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WAVELET BASED INDEPENDENT COMPONENT ANALYSIS FOR PALMPRINT IDENTIFICATION

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Abstract:

This paper presents a multi-resolution analysis based Independent Component Analysis (ICA) method for automatic palmprint identification. The ICA is well known by its feature representation ability recently, in which the desired representation is the one that minimizes the statistical independence of the components of the representation. Such a representation can capture the essential feature and the structure of the palmprint images. At the same time, the palmprints have a great deal of different features, such as principal lines, wrinkles, ridges, minutiae points and texture, which can be regarded as multi-scale features. Then, it is reasonable for us to integrate the multi-resolution analysis method and ICA to represent the palmprint features. The experiment results show that the integrated method is more efficient than ICA algorithm.

Keywords:

Independent Component Analysis; Palmprint Identification; Multi-resolution Analysis

1. Introduction

Biometrics based technologies have drawn a great deal of attention in the last few years, and have been considered having a wide application future. One of the earliest and well-known biometrics technologies is fingerprint recognition, which has been used for hundreds of years. Now a lot of other biometrics technologies are beginning to emerge, such as iris, face, palmprint, voice, hand geometry and signature recognition. Palmprint, unlike hand geometry that measures a hand's size and a fingers' length, is concerned with the inner surface of a hand and looks at line and texture patterns. A palm is covered with the same kind of skin as the fingertips and it is larger than a fingertip in size. Hence, it is quite natural to think of using palmprint to recognize a person. In the last years, palmprint recognition has attracted much research effort and been greatly developed. Lots of interesting and meaningful research results have been achieved at the same time. D. Zhang et al. and N. Duta et al. did much work on the line features and point features [1, 2]. However those kinds of line and point features are very difficult to be extracted from the low resolution palmprint images. D. Zhang et al. and Wen Li et al. then presented a series of methods to extract the texture features from the palmprints [3, 4], and had gotten many interesting experiment results. But the recognition rates are still not satisfactory. So it's necessary for us to find more efficient methods to overcome those problems.

Independent component analysis (ICA) has recently attracted a great deal of attention in signal processing and feature extraction fields, and has been regarded as an efficient tool for modeling and understanding the hidden factors that underlie sets of random variables, or signals. ICA defines a generative model for the observed multivariate dataset, which is typically given as a large database of samples. In this model, the dataset is assumed to be linear mixtures of some unknown latent variables, and the mixing system is also unknown. The latent variables are assumed nongaussian and mutually independent, and they are called the independent components of the observed data. ICA attempts to discover from observed signals a set of unobserved and underlying independent components (ICs) that are as statistically independent as possible [5].

At the same time, the palmprint images have a great deal of different features, such as principal lines, wrinkles, ridges, minutiae points, singular points and texture, which can be regarded as multi-scale features. Then, it is reasonable for us to combine the multi-resolution analysis with independent component analysis methods to represent the palmprint features. The experiments show that the integrated method is more efficient than ICA method.

This paper is organized as follows: Section 2 presents a brief introduction to the integrated palmprint feature extraction method. Experimental results and some conclusions are given in Section 3 and Section 4 respectively.

2. Wavelet based Independent Component Analysis for Palmprint feature extraction

Feature extraction is to describe a palmprint in a concise feature set other than the original image. How to define the feature is the key point of palmprint identification. A good feature must well distinguish the palmprint from different persons and at the same time, be similar to each other from the same persons' palmprints. In this paper, we present a novel method, which combines the multiresolution analysis with ICA method for palmprint feature extraction.

2.1. Wavelet decomposition

Initially, wavelet transform just focused on the 1-D situation. However, multidimensional wavelets are also available, especially the two dimensional (2-D) wavelets. In the same way, the 2-D wavelet transform can be treated as two 1-D wavelet transforms: one 1-D wavelet transforms along the row direction and the other 1-D wavelet transforms along the column direction. Thus, the 2-D wavelet transform can be computed in cascade by filtering the rows and columns of images with 1-D filters [6]. Generally, the 2-D wavelet decomposition of I octaves of an image $g(m, n)$ represents it by $3I+1$ sub images

$$\left[g_I, \left\{g_i^1, g_i^2, g_i^3\right\}_{i=1\cdots I}\right], \tag{1}$$

where g_I is a low frequency component of the original image, and g_i^d are the wavelet sub images containing the image details at different scales (2^j) and orientations (d). The wavelet decomposition coefficient g_i^1 corresponds to the vertical high frequencies, g_i^2 corresponds to the horizontal high frequencies, and g_i^3 corresponds to the high frequencies in both directions. The coefficients obtained by applying the 2-D wavelet transform on an image are called the sub images of the wavelet transform.

2.2. Brief introduction to ICA

The general idea of ICA is to represent the observed data by its basis functions (independent components), where the basis functions are statistical independent or as independent as possible [3]. The basic definition of ICA can be modeled as the following statistical function:

$$y = Ax, \tag{2}$$

where $y=(y_1, y_2, \ldots, y_n)^T$ is an observed random vector with n components, and A is a mixing matrix for the independent components x. Our goal here is to find out the x using only the observed vector y. Assuming that the inverse of the mixing matrix A is w, then, the independent components are calculated using:

$$x = A^{-1}y = wy. \tag{3}$$

Since the mixing matrix A and the independent components x are unknown, we have to estimate them only by the observed random vector y. Two main assumptions must be done to solve this problem: (a) The independent components x must be statistical independent; (b) The independent components must have nongaussian distribution [7]. Based on the two constraints, Aapo Hyvärinen et al. present a computationally highly efficient method for performing the estimation of ICA, in which the negentropy is used as the criterion to measure the nongaussian, since a gaussian variable has the largest entropy among all random variables of equal variance. However, the estimation of negentropy is difficult. In practice, the negentropy is approximated by using the contrast function, which is specified in the following form:

$$J(w) \approx [E\{G(wy)\} - E\{G(v)\}]^2 \tag{4}$$

where v is a standardized gaussian variable. G is a non-quadratic function. Usually, the following functions for G can be selected: $G_1(x) = \frac{1}{a_1}\log\cosh(a_1 x)$, $G_2(x) = -\exp(-x^2/2)$, where $1 \le a_1 \le 2$. To maximizing $J(w)$ we can estimate w_i by:

$$w^+ = E\{yg(w^T y)\} - E\{g'(w^T y)\}w \tag{5}$$

$$w = w^+ / \left\|w^+\right\| \tag{6}$$

where g, g' are the first and second derivatives of G, respectively. Then we can get the mixing matrix A. Since each palmprint image y_i is represents by a linear combination of the independent components ($x_1, x_2, \ldots, x_n$), the mixing matrix A can be considered as the feature matrix of all the training samples.

Before applying the ICA algorithm on the observed data, it's usually very useful and necessary to do some preprocessing. The most useful steps are centering and whitening. Centering means to make y a zero-mean variable. That is $y_i = y_i - E\{y_i\}$. Whitening is to make the covariance matrix of the observed data equal unit,

$$E\{\tilde{y}\tilde{y}^T\} = I \tag{7}$$

The whitening is always possible by some linear transform, such as eigenvalue decomposition [8].

In the process of feature extraction, the palmprint images are decomposed into multiresolution representation by 2D wavelet transform first. Then, the decomposed images in low frequency g_l are selected and are fed into ICA computation, which can represent the palmprints by using its independent components. Then we can get the feature matrix A of all the training palmprint samples.

3. Experiment results and analysis

In order to collect the palmprint samples easily and friendly, we have designed an online palmprint capture device, which is based on CCD camera [1]. The Figure 1 shows the architecture of our online acquisition device. A database containing 400 different palms is established. The palmprint samples are captured in size 384×284 with 256 gray levels. Each palm is captured 10 times by different rotation and translation. Therefore there are 4000 samples in our testing database. Since the palmprints are collected from different persons, and are varied from each other, it is necessary to align all palmprints and normalize their sizes for further processing. In this paper, a fixed size sub-image (128×128) is extracted from each captured palmprint image [9]. Figure 2(a) shows some typical sub-palmprint images in the database, and Figure 2(b) shows the corresponding ICA palm images.

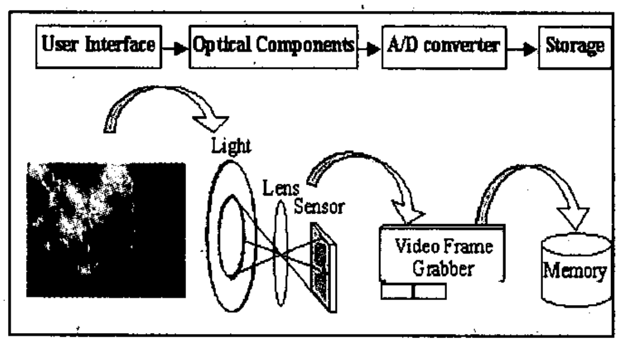
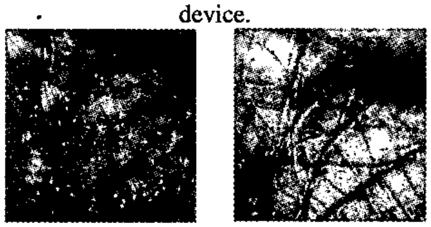


Figure 1. The architecture of our palmprint capture device.



(a)

(b)

Figure 2. (a) Sub-palmprint samples in our training set. (b) The ICA palms derived from the above samples.

To evaluate the efficiency of this integrated method (for short: W+ICA), the experiments were designed as follow: Two (three or four) samples of each palm were randomly selected for training, and other 4 samples were selected for authentication, respectively. For each scheme, different number of Independent Components (ICs) was chosen separately, such as 150, 200, 250, 300 and 350 ICs. The matching was conducted independently based on Euclidean distance classifier and the results are shown in Table 1. From the results we can find that the accuracy can be greatly improved with the growth of the selected ICs and the training samples. When 2 samples are used for training and the 150 ICs are selected, an accuracy of 95.50% can be achieved. When 4 samples are used for training and 300 ICs are selected, a higher accuracy of 98.44% can be gotten. Figure 3 shows the genuine and impostor distribution in this scheme. We can see that our method can separate the genuine and impostors well.

Further experiments are done to compare the proposed method with the ICA method only. The testing results are also shown in Table 1, which clearly illustrate that our method is more efficient in accuracy. Besides, since the sizes of palmprint images sizes become much smaller after the wavelet transform, our method can save more time in the ICA training process.

4. Conclusions

This paper has proposed a novel feature extraction method for palmprint identification which combines wavelet transform with independent component analysis method. The sub palmprint images are decomposed into multiresolution representation by 2D wavelet transform first.

Table 1 Testing results: comparing W+ICA with ICA only.

Training samples	Accuracy (%)	ICs				
		150	200	250	300	350
2	ICA	95.50	95.75	96.06	96.13	96.13
	W+ICA	96.06	96.38	96.81	96.88	96.88
3	ICA	95.94	96.56	97.00	97.00	97.06
	W+ICA	96.69	97.38	97.81	98.12	98.12
4	ICA	96.19	96.88	97.56	97.56	97.56
	W+ICA	97.44	97.88	98.31	98.44	98.38

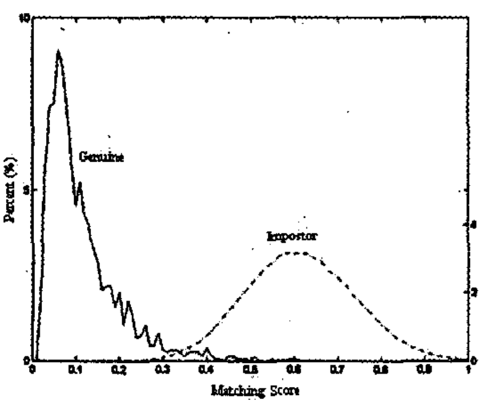


Figure 3. The genuine and impostor distribution of the proposed algorithm, where 4 samples are used for training and 300 ICs are selected at the same time.

Then, the decomposed images in g_l are selected and are fed into ICA computation, which can represent the palmprints by using its independent components that are as statistically independent as possible. To assess the efficiency of this new method, the Euclidean distance is applied, and the results show that the recognition performances are satisfactory. It can operate at high identification accuracy at 98.44% when there are 4 samples to training with 300 ICs.

Acknowledgements

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References

[1] D. Zhang and W. Shu. "Two Novel Characteristics in Palmprint Verification: Datum Point Invariance and Line Feature Matching", Pattern Recognition, vol. 32, no. 4, pp. 691-702, 1999.

[2] N. Duta, Anil K. Jain, K.V. Mardia, "Matching of palmprint", Pattern Recognition Letters, 23, pp. 477-485, 2002.

[3] J. You, W. Li, D. Zhang. "Hierarchical palmprint identification via multiple feature extraction". Pattern Recognition, 35, pp. 847-859, 2002.

[4] W. Li, D. Zhang. "Palmprint Identification by Fourier Transform". International Journal of Pattern Recognition and Artificial Intelligence, vol. 16, no. 4, pp. 417-432, 2002.

[5] Marian Stewart Bartlett, Javier R. Movellan, Terrence J. Sejnowski, "Face recognition by independent component analysis", IEEE Trans. On Neural Networks, Vol. 13, No. 6, pp. 1450-1464, 2002.

[6] Yu Tao, Ernest C.M. Lam, Yuan Y. Tang, "Feature Extraction Using Wavelet and Fractal", Pattern Recognition, 22, pp. 271-287, 2001.

[7] A. Hyvarinen, E. Oja, "Independent component analysis: algorithms and applications", Neural Networks, 13, pp. 411-430, 2000.

[8] Pong C. Yuen, J.H. Lai, "Face representation using independent component analysis", Pattern Recognition, 35, pp. 1247-1257, 2002.

[9] Guangming Lu, David Zhang, Kuanquan Wang, "Palmprint Recognition Using Eigenpalms Features", Pattern Recognition Letters, 24, pp. 1473-1477, 2003.