Image Fusion using PCA in Multifeature Based Palmprint Recognition

Nirosha Joshitha J, R. Medona Selin

Abstract:- ***Biometric technology offers an effective approach to identify personal identity by using individual's unique, reliable and stable physical or behavioral characteristics. Palmprint is a unique and reliable biometric characteristic with high usability. The composite algorithm used estimates the orientation field of the palmprint from which multiple features is extracted. Fusion increases the system accuracy and robustness in person recognition. The first kind of fusion is multiple features from one palmprint image. The existing system uses this technique through multiple features like minutiae, density map orientation, and principal line map from each palmprint image. The proposed paper uses multi-image fusion. The PCA-based image fusion technique adopted here improve resolution of the images in which images to be fused are firstly decomposed into sub images with different frequency and then the information fusion is performed and finally these sub images are reconstructed into a result image with plentiful information. The PCA algorithm builds a fused image of several input images as a weighted superposition of all input images. The resulting image contains enhanced information as compared to individual images. This image is used for palmprint recognition. A database containing multiple images of the same palmprint is used. The task of palmprint matching is to calculate the degree of similarity between an input test image and a training image from database. A normalized Hamming distance method is adopted to determine the similarity measurement for palmprint matching.***

Index Terms — Density map, Hamming distance, Multi-image fusion, Minutiae, PCA, Principal line map.

I. INTRODUCTION

Biometrics refers to technologies that measure and analyze human body characteristics, such as DNA, fingerprints, eye retinas and irises, voice patterns, facial patterns and hand measurements, for authentication purposes. It consists of methods for uniquely recognizing humans based upon one or more intrinsic physical or behavioral traits. The reason for biometrics includes the positive authentication and verification of a person and ensuring confidentiality of information in storage or in transit. In the field of biometrics, palmprint is a novel but promising technology. Palmprint recognition has considerable potential as a personal identification technique. Palmprint is preferred because it is distinctive, easily captured by devices and contains additional features such as principal lines.

Fig. 1 shows a typical palmprint image. There are two basic features in a palmprint: ridges and creases.

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Ridges are formed by the arrangement of the mastoid in the dermal papillary layer. They come into being during the three-to four months of the fetal stage and are fixed in the adolescence stage. The ridge pattern of the palm is unique for an individual, just like the finger tip. But unlike the fingerprint, there are many creases in the palmprint.

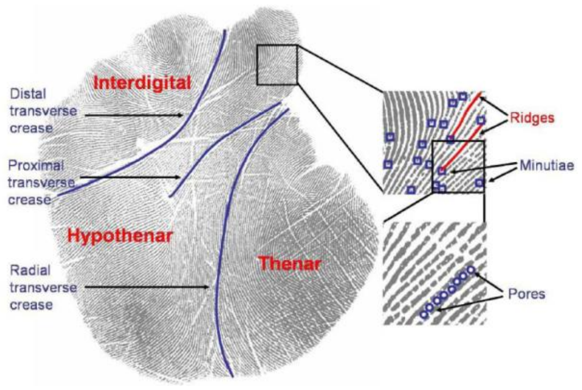

Fig 1. Palmprint Image

The creases can be further classified as immutable and mutable creases. Immutable creases mainly consist of three principal lines, namely, radial transverse crease, proximal transverse crease, and distal transverse crease. They divide the palmprint into three regions: thenar, hypothenar, and interdigital. Mutable creases mainly come from drying cracks, which come into being in spring and winter when the weather is dry and disappear when it is wet in summer and autumn. These are also easily masked by compression and noise. Both the principal lines and ridges are firmly attached to the dermis, and are immutable for the whole life.

A typical palmprint recognition system consists of five parts: palmprint scanner, preprocessing, feature extraction, matcher and database. The palmprint scanner collects palmprint images. Preprocessing 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 preprocessed palmprints. A matcher compares two palmprint features and a database stores registered templates.

II. FEATURE LEVEL RECOGNITION

The palmprint image has many unique features that can be used for personal identification. Palmprints share most of the discriminative features with fingerprints and, in addition, possess a much larger skin area and other discriminative features such as principal lines.

Initially low resolution images of the palm were used for identification. The earlier research investigates the feasibility of person identification based on feature points extracted from palmprint images [7]. In matching of palmprints, a set of feature points were extracted along palm lines and matching score was calculated among two images for recognition. Later, the palmprint was considered as a piece of texture and texture-based feature extraction techniques were applied for palmprint authentication in [6]. A 2-D Gabor filter was used to obtain texture information and two palmprint images were compared in terms of their hamming distance.

Then, online palmprint identification system employed low-resolution palmprint images to achieve effective personal identification [5]. A robust image coordinate system was used to facilitate image alignment for feature extraction. Further in [4], multiple elliptical Gabor filters with different orientations were employed to extract the phase information on a palmprint image, which is then merged according to a fusion rule to produce a single feature called the Fusion Code. The similarity of two Fusion Codes is measured by their normalized hamming distance. A dynamic threshold is used for the final decisions.

In latent palmprint matching, high-resolution palmprints (500 ppi or higher) were used from which more useful information can be extracted [3]. A fixed-length minutia descriptor, MinutiaCode, is utilized to capture distinctive information around each minutia and alignment-based minutiae matching algorithm is used to match two palmprints.

A single feature sometimes fails to be exact enough for verifying the identity of a person. By combining multiple features enhanced performance reliability could be achieved [9]. Recently, multiple features namely minutiae, density map and principal line map were extracted from a high resolution palmprint for recognition [1]. Matching accuracy was achieved with single image of a palm for recognition in all existing systems.

III. IMAGE FUSION

Palmprint is a promising biometric feature for use in access control and forensic applications. Previous research on palmprint recognition mainly concentrates on extraction of multiple features from a single sample of a palmprint. The proposed work adopts multi-image fusion with multi-featured palmprint.

In this paper, Principal Component Analysis (PCA) algorithm builds a fused image of several input palmprints as a weighted superposition of all input images. The resulting image contains enhanced information with improved resolution as compared to individual images. This image is used for palmprint recognition. Multiple features like minutiae, density map, and principal line map are reliably extracted and combined to provide more discriminatory information. The presence of a large number of creases is one of the major challenges in reliable extraction of the ridge information. Creases break the continuity of ridges, leading to a large number of spurious minutiae. Moreover, in regions having high crease density, the orientation field of the ridge pattern is obscured by the orientation of creases as it changes with season. Also the density map feature is proved to be a good supplement to minutiae for palmprint recognition.

A. *Principal Component Analysis*

Fusion is a good way to increase the system accuracy and robustness. The image fusion method tries to solve the problem of combining information from several images taken from the same object to get a new fused image. Multi-sensor image fusion is the process of combining information from two or more images into a single image. The resulting image contains more information as compared to individual images.

The paper presents PCA based image fusion to improve resolution of the images in which two images to be fused are firstly decomposed into sub-images with different frequency and then the information fusion is performed and finally these sub-images are reconstructed into a result image with plentiful information. This paper presents assessment of image fusion by measuring the quantity of enhanced information in fused images.

PCA is generalized to Multilinear PCA (MPCA) that extracts features directly from tensor representations. MPCA is solved by performing PCA in each mode of the tensor iteratively. MPCA has been applied to face recognition, gait recognition, etc.

The most straightforward way to build a fused image of several input images is performing the fusion as a weighted superposition of all input images. The optimal weighting coefficients, with respect to information content and redundancy removal, can be determined by a principal component analysis of all input intensities. By performing a PCA of the covariance matrix of input intensities, the weightings for each input image are obtained from the eigenvector corresponding to the largest eigen value.

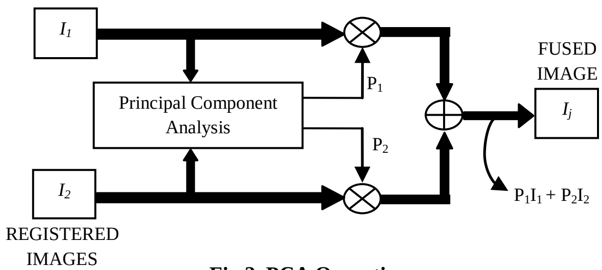

Fig 2. PCA Operation

The weights for each source image are obtained from the eigenvector corresponding to the largest eigen value of the covariance matrices of each source. Arrange source images in two-column vector.

1) Organize the data into column vector. Let S be the resulting column vector of dimension $2 \times n$.
2) Compute empirical mean along each column. The empirical mean vector M_e has a dimension 1×2.
3) Subtract M_e from each column of S. The resulting matrix X is of dimension $2 \times n$.
4) Find the covariance matrix C of matrix X i.e. $C=XX_T$ mean of expectation = cov(X).
5) Compute the eigenvectors V and eigenvalue D of C and sort them by decreasing eigenvalue. Both V and D are of dimension 2×2.
6) Consider first column of V which correspond to larger eigenvalue to compute normalized component P_1 and P_2.

$$P_1 = \frac{V(1)}{\sum V} \quad \text{and} \quad P_2 = \frac{V(2)}{\sum V} \qquad (1)$$

7) The fused image $I_f(x,y)$ is computed as below if the input images are $I_1(x,y)$ and $I_2(x,y)$.

$$I_f(x,y) = P_1 I_1(x,y) + P_2 I_2(x,y) \qquad (2)$$

Hence, Image Fusion is performed using PCA.

B. Feature Extraction

When the input data to an algorithm is too large to be processed and it is suspected to be notoriously redundant (much data, but not much information) then the input data will be transformed into a reduced representation set of features (also named features vector). Transforming the input data into the set of features is called feature extraction. If the features extracted are carefully chosen it is expected that the features set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input.

From the orientation field of the palmprint multiple features like minutiae, density map and principal line map were extracted.

1) Minutiae: For minutiae extraction, first the ridges are enhanced by the Gabor filter according to the local ridge direction and density. Image is then binarized and thinned to get the skeleton ridge image. Minutiae are extracted as the endings and bifurcation points of ridge lines. Due to the presence of large number of creases that break the continuity of ridges many spurious minutiae are formed which are removed. The similarity of two sets of minutiae is computed as the product of matching quantity score and quality score. The matching quantity score is measured by the sum of matched minutiae pairs'. The matching quality score is computed as the proportion of matched minutiae in all the minutiae within the common area.

2) Density Map: The density map is extracted simultaneously with the orientation field. The similarity of density map is product of matching quantity and quality. The matching quantity is measured by the number of matched block pairs. A matched block pair is comprised of two overlapped blocks whose ridge distance difference is within 1 pixel. The matching quality reflects the average ridge distance differences of all of the blocks in the common area.

3) Principal Line Map: The principal lines need to be distinguished from all the detected creases. The creases outside the region are erased to form the principal line energy image and the principal line direction image. The similarity of principal line maps is measured by the proportion of matched principal line energy in all of the energy within the common area. Two energy points are deemed to be matched if they are located at the same position and the direction difference between their corresponding principal lines is less than $\pi/6$.

C. Multifeature Fusion

The fusion could be achieved by simple averaging corresponding pixels in each input image.The matching scores of multiple features, including minutiae, density map, and principal line map are obtained. Then the features are combined to measure the final similarity of two palmprints.

False Accept Rate is the probability that the system incorrectly matches the input pattern to a non-matching template in the database. It measures the percent of invalid inputs which are incorrectly accepted. False Reject Rate is the probability that the system fails to detect a match between the input pattern and a matching template in the database. It measures the percent of valid inputs which are incorrectly rejected.

The discriminative power of different feature combinations is analyzed. The decreasing order of discriminative power is minutiae, density map and principal line map.

D. Palmprint Matching

Given two data sets, a matching algorithm determines the degree of similarity between them. A normalized Hamming distance used is adopted to determine the similarity measurement for palmprint matching. The similarity between the computed features of the input palmprint and the database record is done.

Let *P* and *Q* be two palmprint feature matrices. The normalized hamming distance can be defined as,

$$D_0 = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N}\left(P_R(i,j)\otimes Q_R(i,j) + P_I(i,j)\otimes Q_I(i,j)\right)}{2N^2} \quad (3)$$

where $P_R(Q_R)$ and $P_I(Q_I)$are the real part and the imaginary part of $P(Q)$, respectively; the Boolean operator,"$\otimes$" is equal to zero if and only if the two bits, $P_{R(I)}(i,j)$ and $Q_{R(I)}(i,j)$ are equal and the size of the feature matrices is $N \times N$. It is noted that D_0 is between 1 and 0. The hamming distance for perfect matching is zero.

IV. EXPERIMENTAL RESULTS

Initially the source images of the palm print are given as input. All these images were captured at different seasons at different intervals of time.

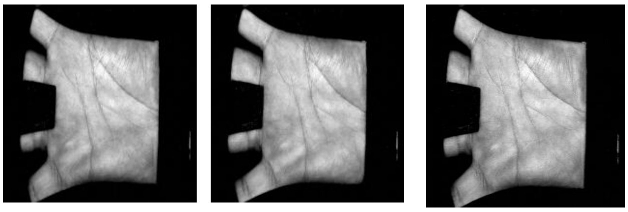

Fig 3. Input Images for feature extraction using PCA

From these input images the endings and bifurcation points of ridges i.e. Minutiae is calculated. The resulting processed image is obtained.

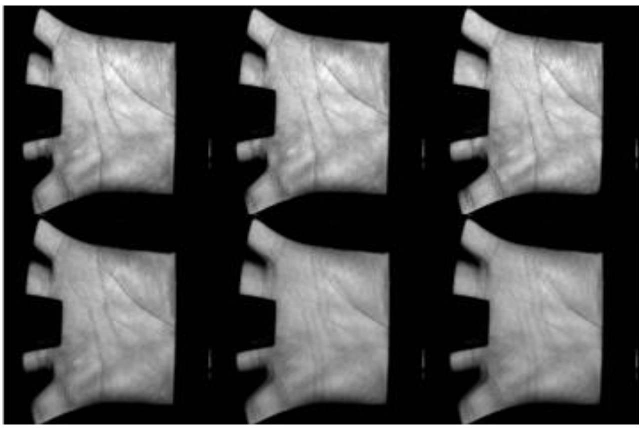

Fig 4. PCA: Image Enhancement for minutiae

The palmprint feature Density Map is extracted using PCA next and the processed image is obtained as below.

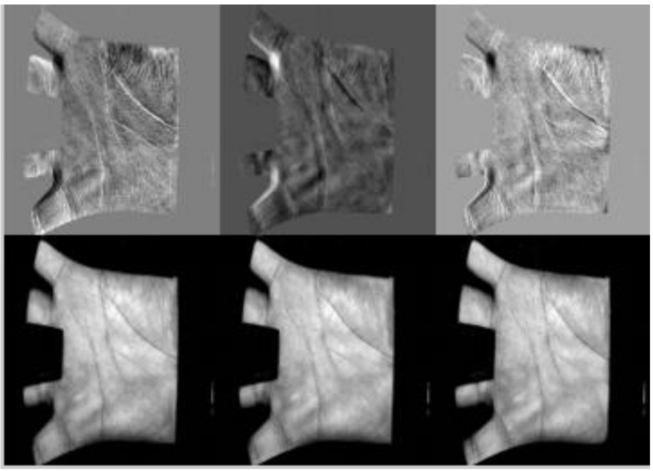

Fig 5. PCA: Density Map Features

The features, minutiae and principal line map are mounted on the skeletal density map illustration of the information fused palmprint. Green indicates the minutiae points and red the crease endings.

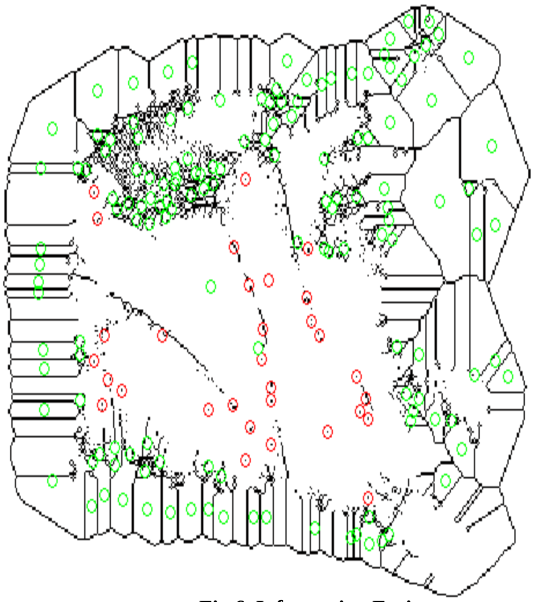

Fig 6. Information Fusion

The variation in these input images which seem similar is presented through the graph of Data bit width vs Total PSNR rate. The light blue indicates image fusion.

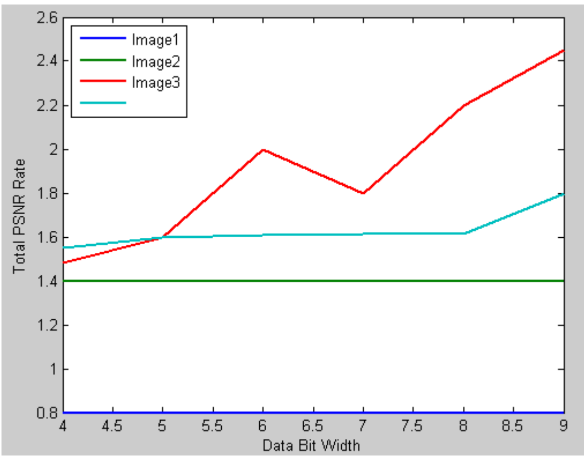

Fig 7. Variation of Input Images

V. ANALYSIS

PCA is a linear transformation that can be used to reduce, compress or simplify a data set. It is the simplest of the true eigenvector based-multivariate analysis.

PCA extraction is compared, in terms of accuracy to other neural extraction methods, such as GHA and APEX. The Generalized Hebbian Algorithm (GHA) by Sanger is a known learning algorithm that allows a neural network to extract a selected number of principal components from a multivariate random process. It applies to a single-layered feed-forward neural network. The Adaptive Principal Components Extraction (APEX) is used for the extraction of components, making use of linear features in addition to feed-forward weights.

Here I distinguish between the well and poorly separated eigenvalue case. The following plots are generated by the pca_error_plots_separated.m and pca_error_plots_close.m files.

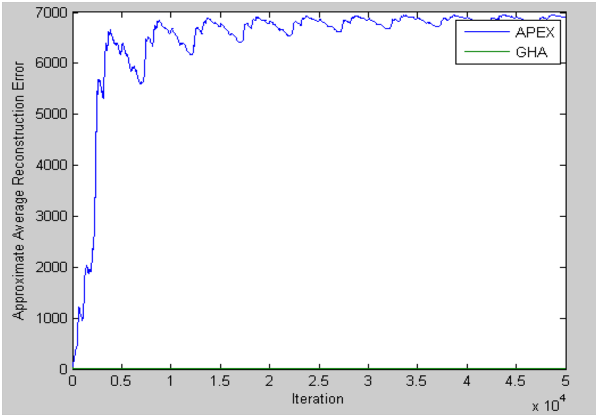

Fig 8. Separated Eigen Values

The above plot shows the approximate error in the PCA subspace for GHA and APEX when the eigenvalues are highly separated. GHA does much better than APEX in this case.

Computing PCA using APEX

Computing PCA using GHA

Final APEX error: 3673.832535

Final GHA error: 1.228504

Minimum error: 0.083817

APEX Deviation from Exact: 4.096946

GHA Deviation from Exact: 0.354842

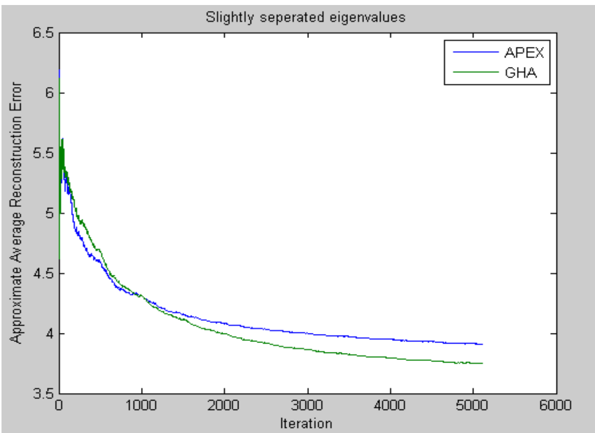

Fig 9. Close Eigen Values

The above plot shows the approximate error in the PCA subspace for GHA and APEX when the eigenvalues are slightly separated. GHA only does slightly better than APEX in this case.

Computing PCA using APEX

Computing PCA using GHA

Final APEX error: 3.830988

Final GHA error: 3.693376

Minimum error: 3.662126

APEX Deviation from Exact: 2.060983

GHA Deviation from Exact: 2.027161

Hence, PCA comparison results with GHA algorithm show higher accuracy.

VI. CONCLUSION

In this paper, many samples of the same palmprint image are fused through multi-image fusion to get an enhanced image using which authentication of the person is achieved. PCA-based image fusion is adopted to obtain the palmprint with improved resolution for higher reliability. Multiple features were extracted from this palmprint containing enhanced information. The discriminative powers of different feature combinations were analyzed and we find that density is very useful for palmprint recognition. Hence, the multi-image fusion with PCA extraction of multiple features for palmprint recognition significantly improves the matching accuracy.

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