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Pattern Recognition Letters 24 (2003) 1463–1467

Pattern Recognition Letters

www.elsevier.com/locate/patrec

Palmprint recognition using eigenpalms features

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Received 9 August 2002; received in revised form 24 October 2002

Abstract

In this paper, we propose a palmprint recognition method based on eigenspace technology. By means of the Karhunen–Loeve transform, the original palmprint images are transformed into a small set of feature space, called "eigenpalms", which are the eigenvectors of the training set and can represent the principle components of the palmprints quite well. Then, the eigenpalm features are extracted by projecting a new palmprint image into the subspace spanned by the "eigenpalms", and applied to palmprint recognition with a Euclidean distance classifier. Experimental results illustrate the effectiveness of our method in terms of the recognition rate.

Keywords: K–L transform; Eigenpalms; Palmprint recognition

1. Introduction

There is a high demand for personal identification and verification for reasons of security. The traditional secure measures, passwords or ID cards, provide only limited protection for safety systems. Thus, they cannot meet secure and automated requirements in the modern, automated world with an ever-growing need to authenticate individuals in various fields. Because one's unique characteristics cannot be stolen, forgotten, duplicated, shared or observed, biometrics-based recognition is emerging as the most reliable solution since it deals with physiological or behavioral characteristics, which can be used to authenticate a person's claim to identity or establish an identity from a database (Jain et al., 1999; Zhang, 2000). Compared with other biometrics technologies, palmprint has become an important complement to personal identification because of its advantages such as low resolution, low cost, non-intrusiveness and stable structure features (Duta et al., 2002; You et al., 2002).

The palm, the inner surface of the hand between the wrist and the fingers, consists of three parts: the finger-root region, inside region and outside region. There are three principle lines made by flexing the hand and wrist in the palm, which are usually defined as life line, heart line, and head line

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0167-8655/02/$ - see front matter
PII: S0167-8655(02)00386-0

(Shu and Zhang, 1998). The previous work on palmprint recognition focused on two aspects: (1) extracting the principle lines and creases in the spatial domain (Zhang and Shu, 1999; Duta et al., 2002; You et al., 2002) and (2) transforming the palmprint images into the frequency domain to obtain the energy distribution feature (Li and Zhang, 2002). In the first approach, the lines and creases of a palm are sometimes difficult to extract directly from a given palmprint image with low resolution. The recognition rates and the computational efficiency are also not sufficient. In the second approach, the abundant textural details of a palm are ignored and the extracted features are greatly affected by the lighting conditions. The problems with these two approaches suggest that new methods are required for palmprint recognition.

The concept of an eigenspace has been widely used in face recognition. That work shows that the extracted "eigenfaces" can effectively represent the principal components of the faces (Peng and Zhang, 1997; Turk and Pentland, 1991). In this paper, we find that it also offers good characteristics for palmprint recognition. Based on the Karhunen–Loeve (K–L) transform, the original palmprint images used in training are transformed into a small set of characteristic feature images, called "eigenpalms", which are the eigenvectors of the training set. Then, feature extraction is performed by projecting a new palmprint image into the subspace spanned by the "eigenpalms".

When capturing a palmprint, the position, direction and stretching degree may vary from time to time. As a result, even the palmprints from the same palm could have a little rotation and shift. Also the sizes of palms are different from one another. It is necessary to align all palmprints and normalize their sizes for further feature extraction and matching (Li and Zhang, 2002). In our biometrics research laboratory, a palmprint input device can on-line capture palmprint images. Both the rotation and translation are corrected by the capture device panel, which can locate the palms by six pillars. Subimages with a fixed size (128×128) are extracted from the captured palmprint images (384×284) so that different palmprints are converted into the same image size for further processing.

The rest of this paper is organized as follows: Section 2 presents a brief introduction to eigenpalms. Experimental results and some conclusions are given in Sections 3 and 4, respectively.

2. Eigenpalms: feature extraction

Usually a palmprint image is described as a two-dimensional array ($N \times N$). In the eigenspace method, this can be defined as a vector of length N^2, called a "palm vector". A sub palmprint image is fixed with a resolution of 128×128, hence a vector can be obtained, which represents a single point in the 16,384-dimensional space.

Since palmprints have similar structures (usually three main lines and creases), all "palm vectors" are located in a narrow image space, thus they can be described by a relatively low dimensional space. As the most optimal orthonormal expansion for image compression, the K–L transform can represent the principle components of the distribution of the palmprints or the eigenvectors of the covariance matrix of the set of palmprint images. Those eigenvectors define the subspace of the palmprints, which are called "eigenpalms". Then, each palmprint image in the training set can be exactly represented in terms of a linear combination of the "eigenpalms".

Let the training samples of the palmprint images be $x_1, x_2, \ldots, x_M$, where M is the number of images in the training set. The average palmprint image of the training set is defined by

$$\mu = \frac{1}{M}\sum_{i=1}^{M} x_i. \tag{1}$$

The difference between each palmprint image and the average image is given by $\varphi_i = x_i - \mu$. Then, we can obtain the covariance matrix of $\{x_i\}$ as follows:

$$C = \frac{1}{M}\sum_{i=1}^{M}(x_i - \mu)(x_i - \mu)^{\mathrm{T}} = \frac{1}{M}XX^{\mathrm{T}}, \tag{2}$$

where the matrix $X = [\varphi_1 \varphi_2 \cdots \varphi_M]$. Obviously, the matrix C is of dimensions $N^2 \times N^2$. It is evident that the eigenvectors of C can span an algebraic eigenspace and provide an optimal approximation for those training samples in terms of the mean-square error. However, determining the eigenvectors and eigenvalues of the matrix C ($C \in \Re^{N^2 \times N^2}$) is an intractable task for a typical image size. Therefore, we need to find an efficient method to calculate the eigenvectors and eigenvalues. It is well known that the following formula is satisfied for the matrix C:

$$Cu_k = \lambda_k u_k, \tag{3}$$

where u_k refers to the eigenvector of the matrix C, and λ_k is the correlative eigenvalue of matrix C.

In practice, the number of the training samples, M, is relatively small. The eigenvectors (v_k) and eigenvalues (a_k) of matrix $L = X^{\mathrm{T}}X$ ($L \in \Re^{M \times M}$) are much easier to calculate. Therefore, we have

$$X^{\mathrm{T}}Xv_k = a_k v_k, \tag{4}$$

and we multiply each side of the Eq. (4) by X,

$$XX^{\mathrm{T}}(Xv_k) = a_k(Xv_k). \tag{5}$$

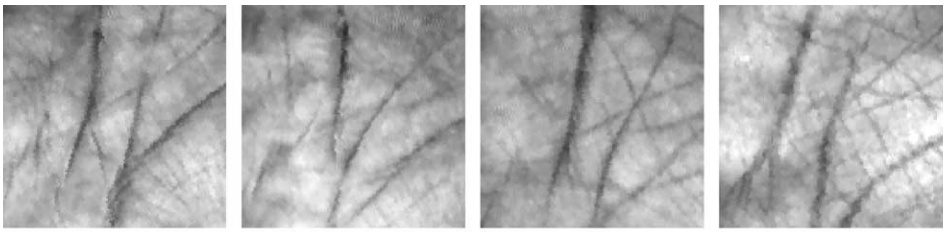
Then, we can get the eigenvectors of matrix C,

$$u_k = Xv_k. \tag{6}$$

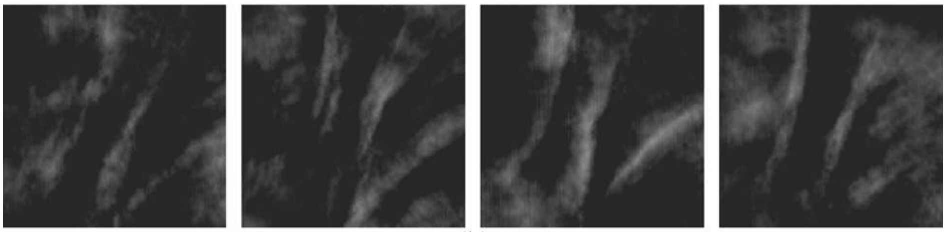
By using this method, the calculations are greatly reduced, where $U = \{u_k, k = 1, \ldots, M\}$ denotes the basis vectors which correspond to the original palmprint images and span an algebraic subspace called unitary eigenspace of the training set. Resizing each of the eigenvectors into the image domain ($N \times N$), we find that they are like palmprints in appearance and can represent the principle characters (especially, the main lines) of the palmprints, which are referred as "eigenpalms". Fig. 1 shows some of the eigenpalms derived from the samples in the training set.

Since each palmprint in the training set can be represented by an eigenvector, the number of the eigenpalms is equal to the number of the samples in the training set. However, the theory of principal component analysis states that it does not need to choose all of the eigenvectors as the base vectors and just those eigenvectors which correspond to the largest eigenvalues can represent the characteristic of the training set quite well. Then the M' significant eigenvectors (u'_k) with the largest associated eigenvalues are selected to be the components of the eigenpalms ($U' = \{u'_k, k = 1, \ldots, M'\}$), which can span an M' dimensional subspace of all possible palmprint images. A new palmprint image is transformed into its "eigenpalms" components by the following operation:

$$f_i = U'(x_i - \mu) \quad (i = 1, \ldots, M), \tag{7}$$



(a)



(b)

Fig. 1. (a) Subpalmprint samples in our training set. (b) The eigenpalms derived from the above samples.

where the weight of the projection f_i ($f_i \in \Re^{M' \times 1}$) refer to the standard feature vector of each person, and M' is called the feature length.

3. Experimental results

Palmprint images were collected in our laboratory from 191 people using our self-designed capture device. Since the two palmprints (right-hand and left-hand) of each person are different, we captured both and treated them as palmprints from different people. Eight samples were captured for each palm with different rotation and translations. Thus, a palmprint database of 382 classes was created, which included a total of 3056 ($= 191 \times 2 \times 8$) images with 384×284 pixels in 256 gray levels. Four kinds of experiment schemes were designed as follow: one (two, three or four) sample(s) of each person was randomly selected for training, and the other four samples were used for authentication, respectively.

During the experiments, the features are extracted by using the proposed eigenspace method with length 50, 100, 150 and 200. The weighted Euclidean distance is used to cluster those features (Zhu and Tan, 2000),

$$d_k = \sum_{i=1}^{N} \frac{(f(i) - f_k(i))^2}{(s_k)^2}, \tag{8}$$

where f is the feature vector of the unknown palmprint, f_k and s_k denote the kth feature vector and its standard deviation, and N is the feature length.

Based on these schemes, the matching is separately conducted and the results are listed in Table 1. A high recognition rate (99.149%) was achieved for the fourth scheme with feature length of 100. It is evident that the feature length can play an important role in the matching process. Long feature lengths lead to a high recognition rate. However, this principle only holds to a certain point as the experimental results show that the recognition rate remains unchanged, or even becomes worse, when the feature length is extended further.

A further analysis of the fourth scheme was made by calculating the standard error rates (false acceptance rate (FAR) and the false rejection rate (FRR)) (Zhang and Shu, 1999). Obviously, for an effective method both rates must be as low as possible, but they are actually antagonists and lowering these errors is part of an intricate balancing act. For example, if you make a system more difficult to enter for an impostor (reducing FAR), you also make the system more difficult to enter for a valid enrollee (i.e., FRR raised). This process operates in the reverse sense too. For a given system, this becomes a question of probabilities, and a company deploying such a system will generally adjust the matching threshold depending on the level of security needed. For instance, a bank needs a very secure system, so it would adjust the threshold very low to reach an FAR close to zero. However, the bank's employees will have to accept false rejections, and they may have to try several times to enter the system. The curves for the FRR and FAR of the fourth scheme are shown in Fig. 2. When the threshold value is

Table 1
The testing results of the three matching schemes with different feature lengths

Training samples	Feature length			
	50	100	150	200
1	94.175%	95.550%	95.175%	93.128%
2	96.073%	97.186%	96.924%	95.942%
3	97.186%	98.429%	98.822%	97.971%
4	97.840%	99.149%	99.084%	98.691%

Percentage values show recognition rate.

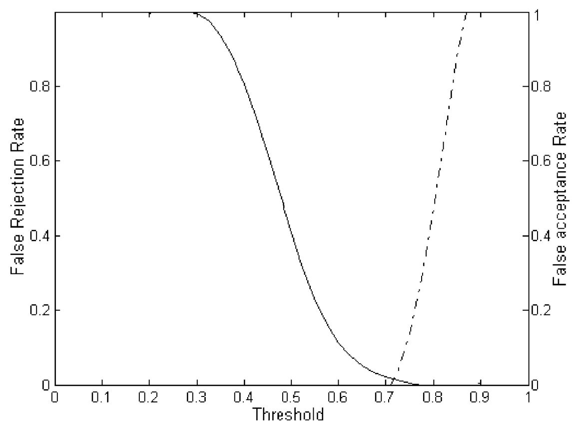


Fig. 2. The FRR and FAR of the proposed algorithm.

Table 2
Comparison of different palmprint recognition methods

	Method		
	Feature points (Duta et al., 2002) (Anil K. Jain)	Hierarchical identification (You et al., 2002) (Jane You)	Eigenpalm proposed (by authors)
Database (samples)	30	200	3056
Features	Feature points	Global texture features & feature points	Eigenpalms
Recognition rate (%)	95	91	99.149

set to 0.71, the palmprint recognition method can achieve an ideal result with an FRR = 1% and an FAR = 0.03%, respectively.

Compared with the approach in (Duta et al., 2002), which used a set of feature points along the prominent palm lines and the associated line orientation of palmprint images to identify the individuals, where a matching rate about 95% was achieved. But only 30 palmprint samples from three persons were collected for testing. It seems that the testing set is too small to cover the distribution of all palmprints. An average recognition rate 91% was achieved by the technology proposed in (You et al., 2002), which involved a hierarchical palmprint recognition fashion. The global texture energy features were used to guide the dynamic selection for a small set of similar candidates from the database at coarse level for further processing. An interesting point based image matching was performed on the selected similar patterns at fine levels for the final confirmation. Since multiple feature extraction methods and matching algorithms are needed, the whole process of recognition is more complex. Nevertheless, the recognition rate of our method is more efficient, as illustrated in Table 2.

4. Conclusions

In this paper, the eigenpalm method is developed for palmprint recognition by using the K–L transform algorithm, which can represent the principal components of the palmprints fairly well. The features are extracted by projecting palmprint images into an eigenpalms subspace. To assess the efficiency of our method, the weighted Euclidean distance classifier is applied. A correct recognition rate of up to 99% can be obtained using our approach.

Acknowledgements

The work is partially supported with UGC/CRC & CERG funds from the Hong Kong SAR Government and the central fund from The Hong Kong Polytechnic University.

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