Proceedings of the World Congress on Engineering and Computer Science 2010 Vol I
WCECS 2010, October 20-22, 2010, San Francisco, USA

Performance Evalution of IRIS Recognition by Key Local Variation Algorithm using Neural Network Classifier

B.G. Patil, A.M.U. Wagdarikar, and S.A. More

***Abstract*—Iris recognition, a relatively new biometric technology, has great advantages, such as variability, stability and security, thus it is the most promising for high security environments. Hence number of IRIS recognition algorithms are proposed, such as ICA(independant component analysis), SVD(singular value decompostion),Characterising key local variation etc. which extracts iris features and competitive learning mechanism to recognize iris pattern.**

***Index Terms*—Biometrics, iris recognition, local sharp variations, personal identification, transient signal analysis, wavelet transform , Neural network classifier (Error Back propagation),results.**

I. Introduction

The use of the Human Iris as a biometric feature offers many advantages over other human biometric features. The iris is the only internal human body organ that is visible from the outside, thus well protected from external modifiers. A fingerprint for example may suffer transformations due to harm or aging, voice patterns may be altered due to vocal diseases. Yet, the human iris image is relatively simple to image and may be done so in a non intrusive way. It is particularly good for automatic recognition because of its complex pattern of many distinctive features such as arching ligaments, furrows, ridges, crypts, rings, corona, freckles, and a zigzag collarette. Human Iris has epigenetic formation and it is formed part from the individual DNA, but a great deal of its final pattern is developed at random. It means that two eyes from the same individual, although they look very similar, contain internal pattern unique. Identical twins would then exhibit four different iris patterns. In this paper the whole procedure of feature extraction includes two steps: a set of one-dimensional intensity signals is constructed to effectively characterize the most important information of the original two-dimensional image; using a particular class of wavelets, a position sequence of local sharp variation points in such signals is recorded as features. The performance evalution is carried out through neural network (Error back propagation algorithm).

The authors are with Walchand College of Engineering, Sangli, Maharastra, 416415, INDIA
Mr. B.G. Patil (Email: patilbg@rediff.com, Mobile:09860918576)
Mr. A.M.U. Wagdarikar (Email: 74.amir@gmail.com, Mobile: 09960499439)
Mr. S.A. More (Email: 007samsung@gmail.com, Mobile:09960499439)

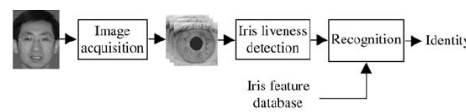

Fig. 1. IRIS recognition flowchart

II. Iris recognition

Fig.1 shows the main steps in Iris recognition system,which consists of Image Acquisition,Image Segmentation,Feature Extraction,Iris Pattern Matching

A. Image Acquisition:

The first step of Iris Recognition is image acquisition. Normally, a camera must have enough resolution to capture the details of the iris pattern (collarette patterns). The illumination angle will determine the dark and light parts of the image. It is very important that one system implements consistent illumination, on the contrary the same iris may generate two different classes under two different illumination angles. Also, the pupil is an open door to the retina, one of the most sensitive organs of our body, and extra care must be taken when shedding direct light over it.

B. Image Segmentation:

The main objective of segmentation is to remove non useful information, namely the pupil segment and the part outside the iris (sclera, eyelids, skin). As, the useful information is there only in the ring like structure i.e. Iris so, the non useful information has to be cropped out. The main steps in Iris Recognition involve:

1) Detecting the Pupillary Boundary
2) Iris Edge Detection

C. Feature Extraction:

Feature extraction step is used to create a biometric template. The biometric template will provide a normalized, efficient and highly discriminating representation of the feature,

ISBN: 978-988-17012-0-6
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

which can then be objectively compared with other templates in order to determine identity.

D. Iris Pattern Matching:

Iris matching step is used to match known templates with unknown templates using neural networks. If the match occurs then the output in the corresponding node is maximum else the corresponding Iris pattern is not in the database.

III. IRIS RECOGNITION BY CHARACTERISING KEY LOCAL VARIATIONS:

The characteristics of the iris can be considered as a sort of transient signals. Local sharp variations are generally used to characterize the important structures of tran sient signals. We thus construct a set of 1-D intensity signals which are capable of retaining most sharp variations in the orig inal iris image. Wavelet transform is a particularly popular ap proach to signal analysis and has been widely used in image pro cessing. In this paper, a special class of 1-D wavelets (the wavelet function is a quadratic spline of a finite support) is adopted to represent the resulting 1-D intensity signals. The position of local sharp variation points is recorded as features.

Generation of $1-$ D Intensity Signals

Local details of the iris generally spread along the radial di rection in the original image corresponding to the vertical direc tion in the normalized image. Therefore, information density in the angular direction corresponding to the hor izontal direction in the normalized image is much higher than that in other directions; i.e., it may suffice only to capture local sharp variations along the horizontaldirection in the normalized image to characterize an iris. In addition, since our basic idea is to represent the randomly distributed blocks of the iris by characterizing local sharp variations of the iris, it is un necessary to capture local sharp variation points in every line of the iris image for recognition. Bearing these two aspects in mind, we decompose the 2-D normalized image into a set of 1-D intensity signals according to the following equation:

$$s_i = 1/M(\sum_{j=1}^{M} I_{(i-1)} * M_j)...........i = 1,2,3....N \qquad (1)$$

$$I = \begin{pmatrix} I_1 \\ . \\ . \\ I_x \\ . \\ . \\ I_k \end{pmatrix} = I_1^T, ..I_x^T, ...I_k^T \qquad (2)$$

Where, I is the normalized image , I_x denotes gray values of the xth row in the image I, M is the total number of rows used to form a signal S_i , N is the total number of 1-D signals.

Feature vector :

Using a dyadic wavelet transform, a position sequence of local

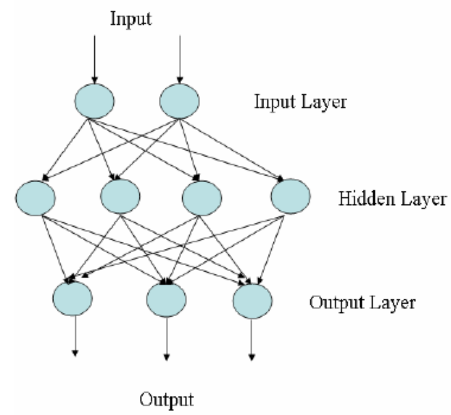

Fig. 2. Architecture of Feed Forward Back propagation Neural Network

sharp variation points in such a signals is recorded as features. The dyadic wavelet transform of a signal S(x) at scale 2^j is defined as follows:

$$WT_{2^j} = 1/2^j \int S(x)\Psi(x - X/2^j)dx \qquad (3)$$

Where,$\Psi(x/2^j)$is the wavelet function at scale 2^j For each intensity signal S_i the position sequence at two scales are concatenated to form the corresponding features:

$$F_i = \{d_1, d_2, .., d_i, ..d_m; d_{m+1}, d_{m+2}, .., d_{m+n}; p_1, p_2\} \quad (4)$$

Where, first m components are from the first scale, next n components from the other scale , d_i denotes the position of a local sharp variation point in the intensity signal, p_1 *and* p_2 respectively represents the property of the first local sharp variation point at two scales. If the first local sharp variation point d_1 is a local minimum of the wavelet transform ,p_1 is set to 1 , otherwise -1.Features from different 1-D intensity signals are concatenated to constitute an ordered feature vector

$$f_i = \{f_1, f_2, ..., f_i, ..., f_N\} \qquad (5)$$

Where f_i denotes the features from the i^{th} intensity signal N is the total number of 1-D intensity signals.

IV. CLASSIFICATION

A Feed Forward Error Back-Propagation neural network is used for classification. Here, the first five patterns of total 7 patterns of each of the 108 classes of CASIA database are used for network training and the remaining two are used for network testing. Our network implements the classical 3-layer architecture: Input layer, Hidden layer and Output layer. The input layer contains as much neurons as the dimensionality of the pattern vector, which is 108 in present case. The number of neurons in the hidden layer is approximately double as that of input layer for good classification results.

ISBN: 978-988-17012-0-6
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

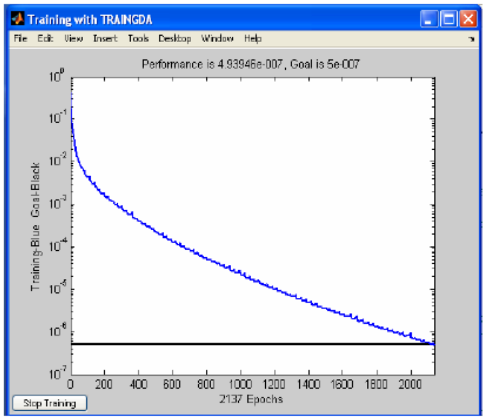

Fig. 3. Training of the Feed Forward Neural Network

V. Network Design

Following are some parameters set for network training:
Training function: traingda (Adaptive learning rate)
Initial learning rate : 0.2
Learning rate increment : 1.05
Epochs : 50,000
Error goal :$5 * 10{-}7$
Minimum gradient :$1 * 10{-}9$
As mentioned earlier, the number of neurons in the output layer corresponds to the number of classes to recognize. When the network is trained in supervised mode, a target vector is also presented to the network. This target vector has every element set to zero, except on the position of the target class that will be set to 1. The idea behind this design decision is that for each input pattern X presented to the network, an output vector Y is produced. This vector has the number of elements equal to numbers of output neurons. Each output neuron implements a squashing function that produces a Real number in the range [0, 1]. To determine which class is being indicated by the network, we select the maximum number in Y and set it to 1, while setting all other elements to zero. The element set to one indicates the classification of that input pattern. Fig.3 shows the convergence behavior of neural network using Gradient Descent algorithm for a typical case as obtained from MATLAB. The various experiments performed to train the neural network and test, the iris pattern include iris basis images.The target classes for classification were varied from 3 to 50 as shown in Table I. While simulating using MATLAB it was found that as the number of classes and cases increased, the network had more difficulty in learning the proper discriminatory weights. The network was able to reach the MSE goal within the specified number of epochs. As for number of classes greater than 10, the MSE goal was not attained anymore, but the MSE kept decreasing until the maximum number of epochs was reached. We feel that increasing the number of epochs may allow the network to eventually converge. However, this may not be justified.

TABLE I
Classification Rate

no. of classes	Classification Rate
3	87.5 %
4	83.3333%
5	77.7778%
6	76.6667%
7	76.1905%
8	74.0741%
9	73.3333%
10	72.9167 %
20	2.5 %
40	1.6667%
50	1.3333 %

TABLE II
Performance evaluation of characterising key local variation

characterising key local variation	
Database	70
Training Time	Large
Classification	Good

VI. Results

TableI shows effect on classification rate when number of training samples are 5 and number of test samples are 2. It can be seen that as the number of classes are increased beyond 9 the system tends to become over biased towards one class and the classification rates becomes poor.It is seen from the table that the classification rate drops abruptly to very low value for classes in excess of 10.So, this method of classification perhaps cannot be applied for classes above 10.

VII. Conclusion

TableII states that performance of characterising key local variation algorithm shows good results upto 70 iris images database on account of more training time.

Acknowledgement

This research paper uses the CASIA Iris image database collected by Institute of Automation, Chinese Academy of Sciences.

References

[1] L. Ma, T. Tan, Y. Wang, D. Zhang, Efficient Iris Recognition by Characterizing Key Local Variations. IEEE transactions on Image Processing, Vol. 13, No. 6, June 2004
[2] Paulo Eduardo Merlotti, Experiments on Human Iris Recognition using Error Back-Propagation Artificial Neural Network, April 2004
[3] C. M. Bishop, Neural Networks for Pattern Recognition, Oxford University Press, New York.1995.

ISBN: 978-988-17012-0-6
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)