A New Iris Recognition Method Based on Gabor Wavelet Neural Network

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Abstract

After a thorough analysis and summarization, a new method based on Gabor wavelet neural network and 2-dimensional principal components analysis (2DPCA) is proposed for iris recognition. A gabor-wavelet neural network model is developed in this study. The extraction algorithm layer of GWNN is used for selecting the feature extraction method and obtaining the optimum wavelet basal function parameter values. In this process, Gabor parameters are adjusted adaptively through Gabor wavelet atomic transform function, once defined, Gabor filtering and wavelet methods are used to extract the iris texture features. This will result in a compact and efficient feature vector. In the next verification stage, the 2D principal component analysis(2DPCA) technique and the classification layer structure perceptron of GWNN, which the followed parts layers of network are employed for dimensionality reduction and classification respectively. In the end network simulation experiments can be completed using Gabor wavelet neural networks to classify. Simulation results showed that the proposed iris recognition method based on the Gabor wavelet neural network is a better recognition performance.

1. Introduction

In the past few decades, the extensive research of iris recognition becomes a hotspot, in which a very wide fields is involved, including machine vision, image analysis and pattern recognition. For the iris feature extraction algorithms, effective extracting the texture feature information from each iris category which contains the inherent characteristics of the iris is essential to iris recognition. Since Daugman[1] made use of two-dimensional Gabor filters to demodulate texture phase structure information of the iris, extracting iris texture characteristics of the local phase, and then to the match, the difference between a pair of iris codes was measured by their Hamming distance. Also, many scholars proposed a variety of iris recognition methods. In reference[2],a algorithm for iris recognition based on the wavelet transform zero-crossing detection was proposed, Boles and Boashash calculated zero-crossing representation of 1D wavelet transform at various resolution levels of a virtual circle on an iris image to characterize the texture of the iris. Iris matching was based on two dissimilarity functions, but the algorithm was sensitive to changes in the gray value, and only set one-dimensional signal in the circle of concentric circles, so Wang Yunhong et al[3] think that the structure of iris texture is two-dimensional, and along the radial direction texture more obvious, in this ideology, they adopted Gabor filtering and Daubechies-4 wavelet transform combination of texture analysis methods. However, the extensive commercial application of the algorithms has proved that 2D Gabor algorithm excellent performance in the large number of iris recognition. In[4], Makram Nabti, et al. proposed the combination method which uses special Gabor filters and wavelet maxima components. A multiscale edge detection approach has been employed as a pre-processing step to localize the iris followed by a feature extraction technique which is based on a combination of some multiscale feature extraction techniques.

Although, a number of iris recognition methods have been proposed, it has been found that several accurate iris recognition algorithms use multiscale and wavelet techniques, which provide a well-suited representation for iris recognition. It is clear that the extracted features should meet at least the following requirements: Efficiency that the extracted iris image features is an effective representation of the original iris image. Compact for the similarity measurement could be computed quickly, And low redundancy that it is fast for data storage and recognition.

A lot of statistical methods and machine learning methods were used in classifier construction of iris recognition. Sanchez Avila, et al.[5] improve the method of Boles, they use a variety of similarity

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matching methods, such as Euclidean distance and Hamming distance; Noh et al[6] complete the final match based on the local characteristics of Hamming distance for Ming et al[7] used 2-D wavelet transform modulus maxima partial extraction of the structural characteristics of the iris pattern, a pattern matching the point method of iris recognition. In the classification methods like using neural networks, a modified competitive learning neural network (LVQ) was adopted for classification by Lim et al.[8]; Based on the self-organizing feature map (SOM) neural network, Fan Kefeng et al.[9], proposed an iris recognition algorithm.

With the research and development of neural networks and theory, the integration of neural network and wavelet theory is breakthroughs of intelligent processing technology. In order to combine compactly the characteristics of Gabor transform, wavelet transform, and neural network. According to the extension of Gabor function and the wavelet function, and analysing performancely the Gabor atoms time-frequency-scale three-dimensional space expression of information. The author proposed an iris classification network algorithm based on adaptive Gabor wavelet network. As a result, the adaptive Gabor wavelet network method, which is applied for target identification of iris image, has a good time-frequency-scale local performance and effectively raised the target recognition rate.

2. Feature extraction based on Gabor wavelet basal functions Cluster

The so-called Gabor wavelet basal functions Cluster is the time - frequency - scale three-dimensional space based on Gabor atom .In that pattern recognition, we must choose a best Gabor basal function that performance characteristics of the signal.

Gabor atoms is defined as:

$$g_{d,u,\xi}(t)=\frac{1}{\sqrt{d}}\,g\left(\frac{t-u}{d}\right)e^{j\xi t} \qquad (1)$$

where： $g(t)=\sqrt[4]{2}e^{-\pi t^2}$ is window function

Gauss window function is used in Gabor transform normally, and its variance is constant, and therefore all basis functions have the same scale $d=d_0$, which resulted that the majority basal functions gathered in the vicinity of location scale d_0 .so it can not be adequately described many small-scale or larger scale signal structure.

Gabor signal expansion is realized on the idea that the signal can be decomposed into discrete sets with times and frequency modulation signal in the time-frequency plane. Here a Gaussian modulation index function is used in this signal expansion:

$$f(t)=\sum_{k=1}^{\infty}B_k G_k(t) \qquad (2)$$

where $B_K=\int f(t)g^*(t)dt$, (3)

Gabor atomic transform is obtained by discreting $g(t)=\sqrt[4]{2}e^{-\pi t^2}$, then calculating B_k 。

Exponential function $G_k(t)$ has the variance function σ_k^2 with an adjustable scale parameters and an adjustable time-frequency center (u_k,ξ_k) , the specific form as follows:

$$G_k(t)=\left(\frac{\sigma_k^2}{2\pi}\right)^2\exp\left[-(t-u_k)^2/2\sigma_k^2\right]\exp(j2\pi\xi_k t) \qquad (4)$$

If we use $g_k(t)$ as the basal function of Gabor function expansion, changing the size of σ_k^2 , many different Gabor atoms can be obtained to form so-called wavelet transform clusters. Here clusters made the fixed time window function of the time-frequency plane, to expansion of the time - frequency - scale space.

If gradually increasing its variance from a small variance of the Gauss window function, and each corresponding Gauss window function make Gabor-function transformation. As a result, there many Gabor transformations will be performed, until optimal time-frequency aggregation characteristics are obtained. The changing time-frequency plane corresponding to the vary basal-function scales constitute a signal Gabor transform volume. This transformed signal 3D volumes made signals in the time - frequency - scale transformation. clearly, a fixed window function Gabor transform is a slice of the basis function volumes cluster that scale is a constant. Directly in time-frequency - scale transformation space.

3. Based 2DPCA the dimensionality reduction of feature

Three-dimensional space contains more information than two-dimensional space from the view of signal classification. But the time - frequency - scale is not very well from the point of view computing or data storage, and the key is how to choose those points that carry more information components for computation and storage, and the classification is completed finally efficiently. So dimensional-reduction is considered for the matrix of Gabor characteristics by 2DPCA, which uses two-dimensional data matrix to build a covariance matrix directly. The obtained covariance matrix is smaller, and computing time is less. Therefore, the

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2DPCA method was used in dimension reduction of Gabor characteristic matrix.

Definition: covariance matrix Gt is the n × n symmetric matrices.

$$G_t = \frac{1}{N}\sum_{k=1}^{N}\left(x_k - \bar{x}\right)\left(x_k - \bar{x}\right)^T \quad (5)$$

Where, $\bar{x}$ is the mean of the total training samples. That is:

$$\bar{x} = \frac{1}{N}\sum_{k=1}^{1} x_k \quad (6)$$

According covariance matrix of the image, to define the optimal criteria function for projection vector:

$$J(x) = x^T G_t x \quad (7)$$

Where x is unit column vector, the criteria function called generalized overall spread guidelines. Then p largest eigenvectors ware chose corresponding the former p largest eigenvalues in covariance matrix Gt of image:

$$\begin{cases} \{x_1, x_2, \cdots, x_p\} = \arg\max J(x) \\ x_i^T x_j = 0, i \neq j, i, j = 1,2,\cdots,p \end{cases} \quad (8)$$

Then image Gabor characteristics will be projected to this vector p-dimensional feature space, and projection coefficients as a feature vector. For an arbitrary the iris image sample given, its projection to this group of optimal projection vector, therefore:

$$y_i = Ax_i, i = 1,2,\cdots,p \quad (9)$$

Where Yi is the n-dimensional column vectors, called principal component vectors of iris image samples, the group will be the principal component vector that n×p size matrix of the S as follows:

$$S = \lfloor y_1, y_{2,}, \cdots, y_p \rfloor \quad (10)$$

Where S matrix called as the projection matrix of sample feature A, which is the extracted characteristics of the iris for the next classification.

4. Gabor Wavelet Neural Network

Gabor WNN (GWNN) can be described as a perception with Gabor-node function as a preprocess unit for extraction feature. Network includes two parts: the first part of the feature extraction layer and the follow-up classification part of the structure.

There are K nodes in input layer $\phi_{ik}, k = 1,2\cdots K$, where ϕ_{ik} expresses that the Kth node of the Gabor basal function related to i group target signal vector. $\phi_{ik}, k = 1,2\cdots K$ can be defined the absolute value of inner-product of the basal function vector $g_k = g(u_k, d_k, \xi_k)$ and objectives vector.

$$\phi_{ik} = \left|\langle g_k, x_i\rangle\right| = \left|\int \frac{1}{\sqrt{d_k}} g^*\left(\frac{t-u_k}{d_k}\right) e^{-j\xi_k t} x_i(t)dt\right| \quad (11)$$

Describe the correlation between K node basis function $g_k = g(u_k, d_k, \xi_k)$ and the i signal $x_i(t)$.

Gabor node:

$$g_k = g\left(\frac{t-u_k}{d_k}\right) e^{j\xi_k t} \quad (12)$$

Component basal function cluster, which is deformation of Gabor basal function g(t), can be adjusted in the course of the training network. u_k is time-lapse parameter, d_k is scaling parameters, and ξ_k describe the frequency modulation parameters. These variable parameters should be relative to Gabor transform function. The exciting function of the hidden layer is the Sigmoid function. The structure diagram of Gabor wavelet network is as Fig 1:

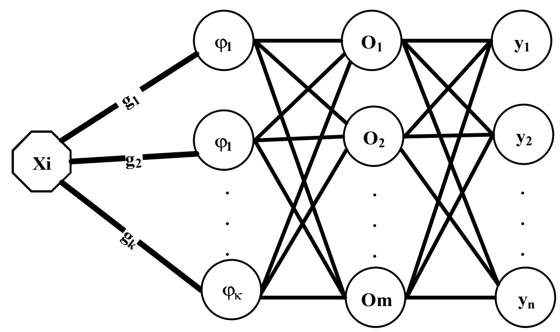

Fig 1. Structure diagram of Gabor wavelet network

Here the method of improved steepest descent algorithm is adopted. In order to get the minimal sum of square errors between expectation output vector and the practical output of the input target vector. In the study stage, the weight coefficients w of the hidden layer and the output layer, and the parameters of Gabor basal function all need to be adjusted adaptably namely.

Objective function is set as following(or also known as the cost function):

$$E(\theta) = \frac{1}{2} E\left\{\left[g_\theta(x) - y\right]^2\right\} \quad (13)$$

where, θ is vector contain the parameters of w_i, d, u, ξ; $g_\theta(x)$ the network output is defined by parameters for the vector θ. These parameters of θ is adjusted along the negative direction of the gradient by the steepest descent method in every iterative step of the training stage until the objective function convergence. Then the obtained Gabor atomic nodes are the optimal time- frequency - scale space for all the given training samples. Gabor basal function which decision-making by the parameters are most reliable for next classification. Optimizated scale and

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translation parameters of the standards Wavelet transform (θ vector), complete the effect to feature extraction and classification, improve the classification efficiency as well as removing redundant.

5. Experimental results and discussion

The proposed algorithm is achieved by matlab 7.0 in the host with 2.66 GHz processor, 512 MB memory. In version 3.0 15 individuals are selected, about 10 images of each eye, put the eyes of these 15 individual images into 30 categories, the previous five images of each category into training, and five images for testingset. The original image size is 320×280 pixels. Then which is normalized into a 240 × 20 pixels rectangular map.

The comparison results including the loose network recognition rate shows that in the following table.

Table 1. Comparision of Recognition rate.

NETWORK	5/10	7/10	9/10
BP	96.10	97.72	98.2
SOM	97.25	97.8	98.25
GaborWNN	98.24	98.75	99.3

if five images in every category of 10 image is used as training samples in the experiment, the recognition rate in the entire images of experiment database including training samples, reached 99.3%.Tab1 shows that the more the number of test samples, the higher the recognition rate. Then the training time will be extended. Its recognition time is nearly one second in 2.66 GHz CPU platform. The identification rate of training samples reached to 100 percent. At the same time, compare to the loose network methods which extract feature through two-dimensional Gabor directly, and complete classification directly through classical neural network such as BP and SOM, the recognition algorithm based on the Gabor wavelet neural network has higher recognition rate. Moreover, the system has strong adaptability because of combining the stages of feature extraction and classification, efficiency of the iris recognition is enhanced by the dimension reduction process before entering feature classification process. Furthermore, the system can make a change to the number of principal component vectors by change the size p of 2DPCA.

6. References

[1]Daugman J G.High confidence visual recognition of persons by a test of statistical independence[J]. IEEE Tans.Pattern Analysis and Machine Intelligence, 1993,15(11):1148-1161.

[2]Boles W,Boashah B.A human identification technique using images of the iris and wavelet transform[J]. IEEE Trans.on Signal Processing, 1998,46(4):1185-1188.

[3]Wang Yun-hong, Zhu Yong, Tan Tieniu.The identification based on iris recognition [J]. Automation Journal,2002,28 (1).1-10.

[4]Makram Nabti, Ahmed Bouridane.An effective and fast iris recognition system based on a combined multiscale feature extraction technique.Pattern Recognition Society. Published by Elsevier Ltd. 41 (2008) 868 – 879

[5]C Sanchez Avila,R Sanchez Reillo.Iris-based biometric recognition using dyadic wavelet transform[J], IEEEAerospace and Electronic Systems Magazine, 2002,17(10):3-6.

[6]S Noh,K Bae,Y Park,et al ,A novel method to extract features for iris tecognition system[G],In:Proc 4th Int'Iconf Audio and Videl Based Biometric Person Authentication, LNCS2688 Berlin:Springer, 2003,862-868

[7]X Ming,T Xu,X Wang,Using multimatching system based on a simplified deformable model of the human iris for iris recognition[G],In:Proc1st INT'1Conf Biometric Authentication(ICBA2004), LNCS 3072 Berlin:Springer, 2004,434-441.

[8]S Lim, K Lee, O Byeon,et al,Efficient iris recognition through improvement of feature vector and clsssifier[J],ETRI Journal, 2001,23(2):61-70.

[9] Fan Kefeng,Pei Qingqi, Wang Zhanwu. Research on algorithm for iris recognition based on Self-organizing feature map neural network[J]. Network security technology and application, 2007,(01),90-91.

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