Multiresolution Independent Component Analysis for Iris Identification

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Abstract: In this paper, the new method to extract the features of iris signals is proposed; Multiresolution ICA (M-ICA) provides good properties to represent signals with time-frequency. The conventional methods were to use the technique of filter bank analysis, while ICA is unsupervised learning algorithm using high-order statistics. M-ICA could make use of strengths of learning method and multiresolution. Also, we performed comparative studies of different feature extraction techniques applied to personal identification using iris pattern. To measure goodness of methods, we use Fisher's discriminant ratio to quantify the class-separability of features generated by various techniques.

1. Introduction

Iris is a physiological biometric feature containing unique texture. Iris identification has a better performance than other biometrics. In general, the iris identification system is composed of three steps. The first procedure is to acquire the eye image including iris region. Then we localize an iris region and extract features. The last procedure is decision by means of matching [1].

A good iris identification methodology should consider representation as well as classification, and a good representation is to find apparent feature in the image. Since 1990s, many works has been done, i.e. Daugman made use of the feature extraction method based on modified 2-D Gabor filter [2], Wildes made use of an isotropic band-pass decomposition derived from application of Laplaican of Gaussian filters to the image data [3] and Boles developed algorithm that decomposes 1-D normalized iris signatures at a few intermediate resolution levels and obtains the iris representation of these signals via zero-crossing of the dyadic wavelets transforms [4]. Most representation methods made use of multi-resolution analysis to detect the distinctive spatial characteristics of the human iris and experimental results showed multiresolution techniques have good performance. However, the conventional methods are fixed transforms, meaning that the basis vectors are fixed once and for all, independent of any data, so it does not mean they are the best representation of iris textures.

So, we propose a new method to generate iris features, M-ICA (Multiresolution Independent Component Analysis). ICA is unsupervised learning algorithm using high-order statistics [5]. In general, it would be desirable to estimate the linear transform from the data itself, in which case the transform could be ideally adapted to the kind of data that is being processed. The introduction of mutiresolution into the ICA has taken strengths of unsupervised learning and multi-resolution analysis simultaneously.

In this paper, we performed comparative studies of different feature extraction techniques applied to various personal identification using iris pattern. The performance of techniques was compared in same condition; we extract iris signals in limited region within iris image and perform different feature extraction methods with same database. To evaluate goodness of methods, we use Fisher's discriminant ratio to quantify the class-separability of features generated by various techniques [6].

In Section 2, we will explain conventional methods that extract iris pattern. In Section 3, the new feature extraction method is introduced. In section 4, experimental results will be presented, and conclusions will be drawn in Section 5.

2. Conventional representation of iris pattern

2.1 Multi-channel Gabor filter

The 2-D Gabor filters can be used in image processing for feature extraction and texture analysis for several reasons. Gabor filters have tunable orientation and radial frequency bandwidths, tunable center frequencies and optimally achieve joint resolution in spatial and frequency domain. 2-D Gabor filters have the functional form,

$$h(x,y) = g'(x,y)\exp(j(\omega_x x + \omega_y y))$$

$$g'(x,y) = \frac{1}{\lambda\sigma^2}g(\frac{x'}{\lambda\sigma},\frac{y'}{\sigma}), \quad g(x,y) = \frac{1}{2\pi}\exp(-\frac{x^2+y^2}{2}) \tag{1}$$

where the parameter σ is the spatial scaling, which controls the width of the filter, and λ defines the aspect ratio of the filter, which determines the directionality of the filters. And it has a spatial frequency $\omega = \sqrt{w_x^2 + w_y^2}$, and direction $\theta = \tan^{-1}(\omega_y/\omega_x)$. By varying the free parameters σ, λ, ω and θ filters of arbitrary orientation and bandwidths are obtained.

2.2 Wavelet transform

The wavelet transform is a very powerful tool for texture discrimination. It is a linear operation that decomposes a signal into components that appear at different scales. This transform is based on the convolution of the signal with a dilated filter. A wavelet is a function

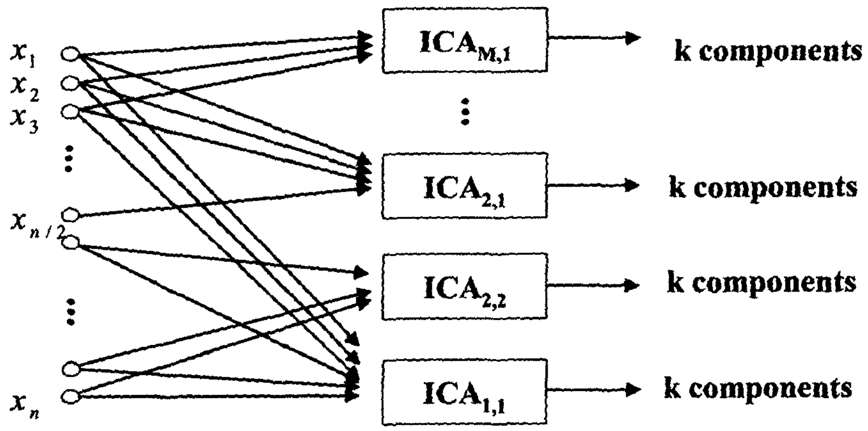


Figure 1. The Architecture of M-ICA

$\psi(x) \in L^2$ such that

$$\int_{-\infty}^{+\infty} \psi(x)dx = 0 \qquad (2)$$

Let us denote by $\psi_s(x)$ the dilation of $\psi(x)$ by a scale s

$$\psi_s(x) = \frac{1}{s}\psi(\frac{x}{s}) \qquad (3)$$

The wavelet transform of a function $f(x)$ at the scale s and position x is given by the convolution product

$$W_s f(x) = f * \psi_s(x) \qquad (4)$$

When the scale s decreases, the support of $\psi_s(x)$ decrease so the wavelet transform $W_s f(x)$ is sensitive to finer details. The scale s characterizes the size and regularity of the signal features extracted by the wavelet transform [7].

3. Statistical Methods

3.1 ICA

ICA is unsupervised learning algorithm using high-order statistics. It would be most useful to estimate the linear transform from the data itself, in which case the transform could be ideally adapted to the kind of data that is being processed. The conventional transforms are fixed transforms, meaning that the basis vectors are fixed once and for all, independent of any data [5]. To define ICA, we can use a statistical latent variable model. We observe n random variables $x_1, \cdots, x_n$, which are modeled as linear combination of n random variables $s_1, \cdots, s_n$:

$$x_i = a_{i1}s_1 + a_{i2}s_2 + \cdots + a_{in}s_n \qquad (5)$$

where the a_{ij} , $i, j = 1, \cdots, n$ are some real coefficients. By definition, the s_i are statistically mutually independent. This is the basic ICA model. The independent components s_i are latent variables, meaning that they cannot be directly observed. Also the mixing coefficients a_{ij} are assumed to be unknown. All we observe are the random variable x_i , and we must estimate both the mixing coefficients a_{ij} and the ICs s_i using x_i. This could be done under general assumptions. If we use vector-matrix notation, the mixing model is written as

$$\mathbf{x} = \mathbf{A}\mathbf{s} = \sum_{i=1}^{n} \mathbf{a}_i s_i \qquad (6)$$

This model is considered as linear combination of basis vector $\mathbf{a}_i$ in image processing. And the basis vectors are clearly localized in space, as well as in frequency and orientation. Our goal is to find a good set of basis vectors to represent iris patterns effectively.

3.2 M-ICA

We propose the new method to generate iris features, i.e. M-ICA (Multiresolution Independent Component Analysis). Introduction of mutiresolution into the ICA has taken strengths of unsupervised learning and multiresolution analysis simultaneously. The Architecture of proposed method is shown in Fig.1. Input signals, $x_1, \cdots, x_n$, is transformed by a set of ICA blocks. They decompose input signals at different resolutions.

4. Experimental Results

Experiments are composed of two parts, one is to evaluate the performance of the different feature extraction methods, and the other is to look into the properties of M-ICA. To evaluate the performance, we collected 400 data acquired from 40 people included the users with glasses in Fig.2.

4.1 Performance evaluations

In this paper, we performed comparative studies of five feature extraction techniques applied to various personal identification using iris pattern: Gabor wavelets, Haar wavelets, DAUB4 wavelets, ICA, and M-ICA. We extract iris signals in limited region within iris image and perform different feature extraction methods with same database as shown in Fig.3.

Iris images without glasses

Iris images with glasses

Figure 2. Iris images

1. Acquire the 2-D image data in right sector.
2. Process the Gaussian average through direction of radius to have 1-D iris signals.
3. Apply different feature extraction methods to 1-D iris signals.
4. Calculate the class-separability of features generated by each method.

To evaluate class-separability that is discrimination between within-class and between-class, Fisher's discriminant ratio in Eq (7) was used.

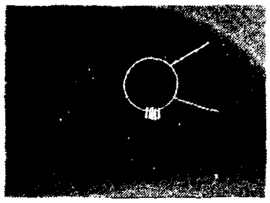
$$FDR = \frac{|m_1 - m_2|^2}{\sigma_1^2 + \sigma_2^2} \tag{7}$$

where $m_i, \sigma_i^2,\ i = 1, 2$ are mean and variance of within-class and between-class.

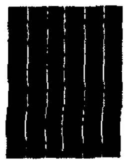
Table.1 showed that Haar wavelets have the best performance. It noted that Haar wavelets have very simple form, but they have a good ability to classify individual iris patterns than other wavelets. But, Haar wavelets are fixed transforms, so it does not mean they are the best representation of iris textures. In experimental results, ICA and M-ICA have lower performance than fixed transforms, but it does not mean that they are not appropriate to apply to iris identification since data size in ICA and M-ICA is lower than that in other methods. Also, when ICA and M-ICA are applied to extract features, a set of parameters such as the number of reduced basis, the dimension of input signal, and so on must be chosen. The variations of resolutions in M-ICA may give the better performance. Most of all, ICA and M-ICA are the first approach using learning methods to identify iris patterns. It is required further researches in learning methods to find the best representation of iris patterns.

Table 1. Comparing glint with the conventional focus values

	Fisher's discriminant ratio
Gabor	15.9
Haar	16.4
DAUB4	13.0
ICA	3.1
M-ICA	14.1



(a)

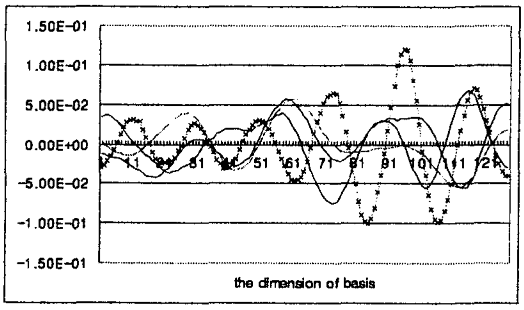


(b)

Figure 3. iris data extraction : (a) extraction region (b) iris signals

4.2 The Properties of M-ICA

M-ICA has many useful properties to extract features in image. In ICA, the basis vectors are clearly localized in space, as well as frequency and orientation. In learning stage, the number of basis vectors may be reduced to process large dimension of input signals easily. Fig.4 showed that the properties of basis vectors are changed according to the number of basis vectors. In M-ICA, the spatial localization of input signals may provide powerful methods to extract the localized features. It is similar to wavelets analysis that allows the use of long time intervals where we want more precise low frequency information, and shorter regions where we want high frequency information. The spatial localization of input means the variation of time interval to analysis. Fig.5 showed the basis of M-ICA had the properties of time-frequency analysis where the dimensions of input signal are 128, 64, 32, and the number of reduced basis is 12.



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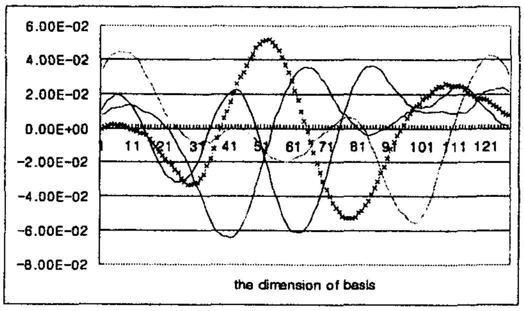
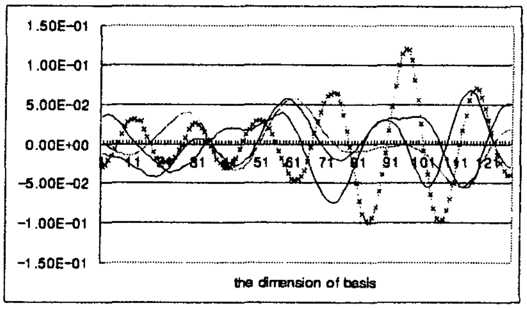


(b)

Figure 4. basis vectors in ICA (parts of 12): (a)the number of reduced basis = 12 (b)the number of reduced basis = 6

5. Conclusions

In this paper, we proposed the new method to extract the feature of iris signals; M-ICA provides good properties to represent signals with time-frequency. The conventional methods to extract features were to use the technique of filter bank analysis, while ICA is unsupervised learning algorithm using high-order statistics. M-ICA could make use of strengths of learning method and multiresolution. Since the new technique is first approaches for feature extracting, they are not showed a good performance on class-separability. But, further research on learning technique on M-ICA would be lead to the best representation for iris signals.



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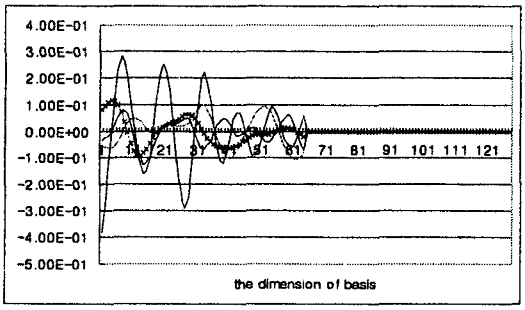
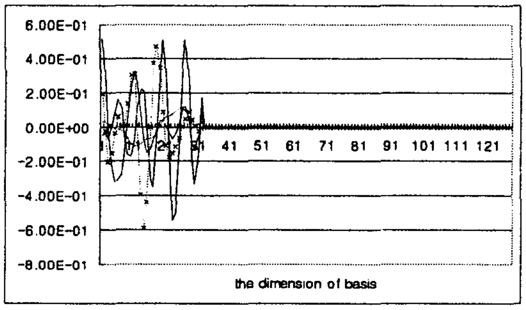


(b)



(c)

Figure 5. basis vectors in M-ICA (parts of 12): (a)dimension of input signal= 128 (b)dimension of input signal= 64 (c)dimension of input signal= 32

References

[1] Yong Zhu, Tieniu Tan and Yunhong wang, "Biometric personal identification based on iris patterns," *Proceedings of 15th ICPR*, 2:805–808, September 2000.

[2] John G. Daugman, "High confidence visual recognition of personals by a test of statistical independence" *IEEE Trans. Pattern Anal. Machine Intell.*, Vol. 15, no. 11, pp.1148-1160, November 1993.

[3] Richard P. Wildes, "Iris recognition:an emerging biometrics technology," *Proceedings of the IEEE*, Vol. 1, no. 85, pp.1348-1363, September 1997.

[4] W.W. Boles and B. Boashash, "A Human identification Technique Using Images of the Iris and Wavelet Transform," *IEEE Trans. Signal Processing*, Vol. 46, no. 4, pp.1185-1188, April 1998.

[5] Aapo Hyvarinen, Juha Karhunen and Erkki Oja, *Independent Component Aanlysis*, Wiley Inter-Science, 2001.

[6] Sergios Theodoridis and Konstantinos Koutroumbas, *Pattern Recognition*, Academic Press, 1999.

[7] Stephane Mallat, "Zero-Crossing of a Wavelet Transform," *IEEE Trans. Information Theory*, Vol. 37, no. 4, pp.1019-1033, July 1991.