INTRAMODAL FEATURE FUSION USING WAVELET FOR PALMPRINT AUTHENTICATION

K.KRISHNESWARI 1
1Tamilnadu College of Engineering, Coimbatore, Tamilnadu, India

S.ARUMUGAM 2
2Nandha Educational Institutions, Erode, Tamilnadu, India

Abstract:
Palmprint recognition has attracted various researchers in recent years due to its richness in amount of features. In this work, palmprint authentication system is classified into palmprint acquisition, preprocessing, feature extraction, feature fusion and matching. In the preprocessing stage we employed a modified preprocessing technique to extract the ROI and it is further enhanced using adaptive histogram equalization. In feature extraction, the single sample representation has become bottleneck in producing high performance. To solve this we propose an intramodal feature fusion for palmprint authentication. The proposed system extracts multiple features like Texture (Gabor), Line and Appearance (PCA) features from the preprocessed palmprint images. The feature vectors obtained from different approaches are in different dimensions and also the features from same image may be correlated. Therefore, we propose wavelet based fusion techniques to fuse extracted features as it contains wavelet extensions and uses mean-max fusion method to overcome the problem of feature fusion. Finally the feature vector is matched with stored template using NN classifier. The proposed approach is validated for their efficiency on PolyU palmprint database of 200 users. The experimental results illustrate that the feature level fusion improves the recognition accuracy significantly.

Keywords: Biometrics; Palmprint; Preprocessing; Feature fusion; Wavelet; Intramodal.

1. Introduction
Biometrics is the science of establishing the identity of an individual based on the physical; chemical or behavioral attributes of the person. Biometrics offers a natural and reliable solution to certain aspects of identity management by utilizing fully automated or semi-automated schemes to recognize individuals based on their biological characteristics [A.K. Jain et al., (2008)]. Various biometric technologies have been proposed and implemented; including iris fingerprint; hand geometry; voice; face; signature and retina. Each of these has its own strengths and weakness. The most widely used hand based biometric feature is the fingerprint. Currently the fingerprint authentication handles clear fingerprints very well but; workers and elders may not provide clear fingerprint because of their skin problems and nature of work. Another popular hand-based biometric technology is hand-geometry. It uses geometric information from the hands. However the simple hand features provide limited information; with the result that hand geometry is not highly accurate. The palmprint is relatively a new hand based biometric trait; has several advantages compared with currently available traits. Palm is the inner surface of the hand between the wrist and the fingers. The palmprints are more distinctive; as it contains more information and they can be captured using low resolution devices. The palm area contains a large number of features such as principal lines; geometry; wrinkle; delta point; minutiae; datum point and texture [D. Zhang, (2004)]. Recently most of the researchers concentrate on fusion techniques to improve system performance. Among various levels of fusion feature fusion has been emerging an effective way to improve the performance of the authentication system.

1.1. Prior work
Palmprint authentication system has received considerable recent research interest since of its low prices; capture devices; fast execution speed; and high accuracy. Research on palmprint authentication focuses on features and methods to represent the palmprint are classified into five Categories; line based; subspace based; local statistical based; global statistical-based and coding based approaches [D. Zhang, (2004)]. The Line based approach either develops edge detectors or employ the existing edge detection methods to extract palm lines. Many of the works are reported on extraction of principal lines [X. Wu et.al., (2004)]. [Han et al., (2003)] proposed principal line extraction using sobel and morphological operation. [Huang et al., (2008)] proposed a
two level modified finite random transform and a dynamic threshold to extract major wrinkles and principal lines. Appearance or subspace based methods include usage of principal component analysis (PCA); independent component analysis (ICA); linear discriminant analysis (LDA); and combination of their variants and have also been reported in achieving good result. It is proven than 2DLPP out performs all other methods. The local statistical approaches transform images into frequency domain and features are then extracted using statistical measures. [Zhang et al., (2002)] used Fourier transform to extract frequency domain features of palmprint and obtained improved result. Global statistical approaches compute moments [Y. Li et al., (2005)]; centre of gravity and density directly from the whole transformed images. Coding approaches encode the filtered coefficients as features. The framework of these methods is first using some mask to filter palmprint image and then code the outputs according to some rule. [Kong et al., (2002)] proposed a competitive scheme to code the outputs of the elliptical Gabor filters with different orientations; which have shown better performance. Researchers have shown promising results on employing these approaches individually. However efforts are still required to improve the performance of the palmprint authentication.

Intra modal fusion has shown a promising result in palmprint authentication. Most of the previous work [A.Kumar and D.Zhang., (2005); L. Nanni, and A. Lumini., (2008)] concentrates on fusion at score level to increase the accuracy of the system and only very few work concentrates on fusion at feature level [Kong et al., (2006)]. The feature fusion aims to introduce extra discriminative information for classification has shown a better performance than at score level. An ideal palmprint based personal authentication system should be able to reliably discriminate individuals using all the available information.

In this paper we propose a new palmprint authentication system by employing a modified preprocessing technique to segment the ROI and extracting multiple features from the enhanced ROI to perform fusion at feature level. From the research works on feature fusion; it is clear that performing feature level fusion leads to a curse of dimensionality; due to the large size of fused feature vector. To reduce the size of feature vector; we experimented the wavelet based fusion as proposed in section 4. Finally decision about accept or reject is carried out using NNC in the projection space.

The rest of this paper is organized as follows. Section 2 describes the block diagram of the proposed system. Section 3 presents feature extraction methods employed in the proposed work. Section 4 details the proposed feature fusion strategy based on wavelets. Experimental results and comparisons are reported in section 5. Section 6 concludes this paper.

2. Proposed System

In this paper; we propose a new technique in palmprint authentication by fusing multiple palmprint representations with an efficient way of dimensionality reduction after feature fusion. The proposed method involves preprocessing; features extraction; features fusion; matching and classification stages.

The block diagram of the proposed technique for palmprint authentication using combination of multiple features is shown in Fig. 1. Our work uses the palmprint database developed at the biometric research centre at Hong Kong Polytechnic University.

In the preprocessing stage; we combined the work of [D. Zhang et al., (2003)] and [W. Li et al., (2002)] to extract the ROI. The combination of these two techniques handles the rotational variation and segment violation errors. The process involves the following steps.

1. Binarize the palm image using Otzu’s binarization.
2. Establish the co-ordinate system using key points determined between the fingers.
3. Line up the key points with the established co-ordinate system to avoid rotation.
4. Compute centroid of the image.
5. Segment the ROI of 128 x 128 pixel size with reference to the centroid.

Palm Image → Preprocessing → Enhanced ROI → Gabor Features → Line Features → PCA Features → Fused Template using Wavelets → Registered Database → Classification → Match Score → Genuine / Imposter

Fig 1 Block diagram of the proposed system
The extracted ROI is further enhanced using adaptive histogram equalization as shown in Fig. 2.

![ROI to Enhanced ROI](image)

Fig. 2. ROI enhanced by adaptive histogram equalization.

The preprocessed image is then used for feature extraction. Feature extraction stage uses the 2D Gabor filter; stationary wavelet transform and principal component analysis for extracting the texture-based, line- and appearance-based features respectively. These features are concatenated to perform feature fusion. On feature concatenation the dimension of the fused feature template becomes larger and hence becomes difficult for match score computations. To overcome this problem; we propose a new wavelet based feature fusion technique which reduces the dimensionality of feature template.

In the enrollment stage; the database containing fused palmprint templates is created and threshold for classification is determined using the training templates. In verification stage; the test template is matched with the registered templates of the database; comparing the Euclidean distance measures between them; using the NN classifier. Based on the scores generated; the test template is identified as genuine or imposter. The performance of the proposed multiple palmprint feature fusion is compared with individual palmprint representations. The results are also compared with the work of [Kumar and Zhang, (2005)] which uses score level fusion. However; the best performance was obtained with proposed fusion strategy.

3. Multiple Feature Extraction

3.1 Extraction of Gabor features

Gabor filters are extensively used for texture segmentation because of their good spatial and frequency localization. It is mathematically given by

\[ G(x;y) = g(x;y) \ast \exp(2\pi i f(x \cos(\theta) + y \sin(\theta))) \] (1)

Here \( g(x;y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2+y^2}{\sigma^2}\right) \). The parameter \( f \) & \( \theta \) represent the frequency and the orientation of the sinusoidal signal respectively. \( g(x;y) \) is the Gaussian function with scale parameter \( \sigma; f; \theta \); and \( \sigma \) constitute the parameter space of Gabor filters where \( \theta \) lies in the interval \([0^\circ-360^\circ]\). Theoretically a Gabor filter is determined by the parameters \( F; \theta; \sigma \) [Namuduri.K.R et al., (1994)]. By carefully selecting the values of these three parameters; the optimal Gabor filter is designed.

**Algorithm**

1. Select value of \( F \).
2. Convert the input image into a 2D matrix.
3. Compute the impulse response of the filter by the following formula

\[ G(x ; y) = g( x ; y) \ast \exp( 2\pi i f (x \cos(\theta) + y \sin(\theta))) \]

Where \( g(x;y) = \frac{1}{2\pi\sigma^2} \exp\left(-\left(x^2+y^2\right) / 2\sigma^2\right) \)
Filter the input image by convolving it through the filter whose impulse response is as calculated in step 3; say r(x,y) is the filtered output. A large value of F results in spurious creases and smaller values unites two nearby creases. Large values of $\sigma$ results in smoothing of lines and creases but better suppression of background noise. On the other hand; smaller values of $\sigma$ are prone to background noise and generate spurious lines. The Gabor filter used in this paper has four scales ($\sigma = \{2; 4; 8; 16\}$) and six orientations ($\theta = 0^\circ; 30^\circ; 60^\circ; 90^\circ; 120^\circ; 150^\circ$). In this paper; the frequency of the Gabor filter is made dependent on the scale ($F = 1/\sigma$) such that the uniqueness of the feature vector is increased. Fig. 3 shows the features extracted from the gabor filter. The feature vector from each of these filtered images is formed by computing the standard deviation among them to uniquely represent a palmprint. 

3.2 Extraction of Line features

Line features has been reported to be powerful and offers high accuracy for palmprint based biometrics. Line based palmprint recognition approaches extract principal lines and dominant wrinkles using line detectors [X. Wu et al., (2006)]; masks [L. Liu and D. Zhang, (2005)] and radon transform [Huang et al., (2008)]. Computationally complex; difficulty in matching; translation and rotation variance; large feature sets; and noise effects are the common problems in such methods. To avoid these complexities; we use a simple wavelet based edge detection method as described in [S.M. Prasad et al., (2009)] with a change of using stationary wavelet transformation instead of discrete wavelet transformation. Horizontal subband contains horizontal line or edge information in the form of strong coefficients. Similarly; vertical and diagonal subbands respectively contain vertical and diagonal line information. Collection of dominant singularity points/coefficients from the HVD subbands are fused using the formula (2); gives the line information of the ROI as shown in Fig. 4.

$$\text{Line}(x;y) = \max(\text{HLine}(x;y); \text{VLine}(x;y); \text{DLine}(x;y)).$$ (2)
3.3 Extraction of PCA features

Palmprint image also consists of certain local and global features that can be used for identification. PCA is a standard decorrelation technique to extract those features. PCA aims to find a linear mapping which preserves total variance by maximizing the trace of feature variance. The optimal mapping is the leading eigenvectors of the data’s total variance matrix associated with the leading eigenvalues. The extraction of appearance features used in our experiments is same as detailed in [Turk and Pentland, (1991)]. Fig. 5 shows the extracted Eigen palms using PCA.

![Fig. 5. Extracted Eigen palms.](image)

4. Feature Level Fusion

Fusion is a promising approach that may increase the accuracy of biometrics systems. Fusion can be performed at 3 different levels: (a) Fusion at the data or information level (low level fusion); (b) Fusion at the feature level (intermediate level fusion) and (c) Fusion at the decision level. Fusion at the feature level deals with selection and combination of features to remove redundant and irrelevant features. From the reported few researches on feature fusion; it is clear that feature fusion leads to dimensionality problems due to large dimensions of the fused feature vectors. In this work we used the wavelet based fusion technique shown in Fig. 6 to reduce the feature space in the fused image.

![Fig. 6. Wavelet based feature technique.](image)
The principle of image fusion using wavelets is to merge the wavelet decompositions of the two original images using fusion methods like mean-mean; max-min; img1; img2; mean-max; applied to approximation coefficients and detail coefficients. Due to the difference in correlation among PCA; line and Gabor; we use the mean-max fusion method. The processes involved in the feature fusion strategy are as follows.

1. Load the Gabor and line feature vectors and extend the vectors using wavelet extension to achieve similar dimensions.
2. Perform wavelet decomposition using 2D haar wavelet transformation for 5 levels on both feature vectors.
3. Perform image fusion using mean rule.
4. Load the PCA feature vector.
5. Perform wavelet decomposition similar to step2 on PCA features.
6. Perform image fusion using max rule.

The combined feature vectors are classified by measuring the Euclidean distance among the training and testing template using the nearest neighborhood classifier. Based on the match scores so obtained the template is classified as genuine or imposter.

5. Experimental Results And Comparison

5.1 Description of the database

The proposed algorithms are validated on PolyU palmprint database [18]. This database contains 8000 gray scale; low resolution (75 dpi) palmprints captured using CCD camera under pegged environment. Each palm contains twenty samples; out of which ten samples are taken in first session and another ten are taken in second session. The average time interval between the first and the second session is two months.

5.2 Experimental Setup

This section describes about the experimental setup of our proposed work. We used left palmprints of 200 users for our experimentation. Each individual has 20 images with size 128 X 128 pixels. False Reject Rate (FRR) is the frequency with which genuine person is rejected. False Accept Rate (FAR) is the frequency with which the imposter is accepted. EER is the error rate at which FAR and FRR become equal. ROC is the plot of FRR versus FAR. We use EER to interpret the performance of the proposed system. The palmprints from session II were used for fixing the parameters of feature extraction algorithms. The proposed algorithm randomly selects samples of palmprints from session 1 to evaluate the performance for both verification and identification.

5.2.1 Palmprint Verification:

Palmprint verification is comparing a particular palmprint against the claimed identity which is also known as one to one comparison. To validate the performance of the proposed algorithm we used a template database of 200 users containing 1000 samples taking five samples per user.

![ROC using fusion of Gabor, Line and PCA features for Verification](image.png)
During the verification test; 10,000,000 comparisons are made comparing each palmprint template with all of others using the NN classifier. The number of correct matching obtained was 6805 and the rest were incorrect matching. Fig. 7 depicts the corresponding ROC curve which is plot of FAR against GAR. Based on the results; our system can operate at a 99% genuine acceptance rate (GAR) and 0.03% false acceptance rate (FAR) with the corresponding threshold of 0.46 Euclidean measures. The system’s EER is 0.31%. This result is compared with palmprint verification systems based on individual features in the Table 1.

![ROC curve](image)

**Table 1: Comparison of results for Verification (0.46 Threshold)**

<table>
<thead>
<tr>
<th>Features</th>
<th>EER</th>
<th>FAR</th>
<th>FRR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gabor</td>
<td>0.03</td>
<td>0.04</td>
<td>4.63</td>
</tr>
<tr>
<td>Line</td>
<td>0.89</td>
<td>0.11</td>
<td>5.46</td>
</tr>
<tr>
<td>PCA</td>
<td>0.93</td>
<td>0.22</td>
<td>5.52</td>
</tr>
<tr>
<td>Score Fusion</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Feature Fusion</td>
<td>0.31</td>
<td>0.03</td>
<td>4.08</td>
</tr>
</tbody>
</table>

5.2.2 Palmprint Identification:

Palmprint identification is a process of comparing one image against N images. In our experiment; we created a reference database of 100 users containing 500 templates taking 5 samples per user. We also created a test database of 200 users containing 20 samples per user.

Each of the palmprint images in the testing database is matched with all palmprints in the reference database using the NN classifier. The results of the experiment are depicted in the ROC curve shown in Fig. 8. It was obtained that the system can operate at a 98% GAR and 0.65% false acceptance rate (FAR) with the corresponding threshold of 0.18 Euclidean measures. The system’s EER is 1.95%. This result is also compared with palmprint identification systems based on individual features and fusion at score level in the Table 2.
5.2.3 Speed

Our experiments were conducted on Intel P-D; 2.79GHz; 1GB RAM; windows XP; Matlab 2008a platform. For verification; the total execution time was about 0.638s taking 0.480s; 0.158s and 0.001s for preprocessing; feature extraction and matching respectively. Similarly for identification the 1.098s was the total processing time taking 0.460s for matching. On further optimization of code; the computation time could be further reduced.

Table 2: Comparison of results for Identification (0.18 Threshold)

<table>
<thead>
<tr>
<th>Features</th>
<th>EER</th>
<th>FAR</th>
<th>FRR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gabor</td>
<td>3.96</td>
<td>1.73</td>
<td>4.3</td>
</tr>
<tr>
<td>Line</td>
<td>5.83</td>
<td>2.42</td>
<td>8.62</td>
</tr>
<tr>
<td>PCA</td>
<td>6.58</td>
<td>3.75</td>
<td>8.45</td>
</tr>
<tr>
<td>Score Fusion</td>
<td>3.20</td>
<td>1.02</td>
<td>3.6</td>
</tr>
<tr>
<td>Feature Fusion</td>
<td>1.95</td>
<td>0.65</td>
<td>3.02</td>
</tr>
</tbody>
</table>

5.3 Comparisons and Discussion:

The results of the palmprint authentication system are shown in Table 2 when it uses the proposed feature extraction techniques individually and with fusion at score level. From the results shown; the line based system is efficient for average number of similar users and PCA can be efficiently used for large samples. The 2D Gabor filter with six orientations has shown better performance. The proposed wavelet based feature fusion method outperforms all other methods. When compared with the similar work of [Ajay Kumar and David Zhang , (2005)]; which fuses the gabor; line and PCA features at score level; the proposed work has shown significant improvement in both accuracy and speed because of minimum comparison time and removal of redundant features.

6. Conclusion

We have presented a feature level fusion scheme for palmprint verification and identification system using the combination of three palmprint representations. The extracted Gabor; Line and PCA features are fused using a wavelet based feature fusion technique supported by wavelet extensions for feature reduction and mean-max fusion rule to avoid correlation. The experimental results show that the combination of 2D gabor; Line and PCA outperforms than using them individually. Finally; the proposed work obtains 98.5% of GAR at 0.34% of FAR with a corresponding threshold of 0.2 Euclidean measures as an average for both verification and identification.

We can use intramodal biometric fusion to obtain improved performance of verification or identification when multi modal biometric data is not available and the case in which the data capturing are expensive in terms of cost.

References

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PolyU Palmprint Database; http://www.comp.polyu.edu.hk/ biometrics/.