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Analysing the Features Extracted from the Detail Coefficients of Discrete Wavelet Transform for Palmprint Biometric Authentication System

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Abstract— It has been advantageous to incorporate biometric verification systems using Palmprints since they inherently have many features. Selecting an appropriate feature set is an important step to ensure the accuracy of the system. Discrete Wavelet Transform has been widely used in texture analysis. This paper presents the extraction of features after post processing on the wavelet coefficients. Wavelet energy, Standard deviation and Area of binarised image have been used as features in this work. Feature matching has been implemented with the help of neural network. This paper gives the results obtained from the confusion matrix and analysis of these results.

Keywords— Biometrics, Discrete wavelet transform, texture, neural network, confusion matrix

I. INTRODUCTION

Biometrics is the science and technology of measuring and analysing biological data. Now a days, everywhere in the world, security is given top priority and hence biometrics is being increasingly adopted for personal verification and for identification [1]. Identification is one to many system. Biometrics can be used to determine a person's identity even without knowledge or consent. Verification is one to one system. Palmprint is a perfect biometric identifier because of its stability and uniqueness. Palm prints are rich in features such as principal lines, wrinkles, ridge, datum points and minutiae points [2] [3]. Palmprints have a much larger surface area which means that more features can be extracted from it [2]. Using hand features as a base for identity verification is relatively user-friendly and convenient. Apart from being user friendly, the Palmprint identifiers use less data amount and can be operated using cheap electronic imaging device. After processing, a palmprint is stored only by a few bytes of data signatures [7]. Palmprint features like principal lines and wrinkles can be obtained from a low resolution palmprint image with less than 100dpi [12]. For features such as minutiae points, ridges and singular points, a high resolution image with at least 400 dpi is required. For civil and commercial applications, low resolution palmprint images are more suitable than high resolution images because of their smaller file sizes which results in shorter computation times during pre-processing and feature extraction. Therefore, they are useful for many real time applications [8].

Biometrics systems work by first capturing a sample of the feature. The sample is then transformed using some mathematical function into a biometric template. The biometric template provides a representation of the feature, which is compared with other stored templates in order to determine the identity. Most biometric systems have two stages of operation. An enrolment stage for adding templates to the database and a matching stage where a template is created for an individual and then a match is searched for in the database of the pre-enrolled templates [4].

To build a palmprint based biometric system, the palm image has to be captured and then the image has to be subjected through digital image processing stages such as image acquisition, image pre-processing, extracting ROI, feature extraction and feature matching.

The feature extraction is a very important step for the design of a biometric system. The objective of this step is to extract variables that describe, unequivocally, the forms belonging to the same class while differentiating them from the other classes [6].

This paper presents a different method for extracting the features based on discrete wavelet transform. The coefficients obtained from the transform have been further processed in order to obtain two images in which one image retains the line features and the other image is the binarised image of line features. The resulting first image has been partitioned into square shaped non- overlapping blocks and statistical parameters of standard deviation and normalised energy have been found for each block. Similarly, the resulting binarised image has been partitioned into rectangular overlapping block of same size. The area, which is the number of white pixels, of all blocks have been obtained to generate the features. Section II of this paper gives the basic information of discrete wavelet transform and the various features that have been extracted from the coefficients that have been reported in literature. Section III explains the experimental work carried out. Section IV highlights on the generation of feature set. Section V includes the neural network implementation and the corresponding results obtained. Finally section VI concludes the paper.

II. BASIC INFORMATION

Discrete Wavelet Transform has been widely used in various applications in image processing such as denoising, restoration and compression. It has proven its effectiveness in the texture analysis. Due to the multi-resolution principle, the DWT provides detailed information both in space and in frequency on the image, which allows analyzing texture at different scales [6]. The wavelet transform, as compared to the traditional Fourier analysis, has better space-frequency localization. Thus it is better suited for analyzing images where most of the informative content is represented by components localized in space, such as, edges and borders and by information at different scales or resolutions, with large and small features. Multiresolution analysis of the images is performed by reiterating the wavelet decomposition to an arbitrary number of times on the low frequency part. At the first level, the original image is decomposed in four sub bands leading to the scaling component containing global low-pass information and three wavelet components corresponding to the horizontal, vertical and diagonal details [10].

Wavelet analysis gives approximation and detail coefficients. Approximations are high scale, low frequency components whereas details are low scale, high frequency components. The lines like patterns on a palm print correspond to the detail coefficients.

Statistical parameters on wavelet coefficients have been regarded as features. Statistical approaches are either local or global. Local statistical approaches divide the transformed image into several small regions. Local statistics such as means and variances of each small region are calculated and regarded as features. Global statistical approaches compute global statistical features from the whole transformed images. Moments, centres of gravity and density have been regarded as global statistical features [9].

Dominant Wavelet coefficients have been used to generate the feature vector. In this method the wavelet coefficients greater than threshold value are considered as dominant coefficients. The wavelet coefficients are first sorted in descending order and then the top ϴ % of the coefficients are considered as dominant coefficients. The ROI is split into different modules and threshold can be different for each module. The variation in module size does not affect the recognition accuracy unless it is extremely large or small [5].

Context modelling is done on the wavelet transform to identify the predominant structures according to the appearances of principal lines in each sub bands. Each sub band is characterised by a set of statistical signatures. Some of the statistical signatures used are average gravity centre, density, spatial dispersitivity and energy [7].

The global and local palmprint features can be combined in a hierarchical fashion to facilitate coarse-to-fine palmprint pattern matching. The global texture energy can represent the global palmprint feature, which is characterized with high convergence of inner-palm similarities and good dispersion of inter-palm discrimination. Such a global feature is used to guide the dynamic selection of a small set of similar candidates from the database at a coarse level for further matching. Similar features are used as local features and final identification at fine level is carried out by local feature matching [11].

A method in which palm images are fused at low level by wavelet transform and then represented by Gabor wavelet transform to capture the palm characteristics in terms of neighborhood pixel intensity changes has also been studied [13].

Palm images are decomposed by Haar wavelet for single level. Smoothing masks are applied before and after wavelet transform. The magnitudes of pixels within one standard deviation are set to zero. Values of the rest of the pixels are projected onto a logarithmic scale in order to minimize variations between two images. Each of the detailed images is divided into sectors of non-overlapping elliptical half-rings. Mean energy of each sector forms the feature vector [14].

III. EXPERIMENTAL WORK

IIT Delhi has created a database of palm print images using a touch less imaging setup. The database contains images of left hand and right hand of 235 users. The resolution of the images is 800x600 pixels. In addition 150x150 automatically cropped images are also available. Access to this database has been obtained for the study in this work.

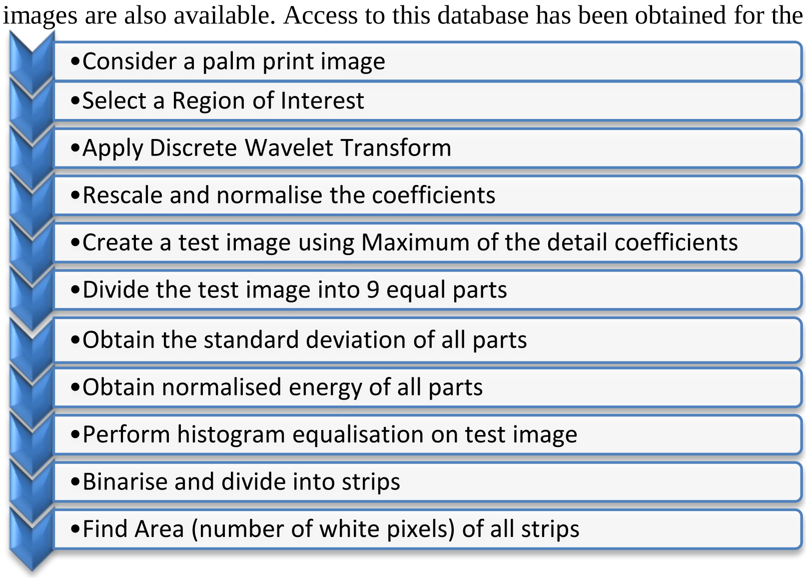


Figure1: Sequence of experimentation

The Image Processing Toolbox and Neural Network Toolbox of MATLAB R2012 has been used for the experimentation.

Palm print Region of Interest has been considered in the experimental work carried out to extract different features. Haar Wavelet transform has been applied to the ROI. This paper presents a different technique of post processing on the wavelet coefficients. The maximum values amongst the three detailed coefficients (Horizontal, Vertical, Diagonal coefficients) have been chosen. The resulting matrix has been rescaled and normalized. This image has subjected to stretching and histogram equalisation. Finally a self adaptive threshold has been used to obtain a binarised image. Figure 1 shows the sequence of processing undertaken in order to obtain the feature vector.

Figure 1 contains the sample images of ten palms of different persons that have been chosen from IITD database for experimental work.

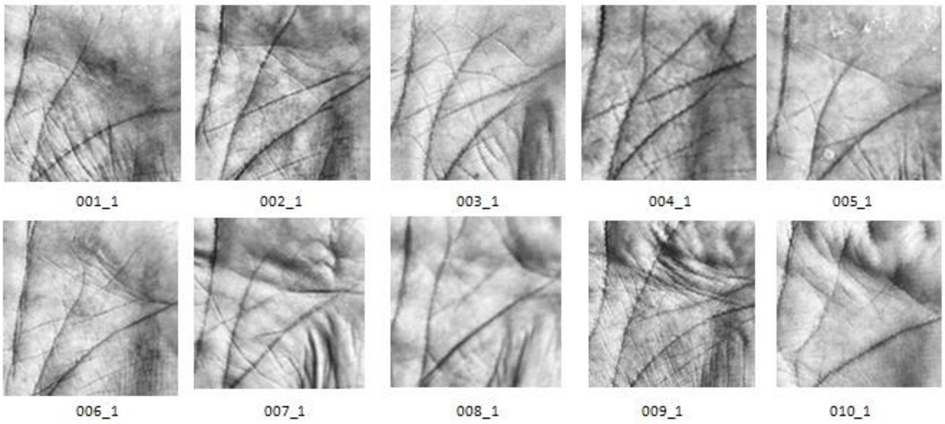
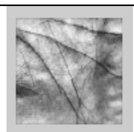
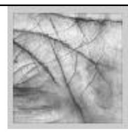
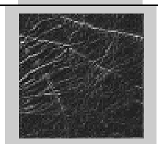
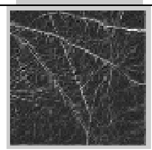
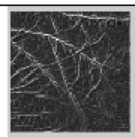
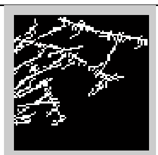
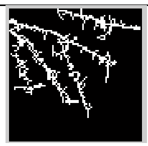
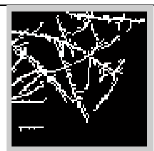


Figure 1: Sample ROI of different persons

The square shaped ROI has resolution of 150x150 pixels. Wavelet transform and feature extraction has been done of the ROIs. Table I shows the processing stages of sample images.

Sample images	Person 1	Person 2	Person 3
Palm Image			
ROI			
Maximum of H,V,D detail wavelet coefficients			
Binary ROI			

IV. FEATURE EXTRACTION

The features extracted are Standard deviation, Wavelet energy and Area.

For finding standard deviation, the test image has been subjected to stretching. Histogram stretching is used to shift the pixel values to fill the entire brightness range, resulting in high contrast. This stretched image has been divided into 9 parts each of size 25x25 so as to ensure that the corresponding parts of the palm image are compared. The standard deviation is a commonly used statistical parameter for measurement of variability from the average. Hence standard deviation values for all 9 parts have been found and considered as feature vector.

For finding energy, the same stretched image obtained above has been used. Energy has been computed as square root of sum of squares of pixel values. Normalised energy for all 9 blocks is chosen as feature set.

For finding Area, Histogram Equalisation has been performed on the test image. This image has been binarised using a self adaptive threshold. The resulting image has been divided into 3 horizontal strips in upper region, 3 vertical strips closer to the thumb and 3 diagonal strips in the central region of 10 pixels width. Area, which is the number of white pixels, of all 9 strips have been used as a feature vector.

V. NEURAL NETWORK IMPLEMENTATION

For implementing feature matching, a 3 layer feed forward back propogation neural network has been used. . For the study undertaken 10 persons have been considered from IIT Delhi Palmprint Database with five images of each person Four of these 5 images have been used for training the network.

Analysis has been done by considering individual feature set as well as combination of 2 or 3 feature sets. If only one type of feature is considered, there are 9 neurons in input layer, 10 in hidden layer and 10 in output layer. When 2 feature sets have been combined, there are 18 neurons in input layer, 15 in hidden layer and 10 neurons in output layer. For combination of all three feature sets, there are 21 neurons in input layer, 20 neurons in hidden layer and 10 neurons in output layer.

The confusion matrix has been obtained for each case. Figure 2 shows a confusion matrix. Table II gives the overall accuracy obtained from the confusion matrix for each case.

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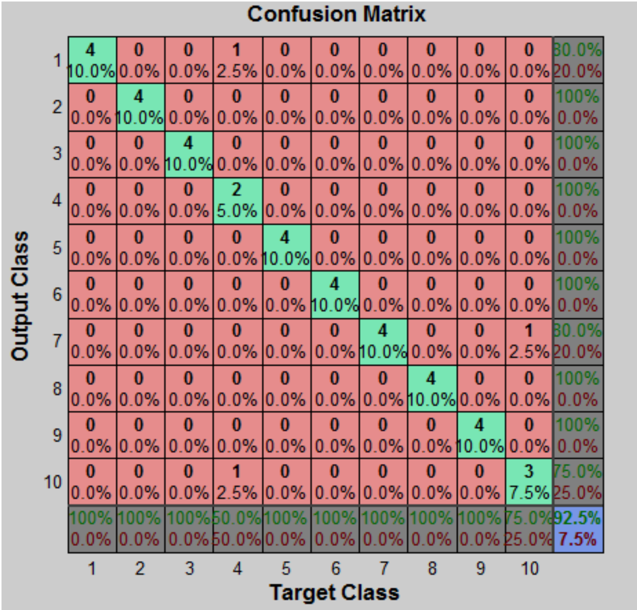

Figure 2: Confusion matrix for feature set with standard deviation values

TABLE II OVERALL ACCURACY FROM CONFUSION MATRIX

Sr.no.	Features considered	Size of feature vector	Overall Accuracy
1	Normalised Energy	9	90%
2	Standard deviation	9	92.5%
3	Normalised Area	9	82.5%
4	Normalised Energy + Standard deviation	18	85%
5	Standard deviation + Normalised area	18	85%
6	Normalised energy and Normalised area	18	87.5%
7	Normalised energy + Standard deviation + normalised area	21	90%

VI. CONCLUSIONS

From the results obtained, it is seen that using standard deviation as feature set has highest accuracy. Incorporating normalized energy also has high accuracy, but area as a feature set comparatively has low accuracy. When area is combined with other features, the accuracy improves. However, there is no significant increase in accuracy, when all the features are used. One can select a small feature vector with the feature values leading to high accuracy. This work can be further continued to identify other features to as to improve the accuracy further. A large dataset can be used for training the neural network and implement it for identifying more number of persons.

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