Palmprint Recognition with PCA and ICA

Tee Connie, Andrew Teoh, Michael Goh, David Ngo
Faculty of Information Sciences and Technology,
Multimedia University, Melaka, Malaysia
tee.connie@mmu.edu.my

Abstract

Palmprint is one of the relatively new physiological biometrics due to its stable and unique characteristics. The rich texture information of palmprint offers one of the powerful means in personal recognition. According to psycho-physiology study, the primary visual cortex in the visual area of human brain is responsible for creating the basis of a three-dimensional map of visual space, and extracting features about the form and orientation of objects. The basic model can be expressed as a linear superposition of basis functions. This idea inspired us to implement two well known linear projection techniques, namely Principle Component Analysis (PCA) and Independent Component Analysis (ICA) to extract the palmprint texture features. Two different frameworks of ICA [1] are adopted to compare with PCA for the recognition performances by using three different classification techniques. Framework I observed images as random variables and the pixels as outcomes while framework II treated pixels as random variables and the images as outcome. We are able to show that ICA framework II yields the best performance for identifying palmprints and it is able to provide both False Acceptance Rate (FAR) and False Rejection Rate (FRR) as low as 1%.

Keywords: biometric palmprint, PCA, ICA, texture analysis

1 Introduction

Biometric has gained much attention in the security world recently. Many types of personal authentication systems have been developed, and palmprint verification is one of the emerging technologies. Biometric palmprint recognizes a person based on the principal lines, wrinkles and ridges on the surface of the palm. These line structures are stable and remain unchanged throughout the life of an individual. More importantly, no two palmprints from different individuals are the same, and normally people do not feel uneasy to have their palmprint images taken for testing. Therefore palmprint recognition offers promising future for medium-security access control system.

An important issue in palmprint recognition is to extract palmprint features that can discriminate an individual from the other. There are two popular approaches to palmprint recognition. One approach transforms palmprint images into specific transformation domains. Among the works that appear in the literature are eigenpalm [2], Gabor filters [3], Fourier Transform [4], and wavelets [5]. Another approach is to extract principal lines and creases from the palm [6]-[9]. However, this method is not easy because it is sometimes difficult to extract the line structures that can discriminate every individual well. Besides, creases and ridges of the palm are always crossing and overlapping each other, which complicates the feature extraction task.

The psycho-physiology study [10] suggested that the primary visual cortex in the brain performs the form and orientation analysis of the visual image formed by retina through the creating a three dimensional map of visual space from the basis functions. [11] gave the basic model which can express an image, $I(x,y)$ as a linear superposition of basis functions $b_i(x,y)$:

$$\boldsymbol{I(x,y)} = \sum_{i=1}^{n} s_i b_i(x,y) \tag{1}$$

where s_i are feature coefficients. These basis functions, $b_i(x,y)$ are able to capture the inherent structure of the palmprint texture, and thus inspired us to employ two well-known linear projection techniques, namely principal component analysis (PCA) and independent component analysis (ICA), to create a set of compact features for effective recognition task. PCA and ICA compute a set of basis vector, $b_i(x,y)$, from a set of palmprint images, and the images are projected into the compressed subspace to obtain a set of coefficients, s_i. New test images are then matched to these known coefficients by projecting them onto the basis vectors and finding the closest coefficients in the subspace. PCA is a canonical technique to find useful image representations in compressed subspace. It finds a set of basis vectors, $b_i(x,y)$ such that in this new basis, b_i are uncorrelated and Gaussian; whereas in ICA, b_i are statistically independent and non-Gaussian. Intuitively, lack of correlation determines the second-degree cross moment (covariance) of a multivariate distribution, while in general statistical independence determine all of the cross moments. Therefore, PCA can only separate pair-wise linear dependencies between pixels whilst ICA offers a more generalized method which can separate higher-order dependency.

According to [1], there are two types of implementation frameworks for ICA in the image recognition task. Framework I treats images as random variables and pixels as observations; while Framework II coins pixels as random variables and images as observations. In framework I, the basis vectors obtained are approximately independent, but the coefficients representing each image are not necessarily independent. On the other hand, framework II finds a representation in which all the coefficients are statistically independent. In the perspective of texture analysis in palmprint images, Framework I and II can be interpreted as local features and global texture features extractor, respectively. Framework I is sparse within images across pixels, it produces localized features that are only influenced by small portions of the image. On the other hand, Framework II is sparse across images and produces global features. Hence, ICA offers a well defined technique either for the local or global palmprint feature extraction.

2 Background

2.1 PCA

PCA has been widely used for dimensionality reduction in computer vision. Result shows that PCA also performs well in various recognition tasks [2], [12], [13]. In our context, the basis vectors, $b_i(x,y)$ generated from a set of palmprint images are called eigenpalm, as they have the same dimension as the original images and are like palmprint in appearance, as shown in Figure 2(a). Recognition is performed by projecting a new image into the subspace spanned by the eigenpalms and then classifying the palm by comparing its position in palm space with the positions of known individuals.

More formally, let us consider a set of M palmprint images, $i_1, i_2, \ldots, i_M$, the average palm of the set is defined as

$$\bar{i} = \frac{1}{M}\sum_{j=1}^{M} i_j \tag{2}$$

Each palmprint image differs from the average palm $\bar{i}$, by the vector $\phi_n = i_n - \bar{i}$. A covariance matrix is constructed where:

$$C = \sum_{j=1}^{M} \phi_j \phi_j^T \tag{3}$$

Then, eigenvectors, v_k and eigenvalues, λ_k with symmetric matrix C are calculated. v_k determine the linear combination of M difference images with ϕ to form the eigenpalms:

$$b_l = \sum_{k=1}^{M} v_{lk}\phi_k, \qquad l = 1,\ldots,M \tag{4}$$

From these eigenpalms, $K(<M)$ eigenpalms are selected to correspond to the K highest eigenvalues.

The set of palmprint images, $\{i\}$ is transformed into its eigenpalm components (projected into the palm space) by the operation:

$$\omega_{nk} = b_k(i_n - \bar{i}) \tag{5}$$

where $n = 1, \ldots, M$ and $k = 1, \ldots, K$.

The weights obtained form a vector $\Omega_n = [\omega_{n1}, \omega_{n2}, \ldots, \omega_{nK}]$ that describes the contribution of each eigenpalm in representing the input palm image, treating eigenpalms as a basis set for palm images.

2.2 ICA

The basic idea of ICA is to decompose an observed signal (mixed signal) into a set of linearly independent signals. When applied in palmprint recognition, the palmprint images are considered as the mixture of an unknown set of statistically independent source images by an unknown mixing matrix. A separating matrix is learnt by ICA to recover a set of statistically independent basis images (Figure 1).

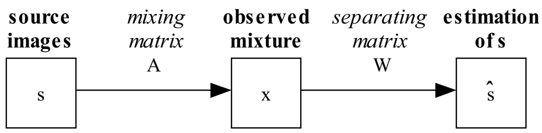


Figure 1: ICA implementations on palmprint recognition.

More formally, let s be the vector of unknown source images and x be the vector of observed mixtures. If A is the unknown mixing matrix, then the mixing process is written as

$$x = A\hat{s} \tag{6}$$

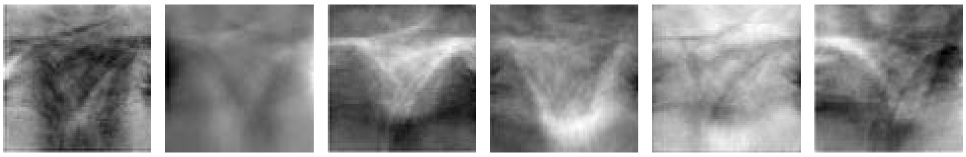
The goal of ICA is to find the separating matrix W such that

$$\hat{s} = Wx \tag{7}$$

However, there is no closed form expression to find W. Instead, many iterative algorithms are used to approximate W in order to optimize independence of $\hat{s}$. Thus, the vector $\hat{s}$ or equivalent to $b_i(x,y)$ in (1), is actually an estimate of the true source s. In this paper, the InfoMax algorithm [1] is deployed.

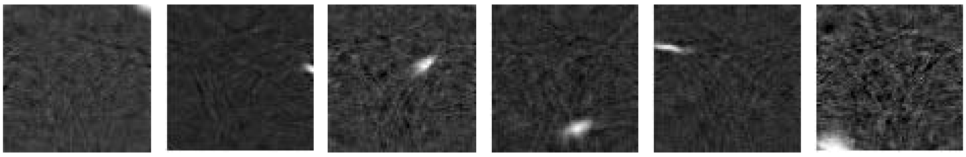
Basis generated by:

i) PCA



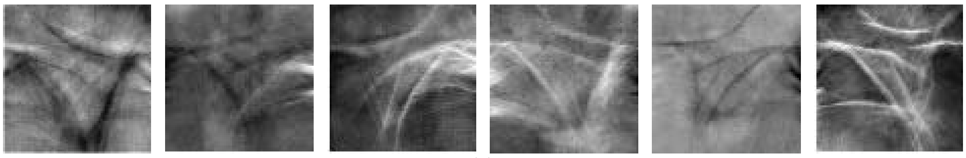
(a)

ii) ICA framework I



(b)

iii) ICA framework II



(c)

Figure 2: Vector basis generated by each technique. (a) represents basis for six eigenvectors with 6 highest eigenvalues for PCA. (b) shows six localized basis vector for ICA framework I. (c) depicts six non-localized ICA basis vectors for ICA framework II.

Sometimes, it is expedient to work on lower dimensionality. Preprocessing steps can be applied to x to reduce the dimension space. There are two common preprocessing steps in ICA. The first step is to centered the images as,

$$\hat{x} = x - E\{x\} \tag{8}$$

such that $E\{\hat{x}\} = 0$. This enables ICA to deal with only zero mean data.

The next step is to apply whitening transform V to the data such that

$$V = D^{-1/2} R^{T} \tag{9}$$

where D is the eigenvalues on the diagonal and R is the orthogonal eigenvectors of the covariance matrix of $\hat{x}$. The whitening process helps to uncorrelate the data so that PCA can work with unit variance.

2.2.1 Framework I: Statistically Independent Basis Image

In ICA framework I, the palm images are variables and the pixel values provide observation for the variables. The source separation is therefore performed on palm space.

In order to reduce the number of independent components produced by ICA, PCA is first applied to the data to obtain an eigenpalm of dimension m (as described by Bartlett and colleagues in [1]). The InfoMax algorithm is then applied to the eigenpalm to minimize the statistical independence among the resulting basis vectors. The pre-application of PCA can discard small trailing eigenvalues before whitening and reduce computational complexity by minimizing pair-wise dependency [14].

To describe framework I more formally, let the input to ICA, V, be a p by m matrix, where p represents the number of pixels in the training image, and m be the first m eigenvectors of a set of n palm images (section 2.1). As rows of the input matrix to ICA are variables and the columns are observations, therefore, ICA is performed on V^{T}.

After that, the independent basis vector, $\hat{S}$, is computed as follows:

$$\hat{S} = W * V^{-1} \tag{10}$$

Next, by taking R as the PCA coefficient where $R = X * V$, with X representing the n set of zero-mean images (image data is contained in each row), the coefficients matrix of ICA can be calculated as

$$B = R * W^{-1} \tag{11}$$

Therefore, the reconstruction of the original palmprint image can be achieved by

$$X = B * \hat{S} \tag{12}$$

The ICA basis images from framework I shown in Figure 2(b) are spatially localized in various portions in the palmprint image, and they bear a striking resemblance to the receptive fields in the primary visual cortex.

2.2.2 Framework II: Statistically Independent Coefficient

The goal in framework II is to find statistically independent coefficients for the input image. Therefore, the input to ICA, *V*, is transposed from framework I, where pixels are variables and images are observation. Thus, the source separation is performed on the pixels. However, in this work, ICA is performed on the PCA coefficients rather than directly on the input images to reduce the dimensionality as in [1].

Next, the statistically independent coefficients are computed as

$$U = W * R^T \tag{13}$$

and the basis vectors are obtained from the columns of $V * W^{-1}$. The basis generated by framework II shows more globalized features, as shown in Figure 2(c).

3 Palmprint Recoginition System

To perform palmprint recognition, a database containing 600 palm images from 100 users, with 6 images from each, is collected. The first three images are used as training data while the remaining three are deployed as testing data. An optical scanner is used as the image acquiring devices as it provides fast and high-resolution capability. Resolution of 200 dpi is adopted in this paper. The users are allowed to place their hands freely on the platform of the scanner when scanned. This results in palmprint images with different shifts and rotation. Therefore, some preprocessing jobs are required to correct the orientation of the image [15]. Next, the region of interest (ROI) of the palm is extracted so that the feature extraction process can be performed on a fixed size image. The ROI used in the experiment is of size 150 x 150.

The proposed palmprint recognition system consists of the following three steps:

i) Off-line: Compute the basis vectors from the training images.
ii) Off-line: Project the images into the subspace.
iii) On-line: Project a new test image into the subspace and obtain the closest matching image as measured in the subspace.

When applying PCA, several feature lengths, from 20 to 100, are tested. At first, larger feature length provide higher recognition rate, however, this is only true to a certain point as the recognition rate become worse when the feature lengths is extended further. Experimental result shows that feature lengths with 55 principal components yield the best performance by using our palmprint database.

After that, these feature lengths are used as the input to ICA calculation. Instead of processing on images with $m = 55$ (instead of $m = 300$) in ICA, the computational load can be reduced significantly.

Both PCA and ICA basis features are data dependent in the sense that they are learned from the training data at hand, and they will be different for different training data. This causes high processing load as every new user to the system require re-calculation of the data.

4 Result and Discussion

The recognition rates of the experiment are shown in Section 4.1. Further analysis is performed to find the verification rate of the system, and some discussion and result are presented in Section 4.2.

4.1 Recognition Rate

The recognition rates of PCA and ICA framework I and II are shown in Table 1 and Table 2, respectively. Three types of classifiers are tested, namely Euclidean distance, cosine measure and probabilistic neural network (PNN). Euclidean distance is the simplest distance matching algorithm among all. Cosine measure can be used since ICA allows the basis vectors to be non-orthogonal, and the angles and distances between images differ from each other. Probabilistic neural network is a kind of radial basis network suitable for classification problems. Table 1 shows the performance recognition rates of PCA using these distance metrics.

Table 1: Recognition rate of PCA using three types of classifiers.

Number of principal component	Euclidean Distance (%)	Cosine Measure (%)	Probabilistic Neural Network (%)
40	89.6667	82.3333	90.0000
45	90.0000	83.6667	90.6667
50	91.3333	84.3333	91.0000
55	91.3333	84.3333	93.3333
60	91.3333	84.3333	91.0000
70	90.6667	84.0000	90.0000

Experimental result shows that PCA with 55 principal components yield the best performance, and the recognition rate drops after this point. This feature length of 55 is then used as the input to ICA calculation. The recognition rates of ICA Framework I and II are provided in Table 2.

Table 2: Recognition rates of ICA Framework I and Framework II by using three types of classifiers.

Method	Euclidean Distance (%)	Cosine Measure (%)	Probabilistic Neural Network (%)
ICA Fr. I	91.6667	94.0000	97.0000
ICA Fr. II	92.3333	95.6667	97.6667

It can be observed that ICA performs better using cosine measure than Euclidean distance; while PCA performs better using Euclidean distance rather than cosine. This shows that cosine measure can be used to retrieve images in the ICA subspace effectively but not in PCA. On the other hand, result shows that probabilistic neural network outperforms the other two measurements. This is due to the reason that PNN can generalized well on the data that it has not seen before. Euclidean distance and cosine measure does not take into account the subtle differences between the images. Therefore, they perform poorly as compared to PNN. PNN can account for these subtle differences and is able to learn effectively the important features of the modelled data.

From the experimental result, it is obvious that both frameworks for ICA outperform PCA no matter what distance metrics were used. The result is of no doubt as ICA has the advantage to decorrelate the higher dependency relationship in the images.

4.2 Verification Rate

Further analysis of the result was performed by calculating the standard error rates (false acceptance rate (FAR) and false rejection rate (FRR)). FAR and FRR are defined, respectively, as

$$FAR = \frac{Number\ of\ accepted\ imposter\ claims}{Total\ number\ of\ imposter\ accesses} \times 100\% \quad (15)$$

$$FRR = \frac{Number\ of\ rejected\ genuine\ claims}{Total\ number\ of\ genuine\ accesses} \times 100\% \quad (16)$$

The system threshold value is obtained based on the Equal Error Rate (EER) criteria where FAR = FRR. This is based on the rationale that both rates must be as low as possible for the biometric system to work effectively. Another performance measurement is obtained from FAR and FRR which is called Total Success Rate (TSR). It represents the verification rate of the system and is calculated as follow:

$$TSR = (1 - \frac{FAR + FRR}{Total\ number\ of\ accesses}) \times 100\% \quad (16)$$

Table 3 shows the verification rates of PCA, ICA framework I and II by using their respective best distance measures, specifically Euclidean Distance for PCA and Cosine Measure for ICA.

Table 3: Verification rate of PCA and the two ICA frameworks.

Method	FAR(%)	FRR(%)	TSR(%)
PCA(PC: 55)	3.0707	3.0000	96.9300
ICA Fr. I	1.8081	2.0000	98.1900
ICA Fr. II	1.0000	1.0000	99.0000

Experimental result shows that both ICA framework I and II outperforms PCA; and ICA framework II outperforms framework I. The first outcome is reasonable as ICA can separate the higher-order dependency among the basis vectors (more important information is always contained in higher-order statistics of the image). The result of the later can be explained from the global versus local features point of view. As framework I is sparse within images across pixels, it produces localized features that are only influenced by small parts of the image. On the other hand, framework II is sparse across image and produces global features. Viewing the nature of the texture of a palmprint image, recognition by parts (using localized features) is not suitable as the prints are made up of many crossing and overlapping ridges. When treated individually, the lines cannot contribute much to the recognition process. Some lines are so thin and unobvious that they will simply be ignored by the feature extraction algorithm. Therefore, localized features of palmprints cannot provide good recognition; and performance can only be improved when all the palmprints are treated as a whole. In other word, palmprint recognition is holistic and requires spatially overlapping feature vectors.

5 Conclusion

In this paper, a palmprint verification system is developed by using PCA and ICA algorithms. ICA is implemented by using two different frameworks, which are called framework I and II respectively. Framework I produces outputs that were sparse in space, therefore it produces local basis images. On the contrary, framework II produces outputs that were sparse across images; therefore it produces holistic basis images. Three types of distance metrics are used to assess the efficiency of the algorithms, and probabilistic neural network is the best classifier among all. Experimental result shows that both ICA representations outperform PCA, while ICA framework II outperforms framework II. A verification rate of 99% can be achieved by using framework II in our system. This shows that palmprint recognition performs well by using global (holistic) features as compared to localized features.

6 Acknowledgements

The authors would like to thank Marian Stewart Bartlett for her generous help and invaluable discussion on this topic.

7 References

[1] Bartlett, M.S., Movellan, J.R., & Sejnowski, T.J., “Face recognition by independent component analysis”, *IEEE Transactions on Neural Networks*, 13(6), pp 1450-1464 (2002).

[2] Lu, G., David, Z., Wang, K., “Palmprint recognition using eigenpalms features”, *Pattern Recognition Letters*, 24(9-10), pp 1473-1477 (2003).

[3] Wai, K.K., David, Z., Li, W.,“Palmprint feature extraction using 2-D Gabor filters”, *Pattern Recognition*, 36(10), pp 2339-2347 (2003).

[4] Li, W., David, Z., Xu, Z., “Palmprint identification by Fourier tranform”, *Int. J. Patt. Recognition. Art. Intell.*, 16(4), pp 417-432 (2002).

[5] Kumar, A., Shen, H.C., “Recognition of palmprints using wavelet-based features”, *Proc. Intl. Conf. Sys., Cybern., SCI-2002* (2002).

[6] You, J., Li, W., David, Z., “Hierarchical palmprint identification via multiple feature extraction,“ *Pattern Recognition*, 35, pp 847-859 (2002).

[7] Duta, N., Jain, A.K., Mardia, K.V., “Matching of palmprint”, *Pattern Recognition Letters*, 23, pp 477-485 (2002).

[8] Wu, X., Wang, K., David, Z., “Fuzzy Directional Element Energy Feature (FDEEF) Based Palmprint Identification”, *Internat. Conf. Pattern Recognition*, 1, (2002).

[9] David, Z., Shu, W., “Two novel characteristics in palmprint verification: datum point invariance and line feature matching”, *Pattern Recognition*, 32, pp 691-702 (1999).

[10] Hyvarinen, A., Hoyer, P.O., “Emergence of Topography and Complex Cell Properties from Natural Images using Extensions of ICA”, *Advances in Neural Information Processing Systems*, 12, pp 827-833 (2000).

[11] De Valois, R. L., Albrecht, D.G., Thorell, L.G., “Spatial-frequency selectivity of cells in macaque visual cortex”, *Vision Res*, 22, pp 545-559, (1982).

[12] Turk, M.A., Pentland, A.P., “Eigenfaces for Recognition”, *Journal of Cognitive Neuro-Science*, 3(1), pp 71-86 (1991).

[13] Wang, X., Kuldip, K.P., “Feature extraction and dimensionality reduction algorithms and their applications in vowel recognition”, *Pattern Recognition,* 36(10), pp 2429-2439 (2003).

[14] Baek, K., Draper, B.A., Beveridge, J.R., She, K., “PCA vs ICA: A Comparison on the FERET data set”, *International Conference on Computer Vision, Pattern Recognition and Image Processing in conjunction with the 6th JCIS*, (2001).

[15] Tee, C., Goh, M., Teoh, A., Ngo, D., “An Automated Biometric Palmprint Verification System”, *3rd Int. Symp. on Communications & Info. Tech. (ISCIT2003)*, to appear in proceeding (2003)