Authentication System using Multispectral Palmprint

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Abstract *Among the numerous biometric systems presented in the literature, multispectral palmprint authentication systems have received a great deal of attention in recent years. This paper presents applications of the Holistic methods such as Gabor + Fisherpalm space, Gabor+Eigenpalm space and Gabor Kernel Eigenpalm space for the multispectral images (Green, near-infrared, Red and Blue). The Gabor filter bank is applied to extract the augmented magnitude feature vector. These vectors are then subjected to subspace projection (i.e., Fisherpalm space). In this paper, a comparison of the Gabor+ Eigenpalm and the Gabor+ Fisherpalm methods respect to multispectral palmrint images is examined. Finally, the nearest neighbor classifier and the cosine Mahalanobis distances are used for respectively the matching and the decision stages. Experimental results show that our proposed system achieves better results than results than other state-of-the-art system.*

***Keywords*:** Multispectral image; Fisherpalm; Eigenpalm; Biometric System; EER.

1. Introduction

Authentification system using multispectral palmprint has been one of the most active research areas in the field of biometrics, and it can be applied in a wide range of applications such as access control, surveillance systems and airport checking, computer or mobile devices systems, etc. [1-2]. The texture of the multispectral palmprint has many advantages, such as low-resolution imaging, low cost, stable structural features and high user acceptance [3]. Given a pair of multispectral images, the goal of the authentication is to determine whether or not they are coming from a single class. The key of the successful of the biometric system is the information fusion. The fusion of information can be done at four different levels: sensor level, feature level, matching score level and decision level. Zhang *et al.* [3] developed a fast multispectral palmprint system using a score level fusion scheme to integrate the multispectral information. Xu.X et al. [4] have proposed another approach for multispectral images based on a Quaternion Matrix. Then, the principal component analysis (PCA) and discrete wavelet transform (DWT) were applied respectively on the matrix to extract palmprint features. Finally, the Euclidean distance and the nearest neighbor classifier are used for respectively measure the dissimilarity and decision stages. Cui.J proposed algorithm for solving the problem of selecting bands from the original four bands, and use the extended general color image discriminant (GCID) model to generate three new color components for further improvement of the recognition performance. In this paper, we proposed a new system to authenticate persons using their multispectrals images.

R. Raghavendra et al. [5] have used a system for Palmprint Verification based on Binarized Statistical Image Features (BSIF) for feature extraction, were the Sparse Representation Classifieis (SRC) is used to perform the subject verification.

In our scheme, firstly, each multispectral image is convolved with a bank of Gabor filters (5 scales, 8 orientations). Secondly, the down-sampling is performed in all magnitude responses, which are then normalized and finally concatenated into the augmented magnitude feature vector. The augmented feature vectors are then subjected to Fisherpalm space (FPS) projection. In this work, we use the FPS method propose by X.Wu [5], in which, Fisher linear discriminant (FLD) is used to project the augmented magnitude feature vector into the lower dimensional feature. Finally the cosine Mahalanobis is used for the decision module. Experimental results show that our proposed systems give a best result compared with the other systems. The remainder of this paper is organized as follows: Section 2 describes the scheme of the proposed authentication system. In Section 3, we present, evaluate and discuss the experimental results obtained by using the multispectral palmprint database. Finally, the last section concludes our work.

2. Proposed method

The Fig.1 shown a diagram of the proposed personal authentication system using multispectral palmprint image, based on the special Gabor filter and Fisher faces (LDA) technique.

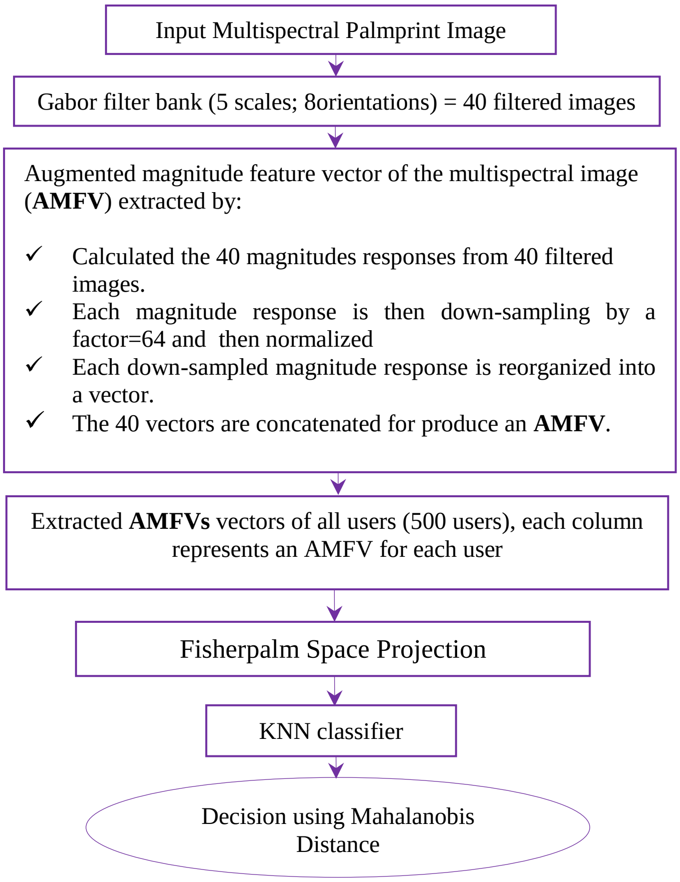

Fig .1 Diagram of the proposed system

The proposed system consists of the feature extraction and modeling, matching and the decision stage. In the first step, the special Gabor filter with 5 scales and 8 orientations is used for the feature extraction stage. This feature vector is reduced using Fisher faces technique. Finally, the nearest neighbor classifier and the cosine Mahalanobis distance are used respectively for the matching and decision stage.

2.1. Gabor Wavelets

Gabor wavelets have been considered as a very useful tool in computer vision and image analysis due to its optimal localization properties in both spatial analysis and frequency domain [6-7]. Gabor wavelets have been used in many image recognition/detection researches. In general, the family of 2D Gabor wavelets can be defined in the spatial domain as follows [8-9-10]:

$$H_{U,V} = \frac{f_U^2}{\pi \cdot n \cdot \lambda} \exp\left(-\left(\frac{f_U^2}{n^2}\right) x_p^2 - \left(\frac{f_U^2}{\lambda^2}\right) y_p^2 \right) \qquad (1)$$
$$\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \exp(j 2\pi f_U x_p)$$

Where: $x_p = x \cdot \cos(\theta_V) + y \cdot \sin(\theta_V)$ and $y_p = -x \cdot \sin(\theta_V) + y \cdot \cos(\theta_V)$ and $f_U = f_{max} / 2^{(U/2)}$ and $\theta_v = v\pi/8$ with f_U, f_{max} are the center and maximal frequency of Gabor filters respectively and θ_v is its orientation. The parameters n and λ describe the size of the Gaussian envelope along X-axis and Y-axis respectively. In our experiments, we use f_{max}=0.25 and $\lambda = n = \sqrt{2}$.

2.2. Gabor Feature Representation

Let multispectral imaging I(x,y). The Gabor representation of a multispectral image, I(x,y), can be obtained by convolving the image with the family of Gabor filters as defined by

$$Y_{(U,V)}(x,y) = I(x,y) \cdot H_{(U,V)}(x,y) \qquad (2)$$

The output $Y_{(u,v)}$ (x,y) has the complex structure, the magnitude of each $Y_{(u,v)}$ (x,y) is then down-sampled by a factor=64 and normalized to zero mean and unit variance. Each down-sampled magnitude response is transformed to a vector by scan columns. The 40 vectors are concatenated to produce the augmented magnitude feature vector of the multispectral image (equation.3). $Y^{(i)}$ is AMFV of user (i).

$$Y^{(i)} = [W_{0.0}, W_{0.1}, W_{0.2}, \ldots, W_{4.7}]^T \qquad (3)$$

2.3. *The reduction of the dimensionality of the augmented magnitude feature vector using the FPS*

In this paper, we apply the FPS technique to reduce the dimensionality of the augmented magnitude feature vector. Let the matrix training Y_T=[X_1,X_2,…,X_q] where X_j is the large augmented feature vector of user (j), with $1 \leq j \leq q$ and each element in the set Y_T, X_j belongs to one of N classes C_1, C2,…,C_N . The within-class scatter matrix Sw and the between-class scatter matrix Sb are defined as follows:

$$S_B = \sum_{i=1}^{N} n_i (\mu_i - \mu)(\mu_i - \mu)^T \quad (4)$$

$$S_W = \sum_{i=1}^{N} \sum_{X_j \in C_i} (X_j - \mu_i)(X_j - \mu_i)^T \quad (5)$$

Where n_i denotes the number of samples in the i-th class, μ_i the mean of training sample belonging to the i-th class and μ represents the global mean of all training samples. Then Fishers linear discriminant (FLD) tries to find a linear transformation Wopt to maximize the Fisher criterion:

$$T(W) = W_{opt} = \underset{W}{\operatorname{argmax}} \frac{\left|W^T S_B W\right|}{\left|W^T S_W W\right|} = \left[W_1 W_2 \ldots W_d\right] \quad (6)$$

T(W) is the fisher discriminant criterion, the fisher discriminant criterion is maximized, when W is constructed by a simple concatenation of the **d** leading Eigen-vectors, which $d \leq c-1$, where c is the number of palmprint classes. W can be obtained by solving the following generalized Eigen-value problem:

$$S_W^{-1} S_B W_j = W_j \lambda_j \quad (7) \quad j = 1,2,\ldots,d$$

To overcome the problem of singular S_W, in this method a K–L transformation step is performed prior to FLD to avoid singularity issues due to a small number of training samples. This method, which has been used efficiently in face recognition (Belhumeur et al 1997) [11], W_{opt} is given by :

$$W_{opt}^T = W_{FLD}^T \cdot W_{KL}^T \quad (8)$$

Where

$$W_{KL} = \underset{W}{\operatorname{argmax}} \left|W^T S_T W\right| \quad (9)$$

And

$$W_{FLD} = \underset{W}{\operatorname{argmax}} \frac{\left|W^T W_{PCA}^T S_B W_{KL} W\right|}{\left|W^T W_{KL}^T S_W W_{KL} W\right|} \quad (10)$$

S_T is the total scatter matrix :

$$S_T = S_W + S_B \quad (11)$$

The matrix of the augmented magnitude feature vector Y is projected into Fisherpalm space by the equation 12:

$$\text{Test\_F} = W_{opt}^T (Y - \mu) = \left[V_1, V_2, \ldots, V_q\right] \quad (12)$$

2.4. *Matching stage*

The matching score is calculated using the nearest neighbor classifier. The cosine Mahalanobis allows calculating the distance (the similarity) between two vectors. Given two vectors V_i and V_j, this distance is obtained by the following relation:

$$d(V_i, V_j) = -\frac{V_i^T \cdot \Sigma^{-1} \cdot V_j}{\left\|V_i\right\| \cdot \left\|V_j\right\|} \quad (13)$$

Vi and Vj are two projections vectors (Fisher palm space), Vi computed from input multispectral image (test) and Vj is enrolled vector saved in the system database. The $\|V_i\|$ and $\|V_j\|$ are computed by:

$$\left\|V_i\right\| = \sqrt{V_i^T \cdot \Sigma^{-1} \cdot V_i} \quad (14)$$

$$\left\|Vj\right\| = \sqrt{V_j^T \cdot \Sigma^{-1} \cdot V_j} \quad (15)$$

Where Σ^{-1} is the inverse covariance matrix of the training data. By comparing the distance d(V_i, V_j) with a threshold, a decision can be made whether V_i and Vj belong to the same person or not.

3. Experimental results and discussion

3.1. Database

In this study, the multi-spectral palmprint database from the Hong Kong polytechnic university (PolyU) [12] is used. This database consists of 6000 images of 500 individuals for each bands (Red, Green, Blue, and NIR). These images were collected in two separate sessions. In each session, the person provides 6 images for each palm, so there are 12 images for each person. In this section, the 3 first multispectral palmprint images (session1) of each person is used for training and the rest multispectral palmprint images for test (9 images).

The Algorithm proposed by D. Zhang et al in [13] is used to extract a region of interest (ROI) for each band. This ROI is used for further feature extraction and matching.

3.2 Result and discussion

The results are tabulated for the down-sampled factor =64. If the FPS technique is used. Our system gives an Equal Error Rate (EER) =0.00% for the Green, Red and Blue bands and an EER=0.04% if the NIR band is used (See table.1). If the Eigenpalm space (EPS) technique is used [14], our system can work with an EER equal to 0.09% for the Green band and an EER= 0.07% for the Blue band. EER was 0.24% for NIR band and EER=0.27% for the Red band. It can safely be seen the benefits of using the method Gabor+Fisherpalm than the Gabor+Eigenpalm (see Table1). Table 2 shows the EER for the different down-sampling factor using the Red band. Fig.2 shows the Receiver Operating Characteristics (ROC) curves for the different bands using the different method of projection.

Table 1. The EER obtained for the different methods and bands

Methods	Green	NIR	Blue	Red
Gabor+ EigenPalm	0.09%	0.24%	0.07%	0.27%
Gabor+FisherPalm	0.00%	0.04%	0.00%	0.00%

Table 2. The EER obtained for the different methods and the down-samplings factors using Red band

	Red band			
Down-sampling factor	32	64	128	256
Gabor+ Eigenfaces	0.28%	0.27%	0.29%	0.38%
Gabor+Fisherfaces	0.00%	0.00%	0.00%	0.00%

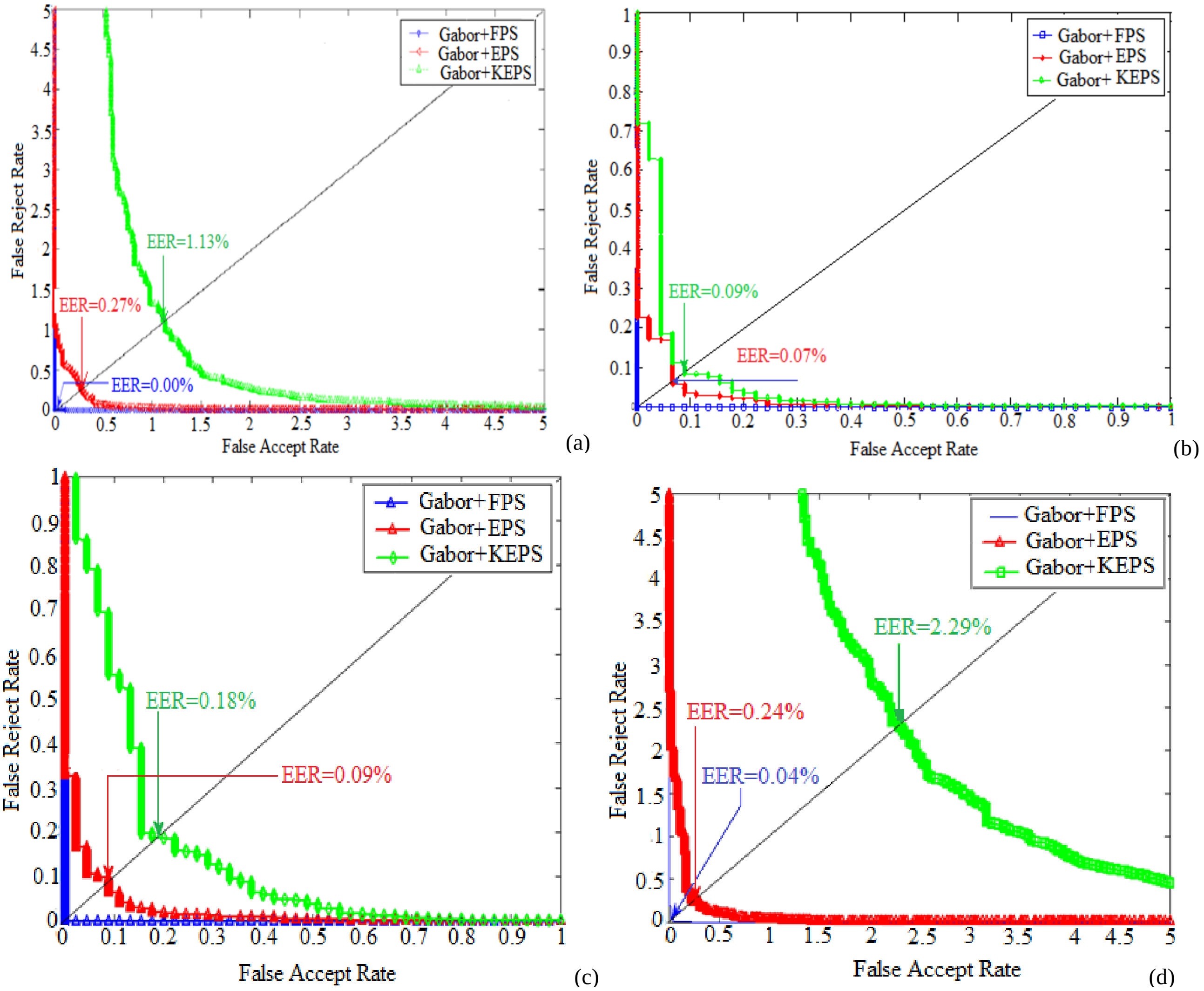

Fig.2 DET courbes : (**a**) Red (**b**) Blue (**c**) Green (**d**)NIR

Table.3 shows the EER for the different bands and the distance measures: Euclidean Distance (Eu), Mahalanobis Distance (Ma), City Block Distance (CB) and Cosine distance (COS). It is clear that the Ma distance achieved the lowest EER for the different bands among the four distance measure using for Gabor+Fisherpalm. Our work is compared with the other works (see Table 4).

Table 3. EER obtained for the different bands and the distance measure

	Green	Red	NIR	Blue
COS	0.0%	0.0%	0.04%	0.0%
Ma	0.0%	0.0%	0.04%	0.0%
Eu	0.03%	0.31%	0.71%	0.02%
CB	0.02%	0.33%	0.52%	0.02%

Table 4. Comparison of our results with the result obtained by other papers in term of EER

Methods	Blue	Green	Red	NIR
[3]	0.0520%	0.0575%	0.0212%	0.0398%
[16]	0.70%	0.40%	0.40%	0.70%
[5]	0.00%	0.00%	0.00%	0.00%
Our method	0.00%	0.00%	0.00%	0.04%

4. Conclusion and future work

In this proposed biometric system, each multispectral image is convolved with the Gabor filter bank of 40 filters. Then, each down-sampled magnitude response is transformed into a vector by scan columns, and then this obtained vector is normalized. The all normalized vectors for different scales and orientations are concatenated for produce the AMFV. The Fisherpalm or the Eigenpalm space is used to reduce the high dimensionality of this vector. The nearest neighbor classifier is used in the matching stage and the cosine Mahalanobis distance is used in the decision stage.

From the simulation results, it has been found that the performance of use the Gabor+Fisherpalm is better than the performance of use the Gabor+Eigenpalm. Our future work will focus on the integration of other biometric traits such as fingerprint or palmprint in order to perform the system performances and get a high accuracy.

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