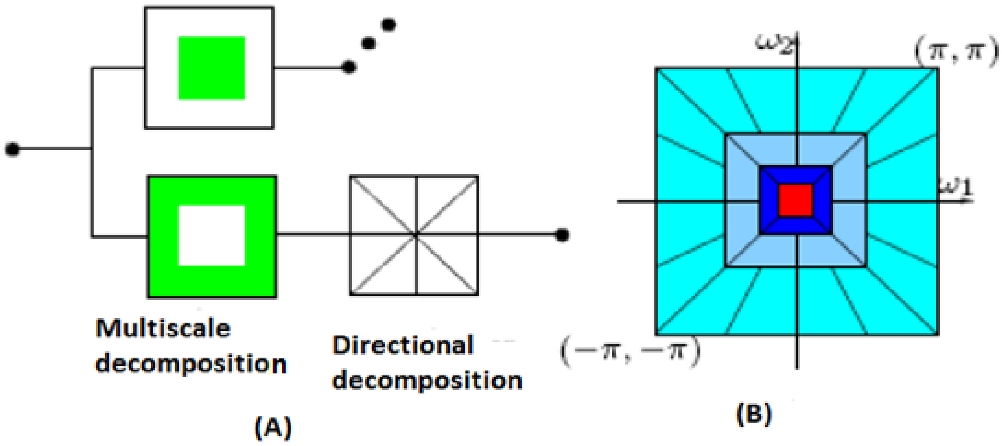

Figure (3.5) Original contourlet transform

3.4 .1 Laplacian pyramid

One way to obtain a multiscale decomposition is to use the Laplacian Pyramid (LP) [24]. The LP decomposition at each level generates a down sampled lowpass version of the original and the difference between the original and the prediction, resulting in a bandpass image shown in Figure (3.6) depicts this decomposition process, where H and G are called (lowpass) analysis and synthesis filters, respectively, and M is the sampling matrix.

The process can be iterated on the coarse (sampled down) signal (Low frequencies). Note that in multidimensional filter banks, sampling is represented by sampling matrices; for example, down sampling gx[n] by M yields xd[n] =x[Mn], where M is an integer matrix[20].

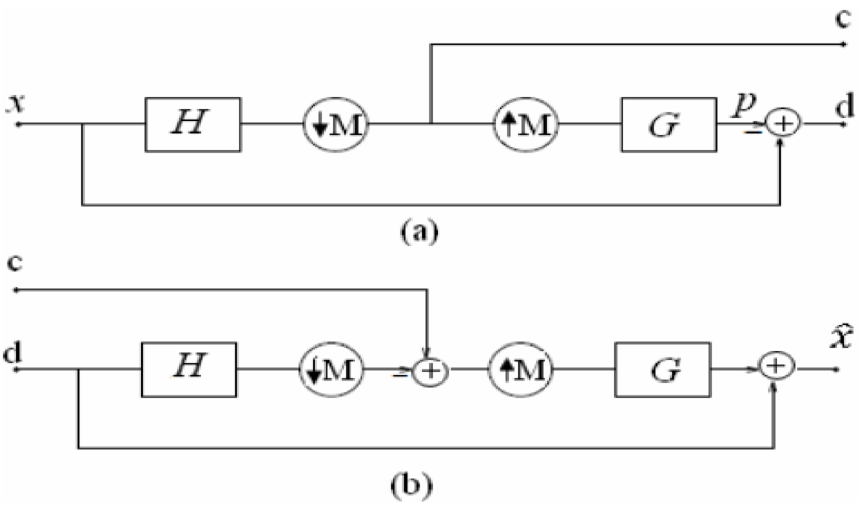

Figure (3.6) Laplacian Pyramid decomposition

Laplacian Pyramid in Figure (3.6a) one level decomposition the outputs are a coarse approximation c[n] and a difference d[n] between the original signal and prediction. In Figure (3.6b) the new reconstruction scheme for Laplacian Pyramid.

3.4 .2 Directional Filter Bank (DFB)

Bamberger and Smith [26] constructed a 2-D directional filter bank (DFB) that can be maximally decimated while achieving perfect reconstruction. The DFB is efficiently implemented via an l-level binary tree decomposition that leads to 2l subbands with wedge-shaped frequency partitioning illustrated in Figure (3.7). The original construction of the DFB involves modulating the input image and using quincunx filter banks with diamond-shaped filters.

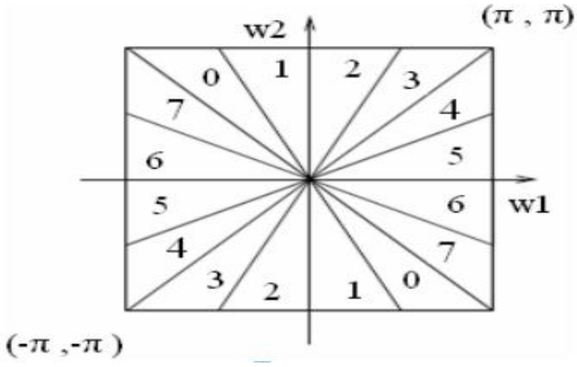

Figure (3.7) Directional Filter Bank portioning

In Figure 12 Directional Filter Bank portioning where l = 3 and there are 23=8real wedge-shaped frequency band. Subband 0-3corresponds to the mostly horizontal directions, while sub bands 4–7 correspond to the mostly vertical directions.

To obtain the desired frequency partition, a complicated tree expanding rule has to be followed for finer directional sub bands. A proposed new construction for the DFB that avoids modulating the input image and has a simpler rule for expanding the decomposition tree. The simplified DFB was intuitively constructed from two building blocks. The first building block is a two-channel quincunx filter bank with fan filters which is clearly seen in Figure (3.8) that divides a 2-D spectrum into two directions: horizontal and vertical [23].

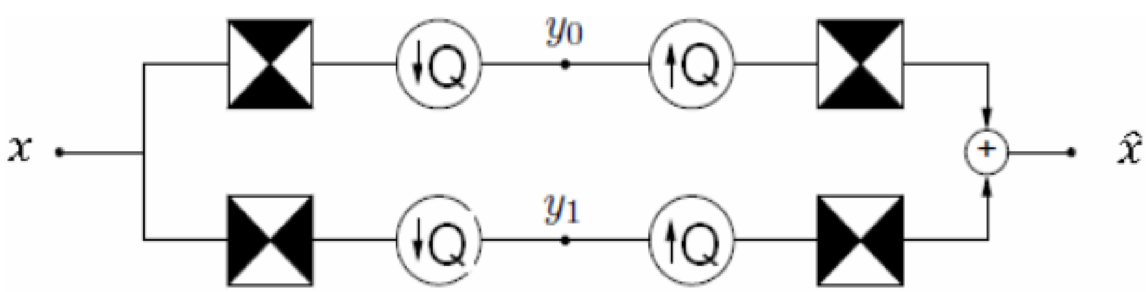

Figure (3.8) two dimensional spectrum partition

The second building block of the DFB is a shearing operator, which amounts to just reordering of image samples. Figure (3.9) shows an application of a shearing operator where a −45◦ direction edge becomes a vertical edge. By adding a pair of shearing operator and its inverse called ("unshearing") before and after respectively, a two channel filter bank in Figure (3.7) obtain a different directional frequency partition while maintaining perfect reconstruction. Thus, the key in the DFB is to use an appropriate combination of shearing operators together with two direction partition of quincunx filter banks at each node in a binary tree-structured filter bank, to obtain the desired 2-D spectrum division as shown in Figure (3.6) [26].

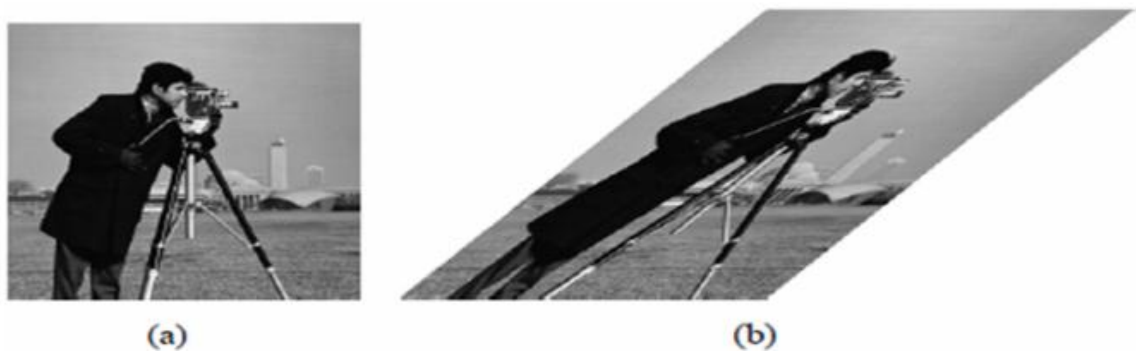

Figure (3.9) Shearing operator application

3.4 .3 Multiscale & Directional Decomposition: The Discrete Dontourlet Transform

Since the directional filter bank (DFB) was designed to capture the high frequency (representing directionality) of the input image, the low frequency content is poorly handled. In fact, low frequency would "leak" into several directional subbands, hence the DFB alone does not provide a sparse representation for images. This fact provides reason to combine the DFB with a multiscale decomposition. Figure (3.10) shows a multiscale and directional decomposition using a combination of a Laplacian pyramid (LP) and a directional filter bank (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 subbands at multiple scales [24].

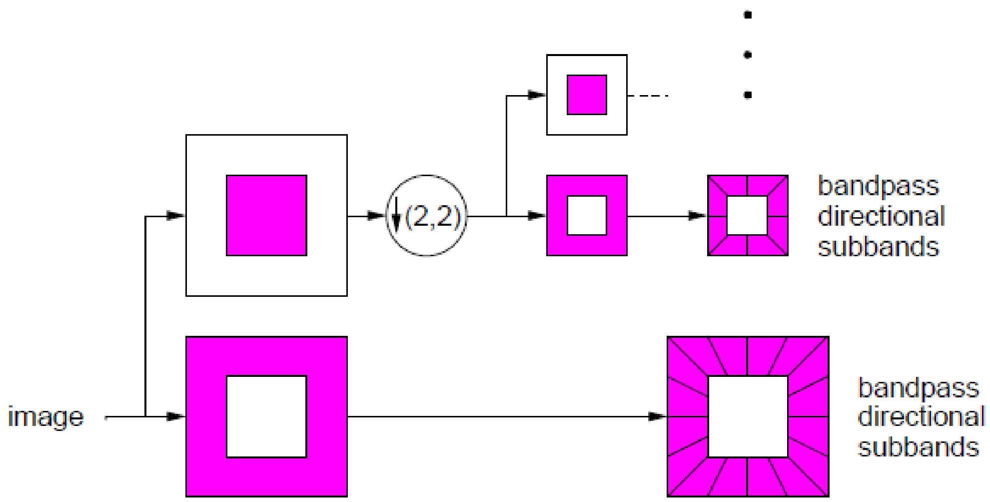

Figure (3.10) The contourlets filter bank

In figure 15 the contourlet filter bank: first, a multiscale decomposition into octave bands by the Laplacian pyramid is computed, and then a directional filter bank is applied to each band pass channel. Suppose an L_j-level DFB is applied at the pyramidal level j of the LP, Then the basis images of the discrete contourlet transform (i.e. the equivalent filters of the contourlet filter bank) have an essential support size of width $\approx c^{2^{j}}$ and length $\approx c2^{j+1_{j-2}}$ [24].

3.4 .4 Contourlets and Directional Multiresolution Analysis

Contourlet filterbank has an association continuous domain in norm square integrable real space which denoted as $L_2((R^2))$ for wavelets filterbank. This connection will be made precise by studying the embedded grids of approximation as in the multi resolution analysis for wavelets. The new elements are multiple directions and the combination with multiscale as shown in Figure (3.11) [24,25].

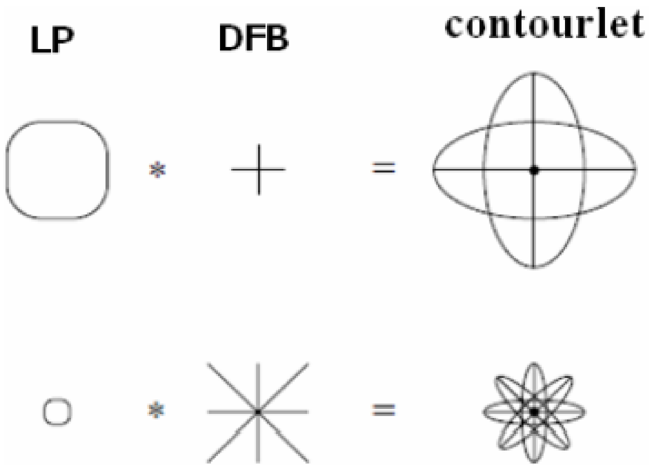

Figure (3.11) The contourlet basis images that satisfies the curve scaling

3.4 .5 Multiscale

Suppose that the LP in the contourlet filter bank uses orthogonal filters and downsampling by 2 in each dimension (that means M = diag(2, 2). Figure 12 shows LP with one level decomposition. LP uniquely defines a unique scaling function $\varphi(t) \in L_2\left((R^2)\right)$ that satisfies the following two-scale equation

$$\Phi(t) = 2\sum_{n \in z^2} g[n]\Phi(2t - n) \tag{13}$$

where n belong to square integers, g[n] synthesis filter and the scaling function of variable t at a certain integration (t) is defined in next hired shifted iteration 2t.

Let

$$\emptyset_{j,n} = 2^{-j}\Phi\left(\frac{t-2^{j}n}{2^{j}}\right), j \in Z, n \in Z^{2} \qquad (14)$$

Where z is a set of integer number, Then the family $\{\Phi_{j,n}\}_{n\in z^2}$ is an orthonormal basis for an approximation subspace vj at the scale 2^{j}vj is a subspace defined on a uniform grid with intervals $2^{j} \times 2^{j}$ interval.

Furthermore,$\{V_j\}_{j\in Z}$ provides a sequence of multi resolution nested subspaces $..V_2 \subset V_1 \subset V_0 \subset V_{-1} \subset V_{-2}..$, LP contain the details necessary to increase the resolution between two consecutive approximation subspaces. Therefore, the difference images lies in a subspace W_j that is the orthogonal complement of V_j in V_{j-1} as show in Figure (3.12)

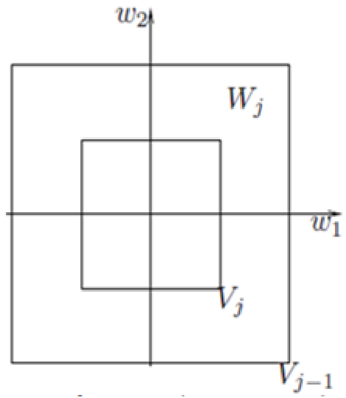

Figure (3.12) Multiscale subspaces generated by the Laplacian pyramid

As for wavelets, we associate with each of synthesis filters in LP continuous function ψ

$$\psi^{i}(t) = 2\sum_{n\in Z^2} f_i\,[n]\,\Phi(2t - n) \qquad (15)$$

Let

$$\psi^{i}{}_{j,n}(t) = 2^{-j}\psi^{i}\left(\frac{t-2^{j}n}{2^{j}}\right), j \in Z, n \in Z^{2} \qquad (16)$$

Then, for scale 2^{j}, $\left\{\psi^{i}{}_{j,n}\right\}, 0 \leq i \leq 3, n \in Z^{2}$ is a tight frame for W_{j}. For all scales $\left\{\psi^{i}{}_{j,n}\right\}, 0 \leq i \leq 3, n \in Z^{2}$ is a tight frame for $L_{2}\left((R^{2})\right)$
In both cases, the frame bounds are equal to 1
Since W_{j} is generated by four kernel functions (similar to multi-wavelets), in general it is not a shift-invariant subspace. Nevertheless, we can simulate a shift-invariant subspace by denoting

$$\mu_{j}, 2n + k_{i}(t) = \psi^{i}{}_{j,n}(t), 0 \leq i \leq 3 \qquad (17)$$

Where μ_{j} is scale coefficient and $\psi^{i}{}_{j,n}(t)$ is continuous function at scale j of LP syntheses filter, μ_{j} is a scale coefficient, k_{i} are the coset representatives for downsampling by 2 in each dimension
$k_{0} = (0,0),\ k_{1} = (1,0),\ k_{2} = (0,1),\ k_{3} = (1,1)$

With this notation, the family $\{\mu_{j}, n\}_{n\in Z^{2}}$ associated to a uniform grid of intervals $2^{J-1} \times 2^{J-1}$on square real space R^{2}provide tight frame of W_{j}.

3.4 .6 Multiscale and Multidirection

Figure (3.13) illustrates the detailed directional subspaces $W_{j,k}^{(l_{j})}$ in the frequency domain. The indices j, k and n specify the scale, direction, and location, respectively. Note that the number of DFB decomposition levels l can be different at different scales j, and in that case will be denoted by l_{j} [24].

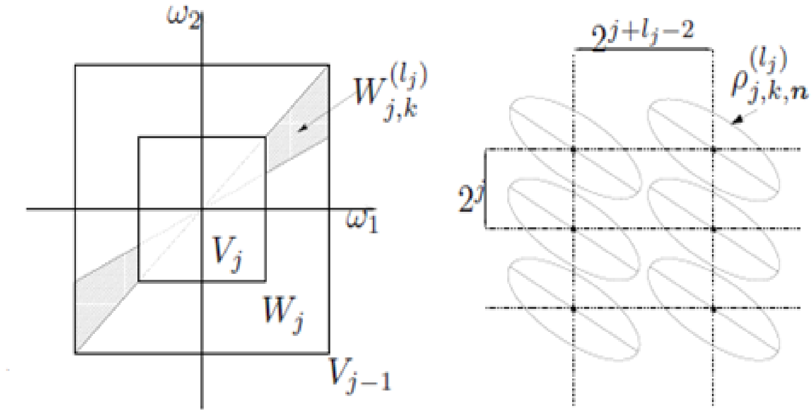

Figure (3.13) Contourlets subspaces

3.4 .7 Contourlet Features

- Define via iterated filter banks → fast algorithms.
- Define on rectangular grids → seamless translation between. continuous and discrete worlds.
- Different contourlet kernel functions for directions.
- These functions are defined iteratively via filterbank.

3.4 2D Principal Component Analysis

Principal Components Analysis (PCA) is one of a family of techniques for taking high dimensional data and using the dependencies between the variables to represent it in a more tractable, lower-dimensional form, without losing too much information. PCA is one of the simplest and most robust ways of doing such dimensionality reduction. It is also one of the oldest, and has been rediscovered many times in many fields, so it is also known as the Karhunen Loeve transformation, the Hotelling transformation, the method of empirical orthogonal functions and singular value decomposition.

Consider an M by N image as $M \times N$ random matrix denoted by A. Let x be an N-dimensional unit column vector. Projecting A onto x yields an M-dimensional vector y [27].

$$y = Ax \tag{18}$$

The purpose of 2D PCA is to select a good projection vector x. To evaluate the goodness of a projection vector, the Yang, et.al. [28] suggested that the use of the total scatter of the projected samples, which can be characterized by the trace of the covariance matrix of the projected feature vectors. Thus, the criterion is to maximize the following:

$$J(x) = tr(S_x) \tag{19}$$

Where S_x is the covariance matrix of the projected feature vectors, written by

$$S_x = E\left(y - E_y\right)\left(y - E_y\right)^T = E[(A - EA)X(A - EA)X]^T \tag{20}$$

Hence

$$J(x) = tr(S_x) = x^T E[(A - EA)(A - EA)^T]x \tag{21}$$

Where tr is trace of covariance matrix; is defined to be the sum of the elements on the main diagonal (the diagonal from the upper left to the lower right).

Given a set of training images $A(1), A(2), \ldots, A(n)$, the criterion (21) becomes

$$J(x) = x^T[\frac{1}{n}\sum_{i=1}^{n}(A(i) - \overline{A})^T(A(i) - \overline{A}]x \quad (22)$$

Where $\overline{A}$ is the average of all training images

$G = \sum_{i=i}^{n}(A(i) - \overline{A}]$, the optimal axis x_{opt} is the unit vector maximizing $J(x)$, i.e. the eigenvector of G corresponding to the largest eigenvalue. Of course, one can compute m best projection axes, which are the m leading eigenvectors of G.

Without loss of generality, all the images have been shifted so that they have zero mean, i.e. $\overline{A} = \frac{1}{n}\sum_{i=1}^{n} A(i) = (0)_{M\times N}$. Thus (22) become

$$J(x) = x^T \sum_{i=1}^{n} A(i)^T A(i)]x \quad (23)$$

3.5 2D Linear Discriminant Analysis

2D LDA [29] directly performs discriminant feature analysis on an image matrix rather than on a vector. 2D LDA tries to find the optimal vector W_{opt}^{2d}

$$W_{opt}^{2d} = \operatorname{argmax}_{W^{2d}} \frac{{W^{2d}}^T S_b^{2d} W^{2d}}{{W^{2d}}^T S_w^{2d} W^{2d}}, \quad (24)$$

Where

$S_b^{2d} = \sum_{k=1}^{L} \frac{N_K}{N}(U_K - U)(U_K - U)^T$ and $S_w^{2d} = \frac{1}{N}\sum_{K=1}^{L}\sum_{i=1}^{N_K}(X_i^K - U_k)(X_i^K - U_K)^T$ are between-class scatter matrix and within-class scatter matrix respectively

Why has 2D LDA been recently reported superior to some 1D-LDA based algorithms.

- The dimensionality of the optimal feature W_{opt}^{2d} extracted by 2D LDA is much smaller than the one W_{opt} extracted by 1D LDA. The number of samples learned for W_{opt}^{2d} is actually much larger than the one for W_{opt}. For 2D LDA each column or each row of an image is a training sample, while for 1D LDA only the whole image is a training sample. Therefore, the number of parameters estimated for W_{opt}^{2d} is much less than the one for W_{opt} and the bias of the estimation of W_{opt}^{2d} could be smaller than the estimation of W_{opt}.

- 1D LDA is always confronted with the singularity problem. For 1D LDA, the strategy to overcome such problem is crucially important. So far some standard approaches are proposed [30][31][32]. It is known that most of the dimension reduction techniques for 1D-LDA would lose discriminant information, such as Fisherface and Nullspace LDA. In contrast, 2D LDA would always avoid the singularity problem.

- The dataset selected for comparison is important. Also, in the experiment, we would find that the back-propagation classifier is indeed an impact in evaluating the performances of recognition when 2D PCA and 2D LDA are used as dimensionality reduction techniques.

3.6 Back-propagation Neural Network

A typical back-propagation network [33] with Multi-layer, feed-forward supervised learning is as shown in the Figure (3.14). Here learning process in Back-propagation requires pairs of input $(x_1, x_2, x_3, .., x_n)$ and target vectors. The output vector 'o' is compared with target vector 't '. In case of difference of 'o' and 't' vectors, the weights are adjusted to minimize the difference. Initially random weights and thresholds are assigned to the network. These weights are updated every iteration in order to minimize the mean square error between the output vector and the target vector [34].

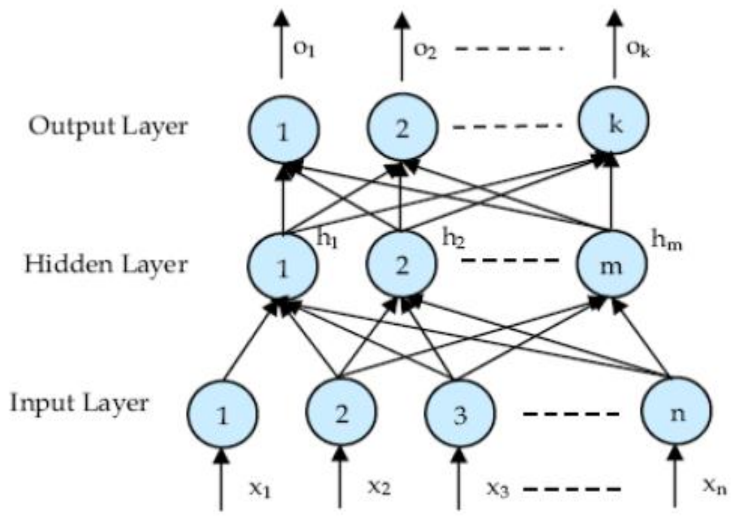

Figure (3.14) Basic block of Back propagation neural networks

Input for hidden layer is given by

$$net_m = \sum_{z=1}^{n} x_z w_{mz}$$
(25)

Where m is index of input layer, z is a set of integer numbers, x are entire pair input and w is weight.

The units of output vector of hidden layer after passing through the sigmoid function as activation function are given by

$$\mathrm{h_m} = \frac{1}{1+\exp(-\mathrm{net_m})}$$

(26)

Where m is index of hidden layer output vector and exp is exponential function.

In same manner, input for output layer is given by

$$\mathrm{net_k} = \sum_{\mathrm{z}=1}^{\mathrm{m}} \mathrm{h_z w_{kz}} \tag{27}$$

Where k is index of output layer, h is output vector of hidden layer and the units of output vector of output layer are given by

$$\mathrm{h_k} = \frac{1}{1+\exp(-\mathrm{net_k})}$$

(28)

For updating the weights, we need to calculate the error. This can be done by

$$\mathrm{E} = \frac{1}{2}\sum_{\mathrm{i=l}}^{\mathrm{k}}(\mathrm{o_{i}}_{-}\mathrm{t_i})^2 \tag{29}$$

$\mathrm{o_i}$ and $\mathrm{t_1}$ represents the real output and target output at neuron i in the output layer, respectively. If the error is less than a predefined limit, training process will stop; otherwise weights need to be updated. For weights between hidden layer and output layer, the change in weights is given by

$$\Delta w_{ij} = \alpha \delta_i h_j$$

(30)

Where α is a training rate coefficient that is restricted to the range [0.01,1.0], h_j is the output of neuron j in the hidden layer as in eq [30], and δ_i can be obtained by

$$\delta_i = (t_i - o_i) o_i (l - o_i)$$

(31)

Similarly, the change of the weights between hidden layer and output layer is given by

$$\Delta w_{ij} = \beta \delta_{Hi} x_j \tag{32}$$

Where β is a training rate coefficient that is restricted to the range [0.001,1.0], x_j is the output of neuron j in the input layer, and δ_{Hi} can be obtained by

$$\delta_{Hi} = x_i (l - x_i) \sum_{j=1}^{k} \delta_i \, w_{ij} \tag{33}$$

x_i is the output at neuron i in the input layer, and summation term represents the weighted sum of all $\delta_i$values corresponding to neurons in output layer that obtained in equation.

After calculating the weight change in all layers, the weights can be simply updated by

$$w_{ij}(new) = w_{ij}(old) + \Delta w_{ij}$$

(34)

This process is repeated, until the error reaches a minimum value [29].

For the efficient operation of the back-propagation neural network it is necessary for the appropriate selection of the parameters used for training. The initial weight will influence whether the net reaches a global or local minima of the error and if so how rapidly it converges. To get the best result, the initial weights are set to random numbers between -1 and 1[33, 34].

Training a Net; the motivation for applying back-propagation net is to achieve a balance between memorization and generalization; it is not necessarily advantageous to continue training until the error reaches a minimum value.

The weight adjustments are based on the training patterns. As along as the error for validation decreases training continues. Whenever the error begins to increase, the net is starting to memorize the training patterns. At this point, training is terminated. If the activation function can vary with the function, then it can be seen that an input, m output function requires at most $2\text{n} + 1$ hidden units. If more number of hidden layers are present, then the calculation for the δ_s are repeated for each additional hidden layer present, summing all the δ_s for units present in the previous layer that is fed into the current layer for which δ_s is being calculated.

In back-propagation neural network, the weight change is in a direction that is a combination of current gradient and the previous gradient. A small learning rate is used to avoid major disruption of the direction of learning when very unusual pair of training patterns is presented.

CHAPTER FOUR FEATURES EXTRACTION AND RESULTS

4.1 Palmprint Database

The Biometric Research Centre (UGC/CRC) at The Hong Kong Polytechnic University has developed a hyperspectral palmprint capture device which can capture palmprint images from 420nm-1100nm, and has used it to construct a large-scale hyperspectral palmprint database. Recently, hyperspectral imaging has attracted considerable research attention because it can acquire more discriminative information.

Hyperspectral palmprint database [31] is anti-spoof database which contain images were collected from 190 volunteers. The age distribution is from 20 to 60 years old. The samples have been collected in two separate sessions. In each session, the subject was asked to provide around 7 images for each palmprint for each wavelength and the size for each palmprint is 128x128 pixels. A palmprint could be imaged at 69 spectral bands with a step-length of 10nm over spectrum 420nm-1100nm. In total, the database contains 5,240 images from 380 different palms for one wavelength. The average time interval between the first and the second sessions 1 month. Zhenhua, et.al [32] suggest using spectral band at 700nm because it contains more discriminative information so it used in our experimental phase in addition to 0630nm spectral band. Figure 20 shows original palmprint images for one person which used in training phase.

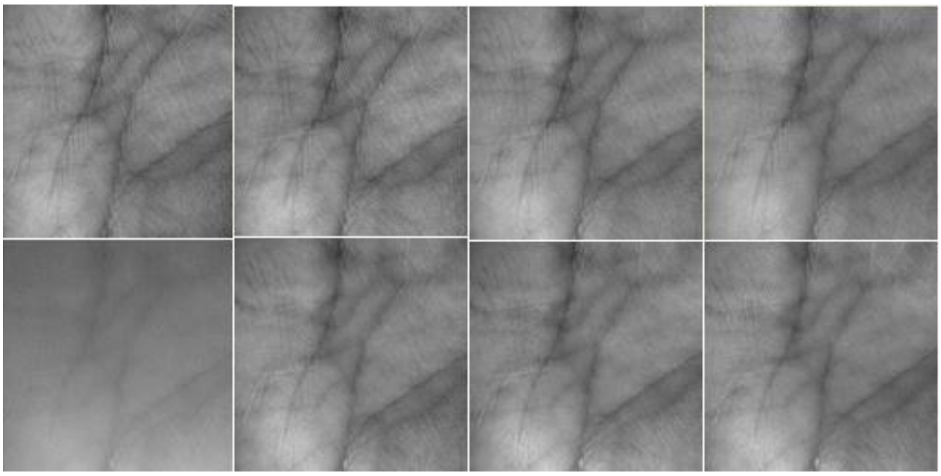

Figure (4.1) Palmprint images for training phase

But palmprint images for the same person which used for testing phase illustrated in Figure 21.

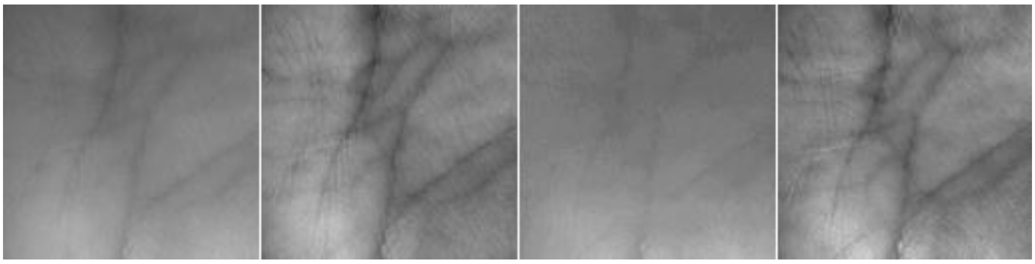

Figure (4.2) Palmprint images for testing phase

4.2 Features Extraction

A palmprint can be represented by some line features from low resolution image. Algorithms such as the stack filter are able to extract the principal lines. However, these principal lines are not sufficient to represent the uniqueness of each individual's palmprint because different people may have similar principal lines in their palmprints [1]. In addition, some palmprint images do not have clear wrinkles. Several techniques have been implemented to extract features from palmprint image such as wavelets, ridgelets, and other but these methods are unable to detect smooth edges which resulted from the conjunctions of principal lines and wrinkles.

In the following the 2D discrete wavelets, ridgelets, curvelets and contourlets features have been extracted. These features have been projected in order to reduce the dimensionality by using 2D PCA and 2D LDA. Finally, the resulted vector is passed to the feed forward back-propagation neural network for training and testing phases.

4.2. 1 2D Discrete Wavelet Features

Applying 2D discrete wavelet transformation leading to different band of wavelets coefficient of the original palmprint images. High frequency components contribute to details and low frequency component contribute to approximation (global description in palmprint) image. A large variation of palmprint image in high frequency component and small effect in low frequency component. Each level of wavelets decomposition divides original palmprint image into four sunband leading to multiresolution analysis. Each subband can be used to extract feature. The 2D discrete wavelets transform are effective technique in representing the palmprint images with isolated points singularities meaning that's the features which will be extracted from palmprints images when the transformation takes place are edges and other isolated points of principal lines and wrinkles. In our experiment 2nd level of 2D discreet wavelet is applied. Figure 22 shows the vertical coefficients of 2nd 2D discreet wavelet decomposition level which are related to palmprints in Figure 20 and are taken as a palmprint features. 2D PCA and 2D LDA have been applied to vertical coefficients leading to single vector which passed to feed- forward back-propagation neural network to be trained or tested.

Figure (4.3) 2D discrete wavelets features

The unique coefficients which used as discriminative features are obtained in our work from vertical coefficients only.

4.2. 2 Ridgelet Features

Linear features play a significant role in palmprint recognition system. The palmprint composed of a different components such as planes, lines and points. The detection of these components is highly affecting palmprint recognition. Ridgelet transform offers a mathematical framework in order to organize the liner information at differand scale and resolution. Firstly, the ridgelet transform is applied to palmprint images in order to convert palmprint images into time-frequency domain leading to ridgelet cofficents. Figure 23 shows 2nd scale of ridgelet transform of palmprint images that was illustrated in Figure 20.

Ridgelets are very effective in representing the palmprint images with singularities along lines so the transformation will capture lines which constitute the principal lines and wrinkles more effective than wavelets.

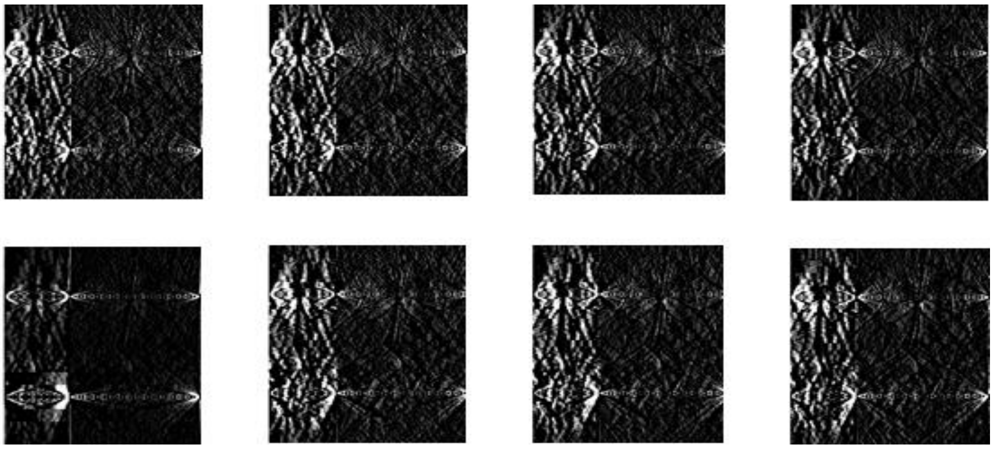

Figure (4.4) Ridgelets features

When the palmprints are transformed by ridgelet transform, 2D PCA and 2D LDA are applied in order to reduce the dimensionally and to get a vector which is resulted from projection. Then the resulted vector is passed to feed forward back-propagations neural network for recognition phase.

4.2. 3 Curvelet Features

The combination between 2D wavelets transform and ridgelets transform leads to curvelet transform. To gain the best feature vector from the polyU hyperspectral palmprint database, the fast discrete curvelet transform must be applied on each palmprint image in the database. In curvelets smooth curves will be captured so it's effective in capturing curves that constitute the wrinkles and principal lines. Each curvelet decomposition level leads to high number of curvelet coefficients. The most curvelets discriminative features could be obtained as shown in Figure 24. According to the evidence, passing all curvelet coefficients to neural network classifier is not suitable so it must be reduced by using the common projection techniques.

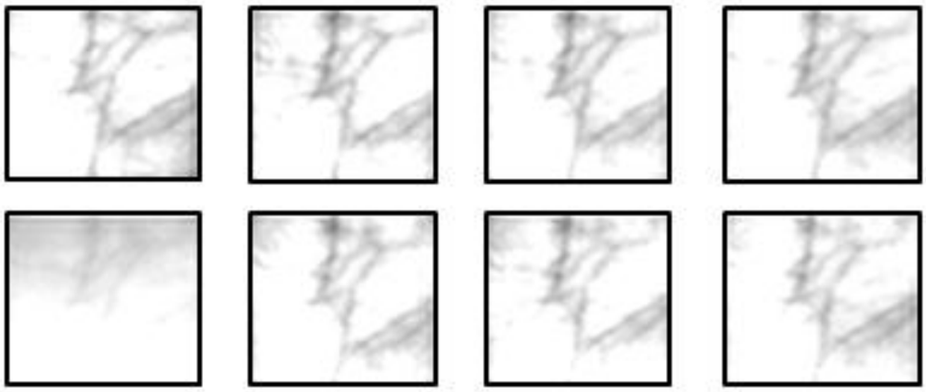

Figure (4.5) Curvelets features

Curvelab 2.1.2 [33] which is a Matlab toolbox includes the mirror extended curvelets has been used to extract curvelet coefficients. 2D PCA together with 2D have been used to reduce the dimensionality in order to pass the most discriminative features to the back-propagations neural networks.

4.2. 4 Contourlet Features

The proposed double filter bank in [20], uses a Laplacian pyramid that is first used to capture the point discontinuities; then, followed by a directional filter bank to link point discontinuities into linear structures. The overall result is an image expansion using basic elements like contour segments; thus, are named contourlets. The contourlet transform can address the features extraction by providing two additional properties: directionality and anisotropy which provide contourlets transform with more efficient representation of the object.

The curvelets relies on features that are different in discrete domain while the contourlets are staring from discrete domain towards continuous domain.

The contourlets can capture most discriminative features from wrinkles, principal lines, and singular points so the resulted features are smooth curves with singular points in palmprints.

To apply contourlet transform to palmprint images by two different steps: in first step Laplacian pyramid applies to decompose the image into two subbands or (cells) the first one is low pass filter and other is high pass filter for edge detection. In our experiment 2nd level of contourlet decomposition applied. The next step is to apply directional filter bank (DFB). The most discriminative contourlets coefficients related to plamprint images in Figure 20   are shown in Figure 25 below.

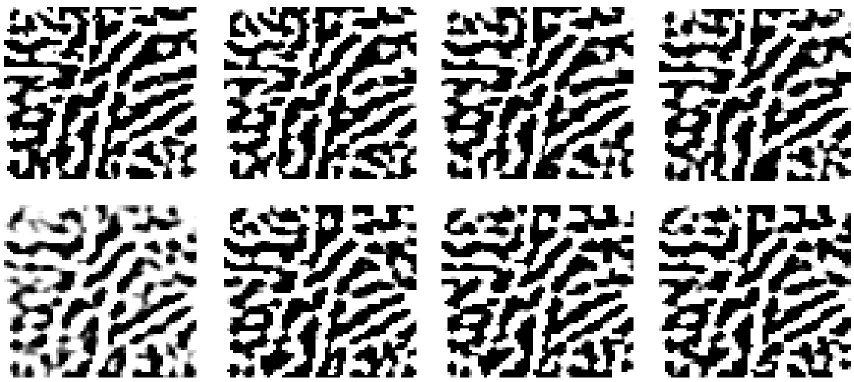

Figure (4.6) Countourlets features

The contourlet coefficients are reduced by using 2d PCA and 2D LDA in order to get a resulted vector to be passed into recognition phase.

4.3 Overall Thesis Work

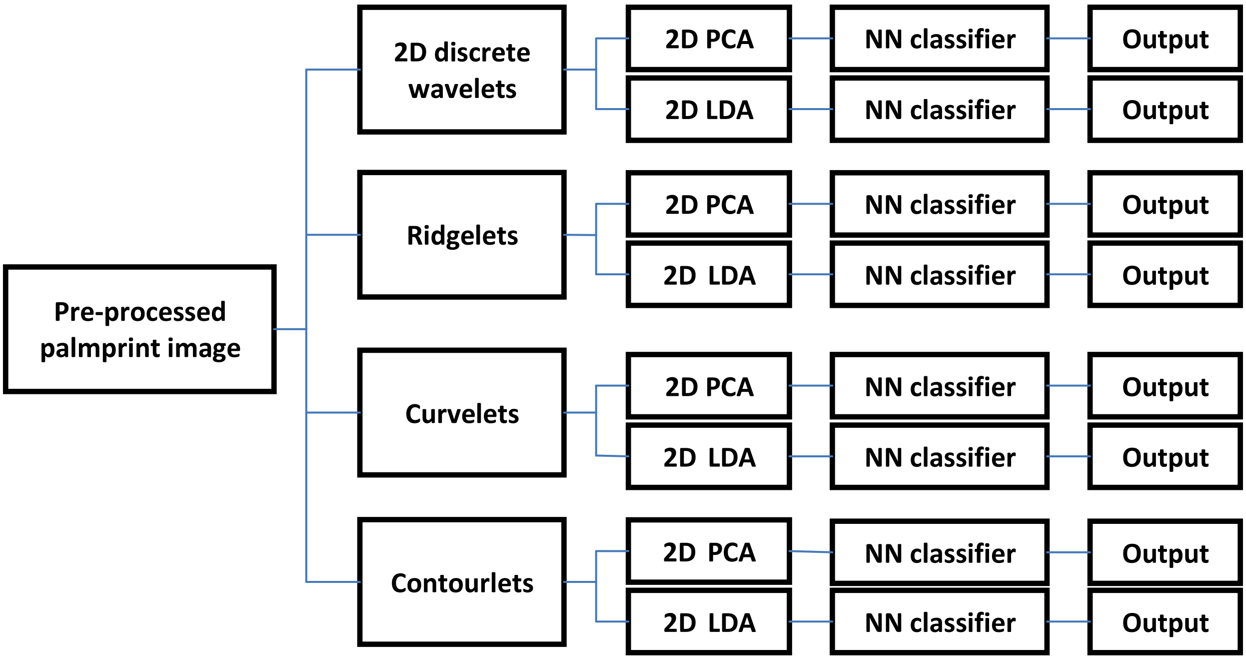

Figure (4.7) feature extraction

Feature extraction phase takes place after the Region Of Interest (ROI) has extracted which called pre-processed palmprint image in Figure 26. Then, the ROI has transformed into frequency domain by using multiscale image transform techniques: 2D discrete wavelets, Ridgelets, Curvelets, and contourlets. The features size is reduced by using dimensionality reduction techniques: 2D PCA and 2D LDA. Finally, the discriminative feature vector is trained or tested by using feed forward back-propagation neural network which referred to in Figure 26 as NN classifier. The output is recognition accuracy that illustrated in Table 1.

4.4 Recognition Phase

Table 1 Recognition results

Multiscale transform	Dimensionality reduction technique	
	2D PCA	**2D LDA**
2D discrete wavelets	87.5%	93.3%
Ridgelets	91.3%	95.8%
Curvelets	97.5%	98.3%
Contoulets	95.8%	99.1%

A test samples of 30 persons have been taken, the total palmprint images which taken were 360 palmprints divided as: 240 palmprints for training phase and 120 palmprints for testing phase. The palmprints images were transformed by using multiscale image transforms: 2D discrete wavelets, Ridgelets, Curvelets and Contourlets in order to extract the discriminative features for individual's. 2D PCA and 2D LDA were used for projection in order to reduce the features size and to get a vector which contains the most discriminative features. The resulted vector which constituted from projection by 2D PCA or 2D LDA have used as input for feed forward back-propagation neural network classifier.

The higher recognition accuracy in Table 1 when the curvelet transform used together with 2D PCA is 97.5% that explains the curvelet transform outperformed the other image transformation techniques. But, the higher recognition accuracy when contourlet transform used together with 2D LDA is 99.1%. The major attributes in the transformed palmprint image are principal line length and width, and wrinkles length and width. 2D PCA applied to this data identifies the combination of attributes that account for the most variance in the *data*. 2D LDA tries to identify attributes that account for the most variance between *classes* so 2D LDA is a supervised method, using known class labels. The class labels field is also called target field. By comparing recognition accuracy when it considered as a function of dimensionality reduction technique as shown in Table 1 2D LDA is outperformed 2D PCA over all multiscale transformation.

The recognition phase in our work has been divided into two stages; the first one is called training stage. Each feature vector which resulted from multiscale transformation and projected by 2D PCA or 2D LDA is passed to feed-forward backpropagtion neural network and trained by using gradient function. The same transformation has been applied to palmprint images which used in test stage but the resultant feature vector didn't trained. The learning rate was 0.05. All trained and tested palmprints which identify 30 persons have been used from polyUhyperspectral palmprint database. Eights palmprint have been used in training stage and four palmprint have been used for test stage.

The recognition accuracy for each multiscal transforms illustrated in table 1. By comparing our work with similar works: in [5] wavelets and 2D PCA in addition to polyU palmprints database used. The recognition accuracy was 97% but different limitations appear in this work such as the sample size was inconsistent, comparison with 1D projection techniques and 10 projection vectors were used in recognition, but our experimental work used only one projection vector. In [6] the combination between contourlet and sub-sampled contourlet was used where Euclidean distance classifier was used. Different levels of accuracy were achieved but the classifier type, image size, and comparison were inadequate. The contorlet transform, PCA, and minimum distance classifier were used for transformation in [7] and the accuracy was 94% but the limitations in the classifier and database made the result inconsistent. In [8] the Kronecker product and hybrid wavelets have been applied and the accuracy was 99.9%. The dependency on highly energy components was insufficient to select the most discriminative feature and the whole recognition algorithm was time consuming and unreliable.

Table 2 Comparison results with other related work

Related work	**Accuracy**
Jiwen, et.al. (2006), [5],	97%
Masood, et.al. (2009), [6],	Different levels from 80% - 93%
Sharkas, et.al. (2010), [7],	94%
H.B.Kekre, et.al. (2012), [8],	99.9%
Our Proposed work	See Table 1

CONCLUSION AND FUTURE WORK

This thesis proposed a novel approach to identify the individuals based on their palmprints. The approach novelty could be found in the combinations between palmprints images transform techniques, features reduction technique and feed- forward neural network classifier. PolyU pre-processed hyperspectral database and Matlab version 7.11 R 2010 b with supporting toolboxes were used in our experiment work. Firstly, each pre-processed palmprint image has read by matlab internal function, and it has transformed by using multiscale toolboxes in order to convert each image into data. The resulted data is projected by dimensionality reduction tool. Finally, neural network toolbox used for recognition training and verification the resulted vectors.

The recognition accuracy were 87.5%, 91.3%, 97.5%, and 95.83% when 2D PCA has used to reduce the vector dimension and: 2D discrete wavelets, ridgelets, curvelets, and contourlets applied respectively. The results show the curvelets transform outperformed the other multiscale transform. But the recognition were 93.3%, 95.8%, 98.3%, and 99.1% when 2D LDA have used to reduce the vector dimensions and: 2D discrete wavelets, ridgelets, curvelets, and contourlets applied respectively.

The richness of hyperspectral palmprint database involve high accuracy and anti-spoof capability because hyperspectral palmprint can acquire more discriminative information for personal identify recognition.

For future work, the combinations between another multiscale image transformations such as shaplet, bandlet, platlet and other will be taken in addition to use another features reduction techniques such as independent component analysis (2D ICA), kernel PCA and other modern techniques are suggested to be used. In addition, the classifier type is suggested to change to show how the recognition accuracy could be improved.

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