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An Efficient Biometric Identification Using Transform Domain and Spatial Domain Techniques

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ABSTRACT: From different methods for personal identification, biometric features are most concerned. One of robust biometrics for personal identification is palm print. Feature extraction from palm area is important issue and can determine complexity and efficiency of identification system. In this paper we propose palm print identification using Transform Domain and Spatial Domain Techniques. Histogram equalization is used on palm print to enhance contrast of an image. The DWT is applied on Histogram equalized image to generate LL, LH, HL and HH bands. Then LL band is converted into DCT coefficients using DCT. PCA is applied on DCT coefficients to generate features. The test and database features are compared using Euclidean Distance (ED). It is observed that the proposed method gives better performance compared to existing method.

KEYWORDS: Pre-processing, Histogram equalization, Discrete wavelet transform (DWT), Discrete cosine transform (DCT), Principle component analysis (PCA), Euclidean distance (ED).

I. INTRODUCTION

In recent years, biometric based personal identification is considered as a reliable method. Biometric are unique, reliable and stable physical or behavioural characteristics that can be effectively used for personal identification. Because of these characteristics these systems can provide a higher level of accuracy is security systems [1].

Iris, fingerprint, hand geometry, and palm print are most used biometric for personal identification. Palm print has several advantages in comparison with other biometrics, which make it suitable for identification [2]. In comparison with fingerprint and hand geometry, palm print contains more rich information, so they are more distinctive. Also, palm print is easily captured even with lower resolution devices, which would be cheaper. By capturing palm print, all palm features such as hand geometry, minutiae features, principal and wrinkles could be combined to build a more accurate and robust multi-modal biometric system.

Feature extraction from palm area is critical step in palm print identification. There are many researches which performed for palm print identification. In general there are two types of features that used in these systems; statistical and structural features [3]. From first category we can mention Eigen palm [4], fisher-palm [5], Fourier transform [6], Gabor filter [7], and wavelet transform [8]. Principal lines, creases, delta points, minutiae [9-11] are listed in structural features.

Texture-based analysis shows more powerful to extract image representation features for classification. For example, Gabor filters can be applied to either the whole palm or the specific palm regions to extract the texture changes of the palm. Due to their superior performance, many works have focused on using the Gabor wavelet representations [12-14]. Because of most benefits of texture-based features, this type of features are used in this paper All of palm print acquired by hand scan device is not suitable for identification. So at first region of interest (ROI) extracted from palm print to reduce redundancy from acquired image. In this paper, we present a new method for ROI extraction based on center of mass of palm print image. Contourlet transform is an efficient tool for extraction of smooth contours by using multi-scale and directional filter banks. Therefore, this transform is applied on ROI to extract contours. Depending on number of decomposition levels, some sub-bands are extracted. The gray-level co-occurrence matrix (GLCM) method is a way of extracting second order statistical texture features. GLCM of each sub-band is calculated to develop feature vector. All features are not suitable and feature conditioning must be performed to reduce the dimensionality of feature vector. For this purpose, linear discriminant analysis (LDA) is used. Support vector machine (SVM) is efficient classifier that is used widely in classification-based systems. Efficiency of proposed system measured by means of correct classification rate (CCR). From available databases, Hong Kong Polytechnic University (PolyU) palm print database is selected to evaluate the performance of proposed system. Experimental results on 200 different palms from this database indicate the robustness of proposed system in palm print identification.

II. LITERATURE SURVEY

Gyaourova and A. Ross [1] have proposed an indexing technique that can either employ the biometric matcher that is already present in the biometric system or use another independent matcher. Index codes are generated for each modality using the corresponding matcher. During retrieval, the index code of the probe is compared against those in the gallery using a similarity measure to retrieve a list of candidate identities for biometric matching. The proposed indexing technique on a chimeric multimodal database resulted in a reduction of the search space by an average of 84% at a 100% hit rate. The main factor for the amount of speedup during identification was the penetration rate of the indexing.

Dai and Zhou [2] introduces high resolution approach for palm print recognition with multiple features extraction. Features like minutiae, density, orientation, and principal lines are taken for feature extraction. For orientation estimation the DFT and Radon-Transform-Based Orientation Estimation are used. For minutiae extraction Gabor filter is used for ridges enhancement according to the local ridge direction and density. Density map is calculated by using the composite algorithm, Gabor filter, Hough transform. And to extract the principal line features Hough transform is applied. SVM is used as the fusion method for the verification system and the proposed heuristic rule for the identification system.

A. Kong and D. Zhang [3] have presented a novel feature extraction method, the Competitive Coding Scheme for palm print identification. This scheme extracts the orientation information from the palm lines and stores it in the Competitive Code. An angular match with an effective implementation is developed for comparing Competitive Codes. Total execution time for verification is about 1s, which is fast enough for real-time applications. The proposed coding scheme has been evaluated using a database with 7,752 palm print images from 386 different palms. For verification, the proposed method can operate at a high genuine acceptance rate of 98.4% and a low false acceptance rate of 3*10-6.

Jiaa, Huanga and Zhang [4] have proposed palm print verification based on robust line orientation code. Modified finite Radon transform has been used for feature extraction, which extracts orientation feature. For matching of test image with a training image the line matching technique has been used which is based on pixel-to-area algorithm.

D. Huang, W. Jia, and D. Zhang [5] proposed a novel algorithm for the automatic classification of low-resolution palm prints. First the principal lines of the palm are defined using their position and thickness. Principal lines are defined and characterized by their position and thickness. A set of directional line detectors is devised for principal line extraction. By using these detectors, the potential line initials of the principal lines are extracted and then, based on the extracted potential line initials, the principal lines are extracted in their entirety using a recursive process. The local information about the extracted part of the principal line is used to decide a ROI and then a suitable line detector is chosen to extract the next part of the principal line in this ROI. After extracting the principal lines, some rules are presented for palm print classification. The palm prints are classified into six categories considering the number of the principal lines and their intersections. From the statistical results in the database containing 13,800 palm prints, the distributions of categories 1–6 are 0.36%, 1.23%, 2.83%, 11.81%, 78.12% and 5.65%, respectively. The proposed algorithm classified these palm prints with 96.03% accuracy.

Zhang, Kong, You and Wong [6] have proposed online palm print Identification. The proposed system takes online palm prints, and uses low resolution images. Low pass filter and boundary tracking algorithm is used in pre-processing phase. Circular Gabor filter used for feature extraction and 2-D Gabor phase coding is used for feature representation. A normalized hamming distance is applied for matching.

J. You, W. Kong, D. Zhang, and K. Cheung [7] proposed a dynamic selection scheme by introducing global texture feature measurement and the detection of local interesting points. Our comparative study of palm print feature extraction shows that palm print patterns can be well described by textures, and the texture energy measurement possesses a large variance between different classes while retaining high compactness within the class. The coarse-level classification by global texture features is e4ective and essential to reduce the number of samples for further processing at fine level. The guided searching for the best matching based on interesting points improves the system efficiency further.

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III. PROPOSED METHOD

The proposed system has divided into few modules: Pre-processing, Histogram equalization, Discrete wavelet transform (DWT), Discrete cosine transform (DCT), Principle component analysis (PCA), Euclidean distance (ED). Initially we had taken test image and apply preprocessing technique like rgb to gray conversion, filtering and enhancement and all, later we had applied dwt transform, once if you apply dwt transform means you will get four sub bands like LL,LH,HL and HH. In that we had taken LL Subband for applying DCT also we had taken PCA features for DCT coefficient. Same process we are applying for all database images and comparing features with test image features using Euclidean distance.

Proposed Method Block diagram:

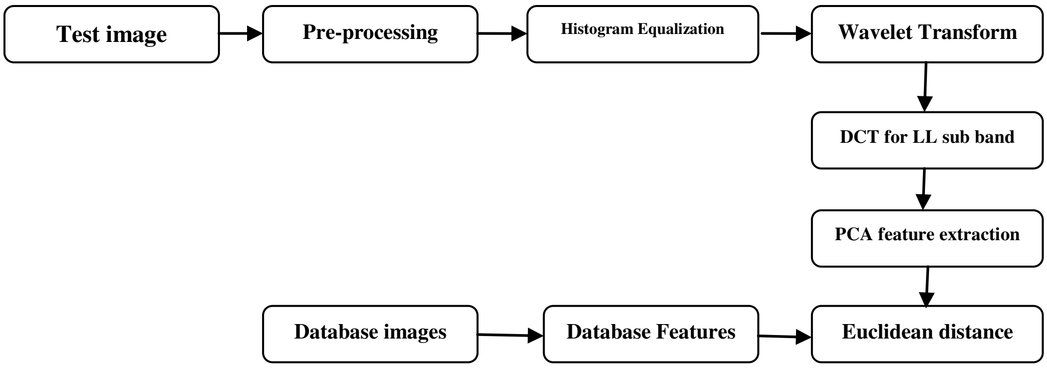

Fig.1 block diagram of proposed method

A. Pre-processing:

In Pre-processing of the proposed system the following steps namely Gray scale conversion, Noise removal is involved. In computing, a gray scale digital image is an image in which the value of each pixel is a single sample, it carries only intensity information. Images of this sort, also known as black-and-white, are composed exclusively of shades of gray, varying from black at the weakest intensity to white at the strongest. Gray scale images are distinct from one-bit bi-tonal black-and-white images, which in the context of computer imaging are images with only the two colors, black, and Gray scale images have many shades of gray in between. Gray scale images are often the result of measuring the intensity of light at each pixel in a single band of the electromagnetic spectrum, and in such cases they are monochromatic proper when only a given frequency is captured. And the gray scale conversion of image is given by [17].

$$\mathrm{gray}(i,j) = \{0.29 * \mathrm{rgb}(:,:,1) + 0.59 * \mathrm{rgb}(:,:,2) + 0.11 * \mathrm{rgb}(:,:,3)\}; \qquad (1)$$

Generally we are using median filter to suppress the noise. The procedures are

1, Arranging matrix pixel value in the form of ascending order.

2, Find the median value of that matrix.

3, Replace that value into that noisy pixel location.

B. Histogram Equalization

Basically the histogram equalization spreads out intensity values along the total range of values in order to achieve higher contrast. This method is especially useful when an image is represented by close contrast values, such as images in which both the background and foreground are bright at the same time, or else both are dark at the same time. Here are the steps for implementing this algorithm.

1. Create the histogram for the image.
2. Calculate the cumulative distribution function histogram.
3. Calculate the new values through the general histogram equalization formula.
4. Assign new values for each gray value in the image.

C. Discrete Wavelet Transform

The wavelet transform uses this approach. The wavelet transform or wavelet analysis is probably the most recent solution to overcome the shortcomings of the Fourier transform. In wavelet analysis the use of a fully scalable modulated window solves the signal-cutting problem. The window is shifted along the signal and for every position the spectrum is calculated.

The discrete wavelet transform (DWT) was developed to apply the wavelet transform to the digital world. Filter banks are used to approximate the behavior of the continuous wavelet transform. The signal is decomposed with a high-pass filter and a low-pass filter. The coefficients of these filters are computed using mathematical analysis and made available to you. See Appendix B for more information about these computations.

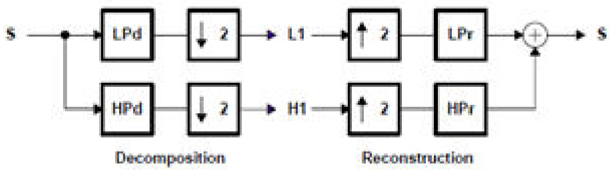

Figure 2 Discrete Wavelet Transform

Where
LPd: Low Pass Decomposition Filter
HPd: High Pass Decomposition Filter
LPr: Low Pass Reconstruction Filter
HPr: High Pass Reconstruction Filter

In wavelet decomposing of an image, the decomposition is done row by row and then column by column. For instance, here is the procedure for an N x M image. You filter each row and then down-sample to obtain two N x (M/2) images. Then filter each column and subsample the filter output to obtain four (N/2) x (M/2) image, the one obtained by low-pass filtering the rows and columns are referred to as the LL image. The one obtained by low-pass filtering the rows and high-pass filtering the columns is referred to as the LH images. The one obtained by high-pass filtering the rows and low-pass filtering the columns is called the HL image. The sub image obtained by high-pass filtering the rows and columns is referred to as the HH image. Each of the sub images obtained in this fashion can then be filtered and sub sampled to obtain four more sub images. This process can be continued until the desired sub band structure is obtained.

D. Discrete Cosine Transform

The objective of this document is to study the efficacy of DCT on images. This necessitates the extension of ideas presented in the last section to a two-dimensional space. The 2-D DCT is a direct extension of the 1-D case and is given by eqn.

$$C(u,v) = \alpha(u)\alpha(v)\sum_{x=0}^{N-1}\sum_{y=0}^{N-1} f(x,y)\cos\left[\frac{\pi(2x+1)u}{2N}\right]\cos\left[\frac{\pi(2y+1)v}{2N}\right],$$

$$f(x,y) = \sum_{u=0}^{N-1}\sum_{v=0}^{N-1} \alpha(u)\alpha(v)C(u,v)\cos\left[\frac{\pi(2x+1)u}{2N}\right]\cos\left[\frac{\pi(2y+1)v}{2N}\right],$$

The 2-D basis functions can be generated by multiplying the horizontally oriented 1-D basis functions (shown in Figure 3) with vertically oriented set of the same functions. The basic functions for $N = 8$ are shown in. Again, it can be noted that the basic functions exhibit a progressive increase in frequency both in the vertical and horizontal direction. The top left basis function of results from multiplication of the DC component with its transpose. Hence, this function assumes a constant value and is referred to as the DC coefficient.

E. Principle Component Analysis

PCA is a useful statistical technique that has found application in fields such as face recognition and image compression, and is a common technique for finding patterns in data of high dimension. It is a way of identifying patterns in data, and expressing the data in such a way as to highlight their similarities and differences. Since patterns in data can be hard to find in data of high dimension, where the luxury of graphical representation is not available, PCA is a powerful tool for analyzing data. The other main advantage of PCA is that once you have found these

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patterns in the data, and you compress the data, i.e. By reducing the number of dimensions, without much loss of information.

Method:

Step 1: Get some data
Step 2: Subtract the mean
For PCA to work properly, you have to subtract the mean from each of the data dimensions.
Step 3: Calculate the covariance matrix
Step 4: Calculate the eigenvectors and eigen values of the covariance Matrix.
Step 5: Choosing components and forming a feature vector and drive new data set.

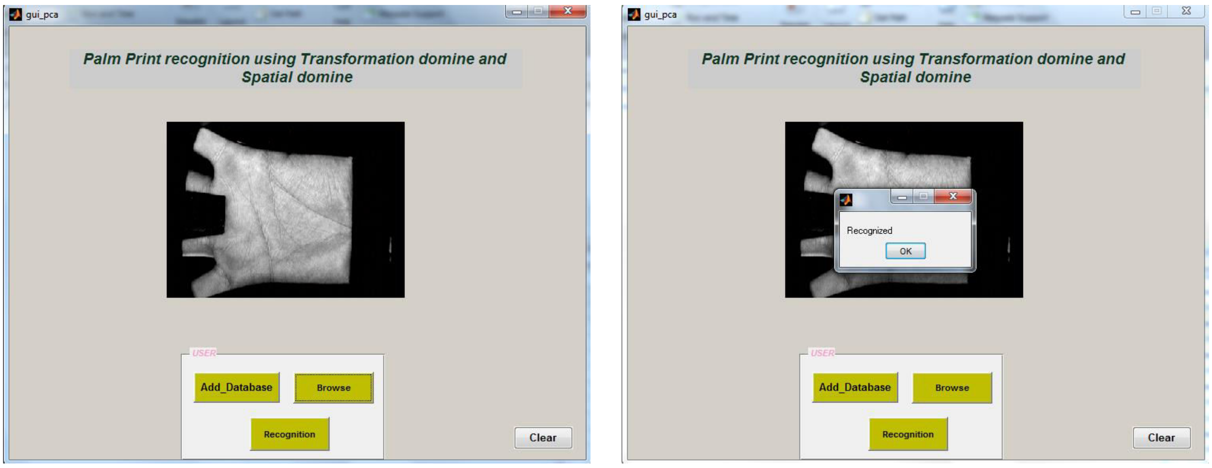
F. Euclidean Distance

The Euclidean distance or Euclidean metric is the "ordinary" (i.e straight line) distance between two points in Euclidean space. With this distance, Euclidean space becomes a metric space. The associated norm is called the Euclidean norm. below we had mention the expression.

$$d(x,y) = ||x-y||^2 = \sum_{i=1}^{k}(x_i - y_i)^2$$

IV. RESULTS AND DISCUSSION

In our proposed method we had implemented multi transform and spatial domain technique, for every test image initially we had applied pre-processing technique, then we had performed wavelet transform and feature extraction using cosine transform and principle component analysis, and this extracted features we had compared with database feature using distance calculation method, according to efficiency, our system has more efficient then other existing methods. We are getting near about 98.8%.



(a) Test image

(b) Result

Fig.3. Result of proposed method (a) Test image (b) Authorized person result.

V. CONCLUSION

In this paper, a new algorithm for palm print identification based on transformation and spatial domain was presented. At first, we introduced a new method discrete wavelet transform, and we had taken LL sub band of that test image and apply discrete cosine transform, and extract the pca features for test image and compare the features with database image using Euclidean distance. Also we got 99.47% for 200 different palms from PolyU database, which shows the efficiency of proposed algorithm in comparison with recently proposed algorithms for palm print identification.

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