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INTRAMODAL FEATURE FUSION BASED ON PSO FOR PALMPRINT AUTHENTICATION

K. Krishneswari[1] and S. Arumugam[2]
[1] *Department of Computer Science and Engineering, Tamilnadu College of Engineering, India*
E-mail: krishneswari@gmail.com
[2] *Nandha Educational Institutions, India*
E-mail: arumugamdote@yahoo.co.in

Abstract
Palmprint recognition has attracted various researchers in recent years due to its richness in amount of features. In feature extraction, the single feature 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), and Line features from the preprocessed palmprint images. The feature vectors obtained from different approaches are incompatible and also the features from same image may be redundant. Therefore, we propose a Particle Swarm Optimization (PSO) based technique to perform feature fusion on extracted features. Being an iterative technique that randomly optimizes the fused feature space, it overcomes the problems of feature fusion. Finally the feature vector is further reduced using Principal Component Analysis (PCA) and 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 illustrates that the feature level fusion improves the recognition accuracy significantly.

Keywords:
Biometrics, Palmprint, Feature Fusion, PSO, 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 [1]. 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.

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 [2]. 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 [2]. 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 [3]. Han et al.[4] proposed principal line extraction using sobel and morphological operation. Huang et al.[5] 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. Hu et al.[6] uses PCA, PCA and LDA, PCA and Locality preserving projection (LPP) and 2DLPP.

Zhang et al.[7] used Fourier transform to extract frequency domain features of palmprint and obtained improved result. Global statistical approaches compute moments [8], centre of gravity and density directly from the whole transformed images. Coding approaches encode the filtered coefficients as features. Kong et al.[9] proposed a competitive scheme to code the outputs of the elliptical Gabor filters with different orientations, which have shown better performance.

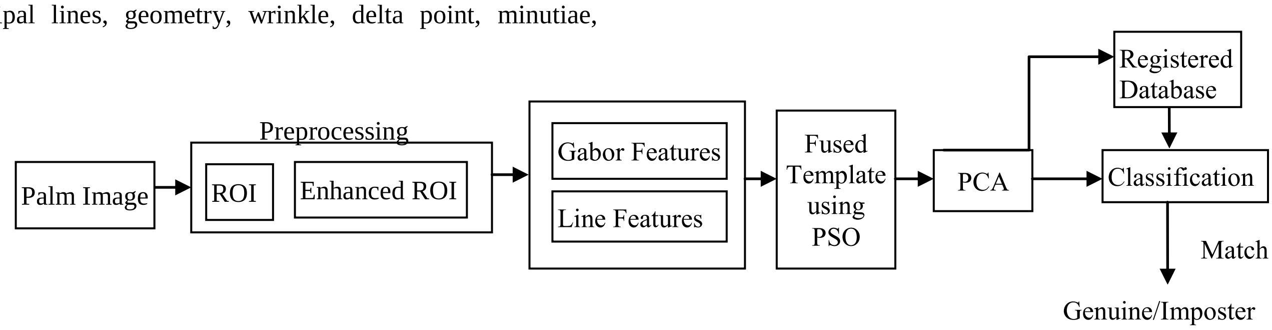

Fig.1. Block diagram of the proposed system

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 [13, 14] concentrates on fusion at score level to increase the accuracy of the system and only very few work concentrates on fusion at feature level [15]. The feature fusion aims to introduce extra discriminative information for classification has shown a better performance than at score 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. Indeed fusion of features from various domains can also result in incompatibility. From the literature on feature level fusion, it can be understood that effective optimization techniques and normalization of different features can overcome the problems of dimensionality and incompatibility respectively. Raghavendra et al.[10] and Iswandy and Koenig [12] have used the Particle Swarm Optimization based feature selection which has been proved to be very efficient on some large scale application problems. To reduce the size of feature vector, we experimented a PSO based fusion as proposed in section 4. Finally the fused vector is further reduced using PCA and 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 PSO and PCA. 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, feature reduction, 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.

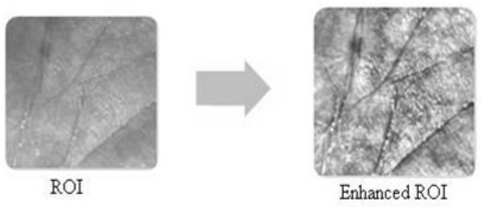

Fig.2. ROI enhanced by adaptive histogram equalization

In the preprocessing stage, we combined the work of D. Zhang et al [16] and W. Li. et al [7] to extract the ROI. The combination of these two techniques handles the rotational variation and segment violation errors. The extracted ROI is further enhanced using adaptive histogram equalization as shown in Fig.2.

Feature extraction stage uses the 2D Gabor filter and stationary wavelet transform for extracting the texture- and line-based features respectively. These features are concatenated to perform feature fusion. Most of the research works involving feature level fusion is performed by feature concatenation followed by a feature selection or reduction technique [10,13,14]. To overcome the problem of large feature template, we propose a PSO based feature fusion technique, combining the image fusion technique followed by Raghavendra et al. [11] in their work, which reduces the dimensionality. The fused vector is reduced further using PCA.

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 a similar feature fusion without PCA. 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,

$$G(x,y) = g(x,y) * exp(2\pi \mathrm{i} f(x cos(\theta)+y sin(\theta))) \quad (1)$$

Here $g(x,y) = (1/2\pi\sigma^2) * exp(-(x^2+y^2)/2\sigma^2)$. The parameter f & θ represent the frequency and the orientation of the sinusoidal signal respectively. $g(x,y)$ is the Gaussian function with scale parameter σ. Theoretically a Gabor filter is determined by the parameters F, θ and σ [17]. By carefully selecting the values of these three parameters, the optimal Gabor filter is designed.

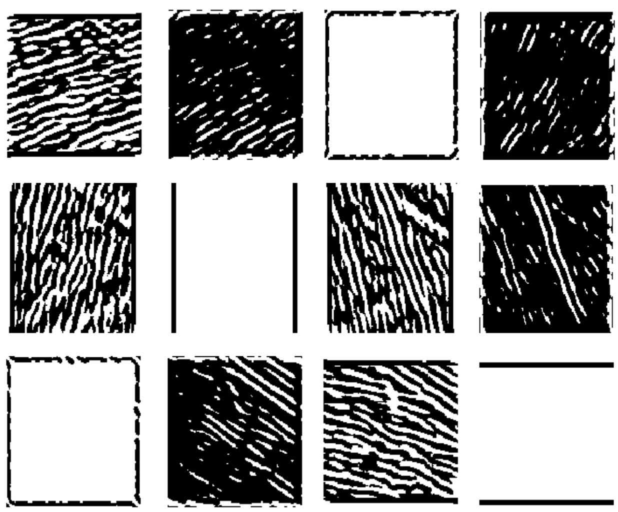

Fig.3. Filtered images using Gabor filter with twelve orientations

A large value of F results in spurious creases and smaller values unites two nearby creases. Large values of σ results in smoothing of lines and creases but better suppression of background noise. On the other hand, smaller values of σ are prone to background noise and generate spurious lines. The Gabor filter bank used in this paper has 12 filters with 12 orientations ($\theta = j\pi/12$, where j=0, 1, 2,…,12). 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 using the following formula,

$$GF(x,y) = max(G_j(x,y)) \quad (2)$$

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 [18], masks [19] and radon transform [5]. 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. Wavelet transform being one the efficient block by block transformation, it overcome the problems of large feature sets and noise. The wavelets applied on an image decomposes the entire image into different and smaller frequency bands which reduces the computational complexity. 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. Collections of dominant singularity points/coefficients from the HVD subbands are fused using the formula Eq.(3). The dominant points from individual subbands represents the tangential direction of every feature point which is computed by obtaining the maximum density points among the HVD subbands. This gives the line information of the ROI as shown in Fig.4.

$$Line(x,y) = max(HLine(x,y), VLine(x,y), DLine(x,y)) \quad (3)$$

4. FEATURE LEVEL FUSION

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 PSO based fusion technique shown in Fig.5 to reduce the feature space in the fused image.

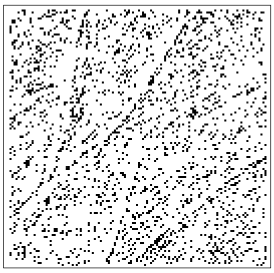

Fig.4. Extracted Line feature

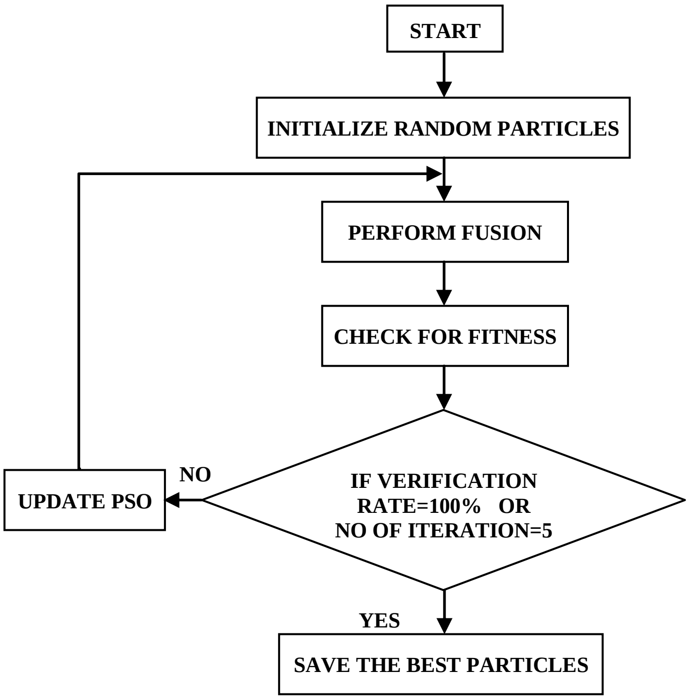

Fig.5. Flow diagram of PSO

PSO is a robust stochastic optimization technique based on the movement and intelligence of swarms. PSO applies the concept of social interaction to problem solving. It uses a number of agents (particles) that constitute a swarm moving around in the search space looking for the best solution. Each particle is treated as a point in a N-dimensional space. Each particle keeps track of its coordinates in the solution space which are associated with the best solution (fitness). This value is called particle best pbest. Another best value that is tracked by the PSO is the best value obtained so far by any particle in the neighborhood of that particle. This value is called global best gbest. The basic concept of PSO lies in accelerating each particle toward its pbest and the gbest locations. The processes involved in the feature fusion strategy are as follows,

Step 1: Initialize population $F(i=0)$, *pbest* and *gbest*

Step 2: Perform image fusion using the formula,

$$F(i) = [f(x)*F(i-1)] + [f(y)*(1-F(i-1))] \quad (4)$$

where, $f(x)$ and $f(y)$ are the Gabor and line feature vectors

Step 3: Verify fitness function and compute verification rate using the formula,

$$V = (F(i) – F(i-1))*(100/gbest) \quad (5)$$

Step 4: If verification rate is 100% or number of iteration is N then goto step 7

Step 5: Update pbest and gbest using the formula,

$$pbest(i) = min(F(i) – F(i-1)) \quad (6)$$

$$gbest = min(pbest) \quad (7)$$

and increment the iteration index as $i=i+1$

Step 6: Perform next iteration

Step 7: Return $F(i)$

Table.1. Comparison of results for verification

Features	GAR at 0.01% of FAR (%) with 90% confidence interval	Dimension of the feature vector	Feature Extraction Time(s)	Matching Time(s)
Gabor	84.15	16384	0.094	0.489
Line	75.35	4096	0.06	0.376
PCA	67.45	256	0.024	0.001
PSO without PCA	93.85	20480	0.154	0.501
PSO with PCA	95.59	384	0.178	0.001

This PSO based fusion technique combines the two feature vectors into a single feature vector without concatenation. Therefore, rather than adding up of dimensions from the two feature sets which results by concatenation, this technique combines them to reduce the feature space. The combined feature vector is reduced using PCA and the reduced vector is classified using the nearest neighborhood classifier.

5. EXPERIMENTAL RESULTS AND COMPARISON

5.1 DESCRIPTION OF THE DATABASE

The proposed algorithms are validated on PolyU palmprint database [21]. 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

We used left hand palmprints of 100 users for our experimentation. Each individual has 10 images with size 128X128 pixels. The palmprints from session 2 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.

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 100 users containing 1000 samples taking ten samples per user.

During the verification test, 10,00,000 comparisons are made comparing each palmprint template with all of others using the NN classifier. The number of correct matching obtained was 6425 and the rest were incorrect matching. Fig.6 depicts the corresponding ROC curve which is plot of FAR against GAR. Based on the results, our system can operate at a 95% genuine acceptance rate (GAR) and 0.01% false acceptance rate (FAR). This result is compared with palmprint verification systems based on individual features in the Table.1.

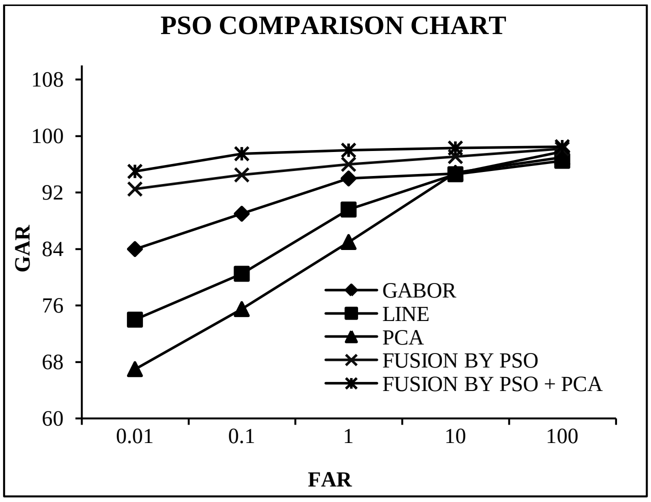

Fig.6. ROC using fusion of Gabor, Line features with and without PCA for Verification

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 100 users containing 10 samples per user.

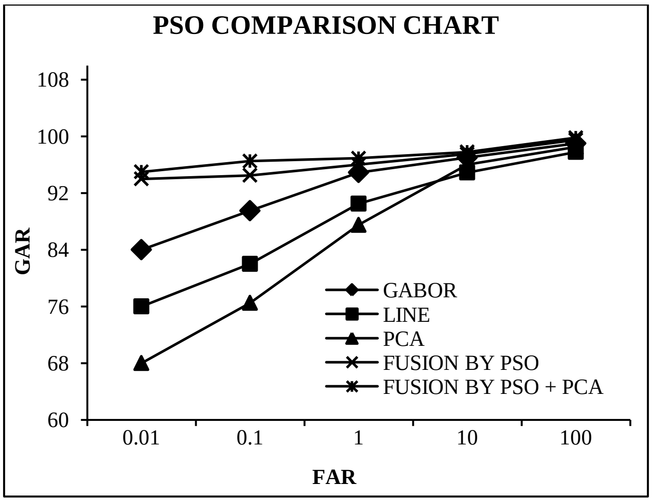

Fig.7. ROC using fusion of Gabor, Line features with and without PCA for Identification

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.7. It was obtained that the system can operate at a 95% GAR and 0.01% false acceptance rate (FAR). This result is also compared with palmprint identification systems based on individual features and fusion at score level in the Table.2.

Table.2. Comparison of results for Identification

Features	GAR at 0.01% of FAR (%) with 90% confidence interval
Gabor	83.35
Line	73.65
PCA	67.45
PSO without PCA	92.23
PSO with PCA	94.89

5.2.3 Speed:

Our experiments were conducted on Intel P-D, 2.79 GHz, 1GB RAM, windows XP, Matlab 2008a platform. For verification, the total execution time was about 0.659s taking 0.480s, 0.178s and 0.001s for preprocessing, feature extraction and matching respectively. Similarly for identification the 1.118s was the total processing time taking 0.460s for matching. On further optimization of code, the computation time could be further reduced.

5.3 COMPARISONS AND DISCUSSION

The results of the palmprint authentication system are shown in Table.1 when it uses the proposed feature extraction techniques individually and with fusion at feature 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 12 orientations has shown better performance.

The 2D Gabor produces better results but it takes a larger dimensional space and comparison time. Though PCA individually takes less time and space for comparisons, the accuracy degrades, whereas the proposed technique just with a little increase in the space and time produces good results. By comparing the experimental results from the Table.1 it can be obtained that the proposed PSO based feature fusion method outperforms all other methods. Table.3 shows the comparison results among the existing intramodal fusion techniques. When compared with the existing works, which uses the Gabor, line and PCA features, 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 two palmprint representations. The extracted Gabor and Line features are fused using a PSO based feature fusion technique supported by PCA for feature. The experimental results show that the combination of 2D Gabor and Line outperforms than using them individually. Finally, the proposed work obtains 95% of GAR at 0.01% 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.

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Table.3. Comparison with performance of similar intramodal fusion techniques

Author & Ref	Features Extracted	Level of Fusion	Fusion Technique Used	No. of Classes	EER (%)
Kumar et al.[10]	Gabor, Line and PCA	Score level	Product of Sum	100	3.20
Nanni et al. [11]	DCT, LBP and Gabor	Score Level	Sum	100	3.20
Wu et al. [19]	Texture	Feature Level	Wavelet	100	2.11
D.R Kisku et al. [20]	Gabor	Sensor Level	DWT + ACO	165	3.125
Proposed	Gabor and Line	Feature Level	PSO + PCA	100	2.0

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