Texture Feature Extraction Approach to Palmprint using Nonsubsampled Contourlet Transform and Orthogonal Moments

M. A. Leo Vijilious and V. Subbiah Bharathi

Abstract—**Due to the proliferation of internet usage in financial and information transaction, authentication becomes mandatory for authorised access. Palmprint recognition is a widely accepted biometric authentication. Richness of feature and the less cost involved in acquisition make it more reliable and user friendly. Texture is one of the vital features in biometric recognition applications. Though many statistical methods are available to extract the texture, non-subsampled contourlet transform is employed in this work as a first step to extract the directional frequency information followed by the statistical moment extraction. In addition to using the Zernike moments as texture descriptors, they are effectively used in reducing the dimensionality of contourlet coefficients. Since Zernike moments are inherently orthogonal and rotation invariant, they are more suitable for palmprint recognition.**

Index Terms—**Biometrics, palmprint, ROI extraction, feature extraction, nonsubsampled contourlet transform, zernike moments.**

I. Introduction

Texture is a property of natural image like smoothness, coarseness and regularity of a region. Though texture is an intuitive concept, there is no commonly accepted definition for it. Texture classification is one of the four problem domains in the field of texture analysis such as synthesis, classification, segmentation and shape from texture. Today it is our routine that we are asked for our identity proof for verification in everywhere. Several measures like passwords, ID cards, PIN etc., are used to avoid unauthorized access. Hence, the traditional way of authentication alone is not sufficient today, because of increased identity impersonation and forgery[1]. Biometrics provides effective authentication at low cost, and a convenience of having nothing to carry or remember. This makes biometrics an edge over other traditional method of authentication. Though there are many unique traits such as iris scanning, face and speech recognition, fingerprints used for personal identification, this research focusses on using palmprints, which is more accurate and effective method in personal identification.

The central part of palm is consisting of three flexion creases, secondary creases and ridges. The flexion creases are otherwise called principal lines and the secondary creases as wrinkles. These flexion and the major secondary creases are formed between the 3rd and 5th months of pregnancy [2] and superficial lines appear after we born. Even though the three major flexions are genetically dependent, most of other creases are not. It is astonishing that even identical twins are having different palmprints. These non-genetically deterministic and complex patterns are very much useful in personal identification. Palmprint research is carried out by using either high resolution or low resolution images. When High resolution images are used for forensic applications, Low resolution images are more suitable for civil and commercial applications like access control. Normally, high resolution refers to 400 dpi or more and low resolution refers to 150 dpi or less[3]. Researchers can extract ridges, singular points and minutia points as features from high resolution images, while in low resolution images they normally extract principal lines, wrinkles and texture. Initially palmprint research focused on high-resolution images[4] but current research is focussing on low resolution images for civil and commercial applications.

The acquisition of palmprint is carried out by using scanners, low cost CCD camera or digital camera. These captured images are subjected to preprocessing, feature extraction, and matching with the database.

In this work, a new method is introduced to extract the region of interest from the palmprint. The Nonsubsampled Contourlet transform is applied to extract features. Zernike moments are calculated for each subband as feature selection process. The nearest neighbour classifier is used to determine the final biometric classification. The remaining of this paper is organised as follows. Section II details Literature Survey, Section III Palmprint Preprocessing. In Section IV Feature extraction & Selection. Experimental Study in Section V, Conclusion in Section VI and finally References are in Section VII.

II. Palmprint Preprocessing

Pre-processing is essential for selecting necessary features and to improve the performance. Normally, Peg free palmprint images are acquired by two ways. One is by capturing the image by palmprint capturing devices, or by taking images by using low resolution digital camera with dark background. In both the cases, there is a likelihood of marginally rotational or translational differences in capturing various images in various times. Therefore, palmprint images have different orientation and size and also subject to noise. Moreover, the region of not-interest (e.g fingers, wrist, image background, etc) may affect the accuracy in processing and verification performance. Hence, image pre-processing before feature extraction is necessary. A new method of rotating the image to the desired position and then extracting ROI is proposed. In the ROI extraction phase, the ROI is extracted from the palmprint images using

Manuscript received April 10, 2012; revised May 15, 2012.

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following methodology[8].

1) Select the palmprint image.
2) Find the threshold level to convert the grayscale image into binary image by using canny edge detection. Threshold level is a normalized intensity value that lies in the range [0, 1].

if $$f(x, y) < T \text{ or } 1 \text{ if } f(x, y) \geq T \tag{1}$$

3) For each connected component in the binary image, measure the regions.
4) Find the centroid for all the regions. The centroids are shown in Fig. 1(a).
5) Calculate the distance between all pairs of centroids.

$$d_{mn}, \ m \neq n$$

6) Find the least two distances among all. In Fig.1(b), the least distances are d_{13} and d_{23}. For any palmprint this will be true due to the image capturing setup.
7) Eliminate the common centroid C3 and Mark the other two centroids as C1 and C2.
8) From the C1 and C2 traverse to the right to find the finger joint and mark these points as K1 and K2. The distance transform chessboard distance metric is used. This measures the path between the pixels based on an 8-connected neighbourhood. Pixels whose edges or corners touch are 1 unit apart. The longest distance is considered as the finger joint.
9) Draw a tangent line between K1 and K2. Draw a right angle triangle as this tangent as one side. the third point is K3. After calculating the angle, align the tangent to Y axis. Crop the ROI of size 128 X 128from this reference line as shown in Fig. 1(d).

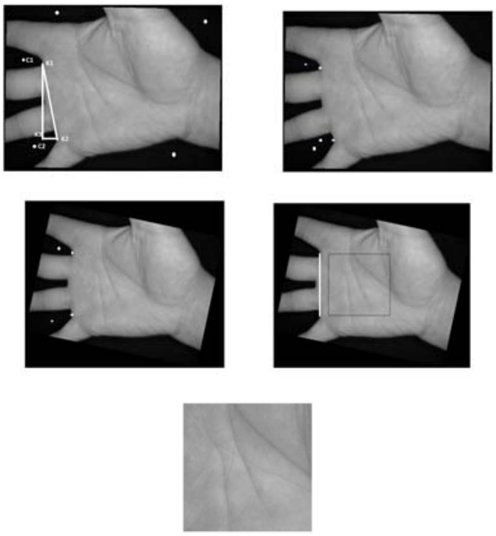

Fig. 1. Preprocessing and extraction of ROI

III. Feature Extraction and Selection

The Contourlet transform(CT), proposed by Do and Vetterli [5], has the ability to capture smooth contours of the images. Contourlet transform uses the Laplacian Pyramid for multiscale decomposition and the Directional filter bank for directional decomposition. The contourlets satisfy the property of anisotropy and can capture intrinsic geometric structure information of images and achieve better representation than discrete wavelet transform, especially for the edges and contours. However, because of the downsampling and upsampling, the CT lacks of shift-invariance and results in bringing artifacts and aliases.

The nonsubsampled contourlet transform (NSCT) [6] developed by Cunha, Zhou, and Do avoids the frequency aliasing problem of contourlet transform and enhances directional selectivity and shift-invariance. The construction reorganises the double filter bank into nonsubsampled pyramid structure for the multiscale property and nonsubsampled directional filter bank structure for directionality. First, a nonsubsampled pyramid split the input into a lowpass subband and a highpass subband. Then a nonsubsampled DFB decomposes the highpass subband into several directional subbands where the number of directions increase with frequency. The scheme is iterated repeatedly on the lowpass subband. Unlike CT, the multiresolution decomposition step of NSCT is realized by shift-invariant filter banks satisfying Bozout identical equation (ref eqn 2). Since no downsampling is done in pyramidal decomposition, the lowpass subband has no frequency aliasing, even the bandwidth of lowpass filter is larger than π /2. Hence, the NSCT have better frequency characteristics than the CT. A nonsubsampled filter bank has no downsampling or upsampling, and hence it is shift-invariant. The perfect reconstruction condition is given as

$$H_0(z)G_0(z) + H_1(z)G_1(z) = 1 \tag{2}$$

This condition is much easier to satisfy than the perfect reconstruction condition for critically sampled filter banks, and thus allows better filters to be designed is shown in Fig.2.

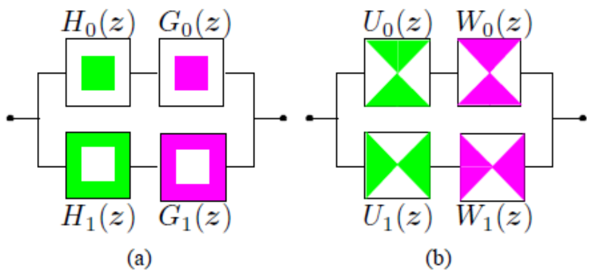

Fig. 2. Ideal frequency response of the building block of:. (a) nonsubsampled pyramid; (b) nonsubsampled DFB.

The two-level NSCT decomposition is shown in Fig.4. which gives flexible multiscale, multidirection, and shift-invariant image decomposition. The NSCT is the nonseparable two-channel nonsubsampled filter bank (NSFB).

The Nonsubsampled contourlet features are extracted from the palmprint ROI. The NSCT is composed of basis function oriented at various directions in multiple scales, with flexible aspect ratios. With this rich set of basis functions, it effectively captures smooth contours that are the dominant feature in palmprint images.

Since the Nonsubsampled contourlet transform has desirable properties of shift invariant palmprint recognition, it is used to extract features to recognize the unknown palmprint images. The ROI is decomposed into subbands by the Nonsubsampled contourlet transform at four different resolution levels,. At each resolution level the ROI is decomposed in 2^n subbands where n = 0,1,2,3,4.... and is the order of the directional filter. As the transform is nonsubsampled therefore each resolution level corresponds to the actual size of ROI i.e. 128x128.Since the features are in larger number, involving the entire coefficients in classification leads to more computation time.

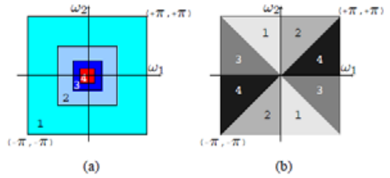
Fig. 3. Frequency divisions of: (a) a nonsubsampled pyramid (b) a nonsubsampled DFB.

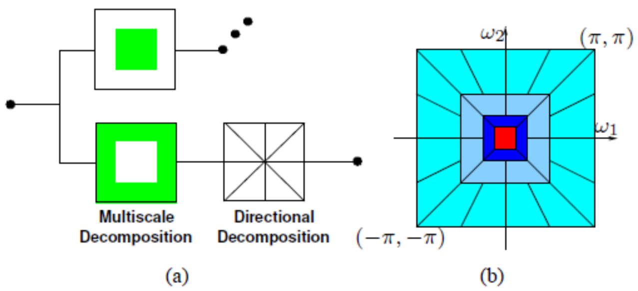

Fig. 4. The NSCT: (a) Block diagram. (b) Resulting frequency division

Moreover, it is not true that classification accuracy will improve with increasing number of features. in this work, feature dimension is reduced by calculating Zernike moments[9][11].

Zernike (1934) introduced a set of complex polynomials which form a complete orthogonal set over the interior of the unit circle i.e. $x^2 + y^2 = 1$. These polynomials are defined as,

$$V_{pq}(x,y) = R_{pq}(x,y) \quad \exp\left[jq \tan^{-1}(y/x) \right] \tag{2}$$

where p: positive integer or zero

q: positive and negative integers subject to constraints p-|q| even and $|q| \leq p$

Rpq (x, y): radial polynomial defined as,

$$R_{pq}(x,y) = \frac{\sum_{k=0}^{p-|q|/2} -1^k \left(x^2+y^2\right)^{(p/2)-k} (p-k)!}{k! \left(\frac{p+|q|}{2}-k\right)! \left(\frac{p-|q|}{2}-k\right)!} \tag{3}$$

Teague (1980) proposed the concept of orthogonal moments, based on orthogonal polynomials[10]. Zernike moments of order 'p' with repetition 'q' for a digital image function f(x, y) are given by,

$$A_{pq} = \left(\frac{p+1}{\pi}\right) \sum_x \sum_y \left[V_{pq}(x,y)\right]^* f(x,y), \tag{4}$$

$$x^2 + y^2 \leq 1$$

While computing Zernike moments of a given image, the center of the image is taken as origin and pixel coordinates are mapped in such a way that $(x^2 + y^2) \leq 1$. Those pixels falling outside the unit circle are not used in the computation.

Likewise, each computed energy value can be used as an element to form a feature vector, which is denoted as the energy feature vector. The energy features were adopted in this study merely for comparison purpose. Achieving higher recognition rate using short feature vectors is desired.

There is no restriction on the order of Zernike moment to be computed for a given size of the image. It is a fact that the lower order Zernike moments capture the gross shape features and higher order moments represent the fine details of the image. Also it has been established in [14] that the orthogonal moments are effective in representing textural properties for classification applications. However, not all the moments possess information related to the textural properties of the image function. Feature selection methods are adopted, usually to identify the best moment features and thereby to reduce the dimension of the feature vector.

IV. Experimental Study

Experiments are conducted by using CASIA Palmprint Image Database which contains 5,502 palmprint images captured from 312 subjects. For each subject, the palmprint images are collected from both left and right palms.

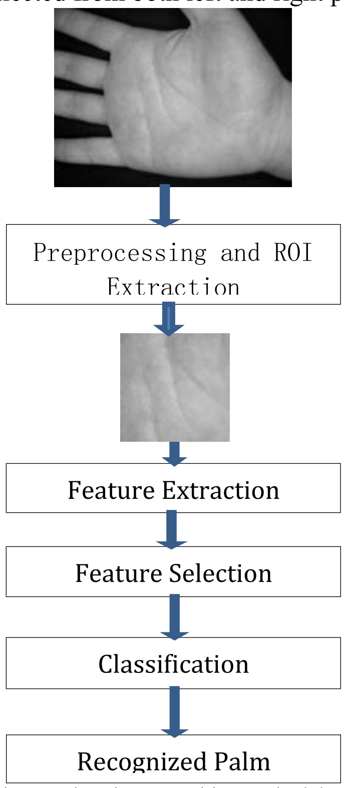

Fig. 5. Palmprint recognition methodology

All palmprint images are 8 bit gray-level JPEG files. Here for our experiment purpose right hand images of 100 subjects are used. The training and test data sets were prepared according to the "leave-one-out" strategy. Then one of the sampled blocks was used as the test sample, and the remaining blocks were used as training samples. 7 images are used for training and 1 for testing. The "leave-one-out" strategy avoided biases that might otherwise be introduced into the results due to inappropriate data sampling[7]. A new methodology is used to extract ROI. The ROI is resized to 128 X 128 to maintain uniformity in image inputs for further work. The ROI is decomposed into subbands by the Nonsubsampled contourlet transform at four different resolution levels, at each resolution level the ROI is decomposed in 2^n subbands where n = 0,1,2,3,4.... and is the order of the directional filter. As the transform is nonsubsampled therefore each resolution level corresponds to the actual size of ROI i.e. 128x128. Since the features are in larger number, Zernike moments are calculated for each subband image as a feature selection process. Zernike moments of order 12 are calculated for each subband of the decomposed ROI. The 49 moment values computed for order 12 satisfying the constraints p-|q| even and |q| ≤ p, amounting to a maximum of 49 X 8, ie 392 values from the originally extracted NSCT coefficients of 128 X 128 X 8 ie 131072 pixel values. These reduced features are used for classification, A feature vector is formed by using these computed values. Thus the vast number of coefficients is reduced in greater dimension. A simple classification scheme nearest neighbour classifier is used to classify the image. The classification accuracy is achieved in this method is 95.2% which clearly shows the proposed method improves classification accuracy and reduces computation time.

V. Conclusion

In this paper, a new technique is developed to extract ROI. After extracting the ROI, the three levels of NSCT a Nonsubsampled pyramidal directional filter bank is applied. Since the features are in larger number, Zernike moments are calculated for each subband as feature selection process. Our idea here is focused on ROI Extraction, Feature extraction method rather than Classification. The results are very much promising when Nonsubsampled Contourlet transform is combined with Zernike moments calculations and accuracy 95.2% is achieved.

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