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# Hand-based biometrics recognition using Distance Measures

P.Sagunthala,
Research Scholar,
Department of Computer Science,
Periyar University, Salem-636011,
Tamilnadu, India.
Pon.sagu15@gmail.com

H.Hannah Inbarani,
Assistant Professor,
Department of Computer Science,
Periyar University, Salem-636011,
Tamilnadu, India.
hhinba@gmail.com

***Abstract—*** Palmprint and middle finger identification are very useful for personal identification or verification. To find central part of the palmprint for region of interest. For discriminant features, statistical information and structural information are used which are extracted using locality preserving projections (LPP) based on wavelet transform (WT). The proposed work contains different types of Distance Measures algorithms, it includes Euclidean distance, Hausdorff distance, Modified Hausdorff distance and it is compared with PCA algorithm for similarity. The developed algorithms are used to classify training set of images and then testing set of images is used for verification. Providing authorized users with secured access to the services is a challenge to the personal identification system. Performance of the developed algorithm on College of Engineering Pune Palmprint database is compared using various distance measures. Palmprint and middle finger gives efficient solution for verification.

***Keywords***—Biometrics recognition ,Palmprint ,middle finger, ROI Extraction, Feature Extraction, Wavelet transform, Template Matching, Principle component Analysis.

## 1. INTRODUCTION

Biometrics-based personal identification is playing important roles in the applications of public security, access control, forensic, banking, etc. In order to obtain good recognition performance, most of the systems require at least two samples per person for training. When using two enrollment images per user instead of one, the identification error could be significantly decreased [1]. Unfortunately, such a requirement cannot always be satisfied in real-world applications. Biometrics recognition has been investigated and became one of the major research contents [2]. However, HBBR may lead to bad recognition result. Generally speaking, there are two main approaches to improve the performance of HBBR. The first approach is to acquire the additional information of the biometrics. For example, 3D information was acquired and fused with 2D palmprint, which achieved a higher recognition rate [3, 4]; palm vein and palmprint images were combined for achieving lower error rates in palm recognition [5]; and multispectral palmprint analysis could outperform the traditional methods [6]. Another approach is to fuse multimodal biometrics. For instance, face and palmprint have been combined for personal authentication [7]; palmprint and finger-knuckle-print were integrated for single hand-based biometrics [8]. In this paper, we focus on the latter approach combining two hand-based biometrics: palmprint and middle finger. There are two main advantages by doing this: (a) these biometrics can be acquired from the same sensor, which is more economic and convenient; and (b) there is strong supplement between these two traits [9].

There are two popular approaches to palmprint recognition. The first approach is based on the palmprint statistical features while the other on structural features. For statistical-based palmprint recognition approach, the works that appear in the literature include eigenpalm [10], fisherpalm, Laplacianpalm, Fourier transform, wavelet transform (WT) [11], Palm Code, Fusion Code, Competitive Code, BOCV and Ordinal Code, etc. Another important feature extraction approach is to extract structural information, like principal lines, wrinkles, and creases, from the palm for recognition [16].

They usually involve in determining the lengths and widths of the hands and fingers at different points. Subsequently, finger shape features and statistical features of finger inner surface are exploited. Eigenfinger features [10] are extracted from finger-strip region (excluding finger shape); like finger-knuckle-print the structural features contained in the finger inner surface can also be used for individual verification and the whole finger-based systems, which contain finger statistical features and structural features, are considered to obtain better result [9].

By using wavelet transform (WT) on an image, we obtain four sub-bands including the coarse approximation as well as horizontal, vertical, and diagonal details. The coarse approximation contains the highest energy distribution content and yields a better recognition rate, while the high-frequency sub- band contain the principal lines and wrinkles structural information. In order to reduce the influence of affine transform in applying WT, a low-pass filtering is applied on the horizontal and vertical sub-bands of palmprint to remove the trivial information and enhance the robustness of structural information. Because the diagonal detail contains more noise, it is not used for personal recognition. Locality preserving projection (LPP) is used to extract discriminate features from selected sub-bands.

We call the feature based on low-pass sub-band as the statistical feature, while the feature based on high-pass sub-band as structural feature. We fuse each sub-band feature of palmprint at the feature level fusion (FLF) to acquire more effective ability, so does the middle finger image. Considering the weak correlation between palmprint and middle finger, fusion at the matching-score level is used. The final decision (the user is identified or rejected) is based on the thresholding. The advantages of the proposed method are as follows: WT can extract the structural information as well as the coarse approximation. The more sufficient information can be obtained by fusing them; and a low-pass filtering is used to enhance the robustness of structural information and reduce the influence of the affine transformation of palmprint, which improves the discriminant ability of high-frequency sub-bands.

The rest of the paper is organized as follows: Section 2 presents an overview of our system which includes the database acquirement, image preprocessing, statistical information and structural information extraction and fusion, and the corresponding classifier. The experimental results are reported in Section 5. The conclusions and future work are presented in Section 6.

## 2. SYSTEM DESCRIPTION

The proposed hand-based HBBR system mainly includes three stages, i.e., the preprocessing stage, the feature extraction and fusion stage, and the classification stage. The framework of the proposed method is shown in Fig.2. Given an input hand image, the regions of interest (ROI) of palmprint and middle finger are aligned firstly. The parallel feature extractions are implemented for statistical information and structural information extraction. Then, fuse palmprint and middle finger features with the sum rule for final classification.

### 2.1. DATA BASE DESCRIPTION

The database consists of 8 different images of single person's palm. The database consists of total 1306 images pertaining to 166 people. The database was collected over a period of one year. All the images are jpg format. The images were captured using digital camera; the resolution of images is 1600x1200 pixels. Fig.1 Contains Digital Camera.

**Fig.1 Digital Camera**

Input hand image

↓

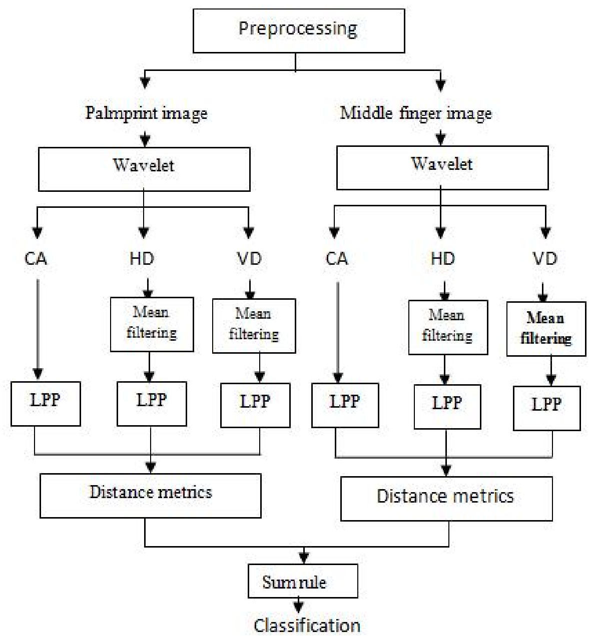


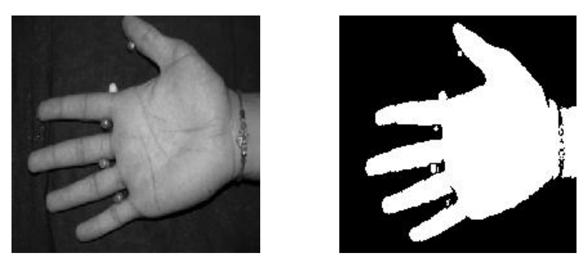

**Fig.2 Block-diagram of the proposed HBBR system**

### 2.2 THE PREPROCESSING STAGE

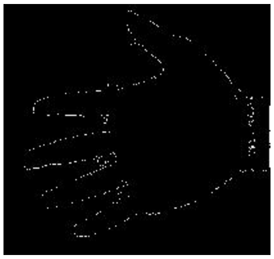
#### 2.2.1 ROI location

Preprocessing is used to align different palmprint images and to segment the central parts for feature extraction. Most of the preprocessing algorithms employ the key points between fngers to set up a coordinate system. Preprocessing involves generally five common steps; the fig.3 shows the Palmprint and Middle finger Image.

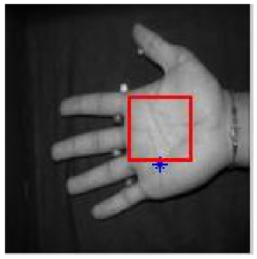
(1) Transform original RGB-mode images to gray-sale mode
(2) Binarizing the hand images
(3) The hand contour
(4) Detecting the key points
(5) Extracting the central parts



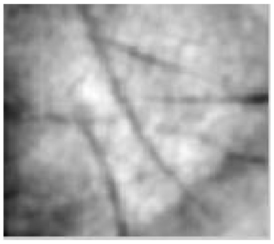
A B



C

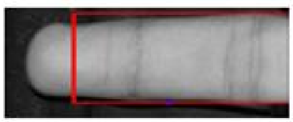


D

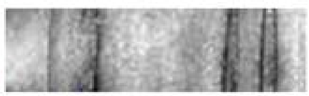


E

F



G



H

Fig.3: Palmprint and middle finger [A.Grayscale Image, B.Binarized Image, C.Contour Image, D.Palmprint Detection Point, E.Palmprint ROI, F.Middlefinger, G.Middle Finger Detection Point and H.Middle Finger ROI]

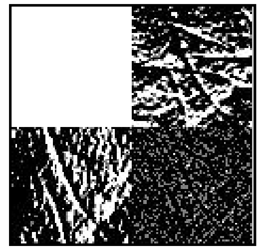
### 2.3 WAVELETS

Wavelet decomposition is useful for image processing successfully. In this used one-level 2D WT type wavelet decomposition on our image set. 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.

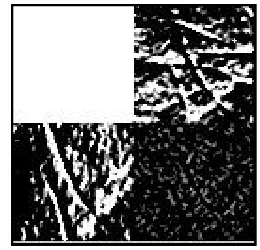
A large variation of palmprint image can be seen in high frequency component and small effect in low frequency component. Each level of wavelet decomposition divides original palmprint image into four sub-bands leading to multiresolution analysis. The sub-band contains coarse approximation horizontal, vertical and diagonal details. Each sub-band can be used to extract features. The 2D discrete wavelet transform is an effective technique in representing the palmprint images with isolated point's singularities meaning that 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 2$^{nd}$ level of 2D discreet wavelet is applied. Fig.4 shows the decomposed image and smoothens with mean filter Image.

After one-level 2D Wavelet, an image I can be represented with it sub-band like,

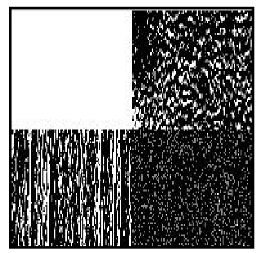
$$\mathbf{I = IA + IH + IV + ID}$$



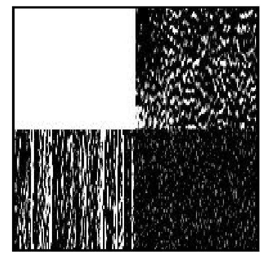
(a) Palm Wavelet Decomposition



(b) Palm Wavelet using mean filter



(c) Middle Finger Wavelet Decomposition



(d) Middle finger Wavelet using mean filter

**Fig.4 Wavelet decomposed and mean filter Images**

### 2.4 THE FEATURE EXTRACTION

More information should be obtained to improve the performance of HBBR. Statistical-based and structural-based Information are two popular approaches to Palmprint and middle finger recognition. These features are extracted by the application of WT on an image. The coarse approximation contains the highest energy distribution content, and the high-frequency sub-bands contain the principal lines and wrinkles structural information. The more discriminate feature can be obtained by fusing statistical and structural information at FLF. In order to reduce the influence of affine transform in applying WT, a low-pass filtering is applied on the horizontal and vertical sub-bands to remove the trivial information and enhance the robustness of Palmprint structural information.

Palm lines are obvious features in Palmprint. The features of the principle line of palm image is shown in Fig.5 Researchers employ existing edge detection methods and develop edge detectors to extract the palm lines. The extracted palm lines are either matched directly or represented in other formats for effective matching. Although at the beginning of palmprint research, some researchers concentrate on line-based approach, it is not the focus of current Palmprint research since it is difficult to accurately extract palm lines from low-resolution palmprint images.

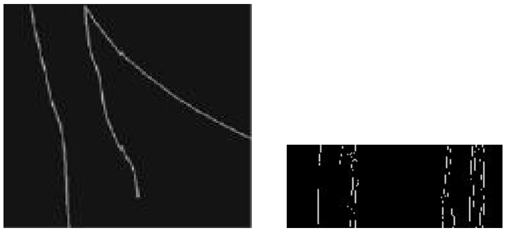


**Fig.5 Palmprint & Middle Finger Feature Extraction Line**

## 3. CLASSIFICATION STAGE

The classification stage we use three different types of Distance Measures algorithm namely, the Euclidean distance, Hausdorff distance, Modified hausdorff distance. Finally we find similarity using PCA algorithm.

### A. Euclidean distance

$$d(x,y) = \sqrt{\sum_{i}^{n} (x_i - y_i)^2}$$

$$= \sqrt{\sum_{i} x_i^2 + \sum_{i} y_i^2 - 2\sum_{i} x_i y_i}$$

### B. The Hausdorff distance

For a set X = {$x_1,\ldots,x_p$} and Y = {$y_1,\ldots,y_p$}

We can define the Hausdorff distance as:

$$H(X,Y) = \max(h(X,Y), h(X,Y))$$

With the directed Hausdorff distance defined as:

$$\vec{h}(X,Y) = \max_{x \in X} \min_{y \in Y} \| x - y \|$$

This means that $\vec{h}(X,Y)$ in effect ranks each point of A based on its distance to the nearest point of B, and then uses the largest ranked such point as the distance. In the end the H(A,B) chooses the maximum of both $\vec{h}(X,Y)$ and $\vec{h}(X,Y)$.

### C. The Modified Hausdorff distance

$$\vec{h}(X,Y) = \frac{1}{N} \sum_{x \in X} \min_{y \in Y} \| x - y \|$$

## 4. EXPERIMENTAL RESULTS

We performed two types of experiments on the established database: identification and verification. In identification, we do not know the class of the input hand image but want to identify which class it belongs to. In verification, the class of input hand image is known and each of the samples is matched with all the other hand samples in the database.

For WT, we use a HAAR type 1-level wavelet decomposition to obtain sub-band images. Because the HAAR wavelet has the smallest vanishing moment, much image structure information is in the high-frequency wavelet coefficients. Fig.6 contains Number of features & Fig.7 shows FAR&FRR for three distances. FAR contains False Acceptance Rate. FRR contains False Rejection Rate. Modified Hausdroff distance gives best result.

**False Acceptance Rate (FAR):**

False acceptance is the number of times the system accepts an unauthorized user incorrectly. Ratio of the number of false acceptance divided by the number of identification attempts.

$$\text{FAR} = \frac{\textit{Number of Accepted Imposter claims}}{\textit{Total number of Imposter accesses}} \times 100\%$$

**False Rejection Rate (FRR):**

False rejection is the number of times the system rejects an authorized user incorrectly. Ratio of the number of false acceptance divided by the number of identification attempts.

$$\text{FRR} = \frac{\textit{Total Number of Rejected Genuine claims}}{\textit{Total number of Genuine accesses}} \times 100\%$$

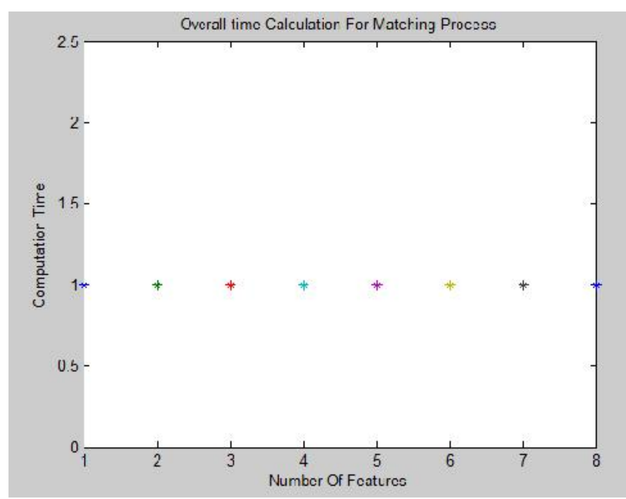



**Fig.6 Features**

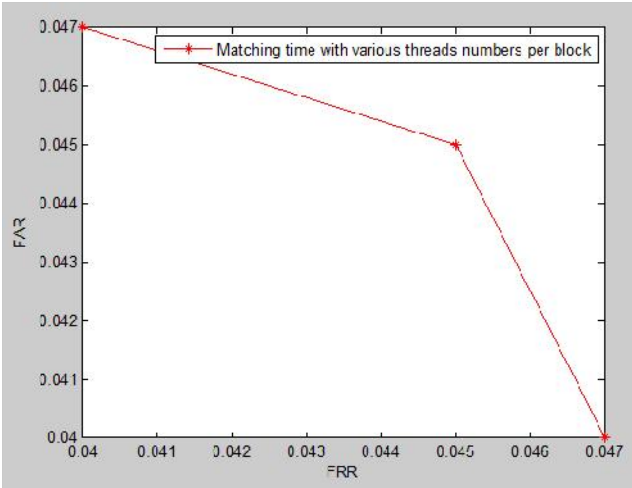



**Fig.7 FAR&FRR for distance Metrics**

### 4.1 VERIFICATION

The verification experiments were performed by using each of the palmprint fusion and middle finger fusion feature. We also let the first sample of each class in the database to be template and use the other samples to match with all of the templates. A successful matching is called intraclass matching or genuine, the unsuccessful matching is called interclass matching or imposter.

### 5. PERFORMANCE COMPARISION

We also compared three distance matching algorithms. The proposed features of palmprint and middle finger give a highest recognition rate compared with other. To use PCA for similarity purpose, its gives better result. The performance analysis shown in Fig.8 Modified hausdroff distance gives better rejection rate 99.5%.

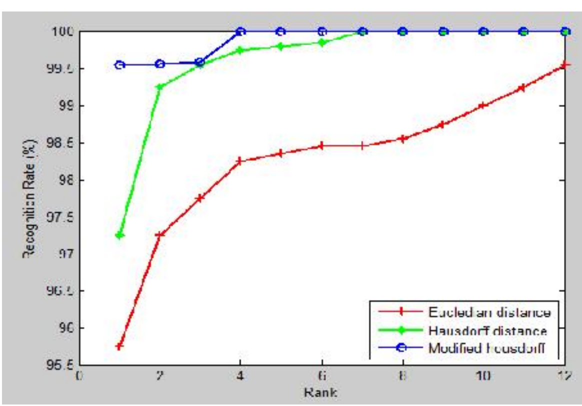



**Fig.8 performance analysis for distances**

### 6. CONCLUSIONS

We have developed a hand-based HBBR system by palmprint and middle finger image. After the hand image was captured, the regions of palmprint and middle fingers were extracted; the statistical and structural information was calculated by using wavelet transform. We utilized smooth operator to enhance the robustness of structural features contained in palmprint high-frequency sub-band. The discriminant features of each modal were extracted by using LPP transform at feature level. Finally, the proposed approach matches and classifies the hand images. A series of verification experiments were performed on the hand database with 1306 samples from 166 individuals. The experimental results showed that the performance of each modal could be improved which was comparable with conventional palmprint and hand-based biometric technologies. The future improvement of this research will continue on developing other fingers or finger-knuckleprint for fusion to improve the ability of single sample hand-based biometrics.

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