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Fragmented Iris Recognition System using BPNN

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ABSTRACT
The authentication of people using Iris based recognition system is the most reliable biometric traits due to its stability, invariant and distinctive features for personal identification. Iris recognition consists of localization of the Iris region, extracting Iris features, generation of data set of Iris images and then Iris pattern recognition. This paper presents Iris recognition system based on partial portion of Iris patterns using Back Propagation Neural Network (BPNN). Experimental results have demonstrated the effectiveness of the propose system in terms of recognition accuracy in comparison with the previous methods.

Keywords
Biometric, Iris recognition, Back Propagation Neural Network, Iris patterns.

1. INTRODUCTION
The High protection mechanism and security is very essential things in grow of computer world. Biometric authentication is in rider seat of the computer society. Biometrics based on the Iris is among the most accurate existing techniques for human identification and verification because of uniqueness and long-term stability [1]. The probability of two individuals having the same Iris pattern is 1 in 10^{78} and even twins has different Iris pattern. Moreover iris patterns remain stable from 6 month of age to death [2].

Iris region is the part between the pupil and white sclera. This field is called Iris texture which provides many minute characteristics such freckles, coronas, stripes, furrows, crypts, etc. Information from Iris patterns is unique [13] for each subject and dispersed randomly and non-uniformly over the region of the Iris, but on notice that there is a concentration of characteristics at the region near the pupil. Due to this great quantity of information, good recognition efficiency can be achieved with only 50% of iris region available for analysis [3].

Today with the development of Artificial Intelligence algorithm, Iris recognition system may gain speed, hardware simplicity, accuracy and learning ability. The experimental results have shown the effectiveness of the proposed system in comparison with other previous Iris recognition system. This paper is organized as follows. Section 2 describes an overall Iris recognition system that includes Iris localization from the original eyes; normalization, enhancement and feature extraction are described. Section 3 presents the training and classification of Iris image using back propagation neural network. Section 4 shows the experimental result and finally conclusions are drawn in Section 5.

2. I R SYSTEM
The overall Iris recognition system includes image acquisition and Iris recognition. The Iris image acquisition includes the lighting system, the positioning system and the physical capture system. The recognition includes preprocessing, feature extraction and Iris classifier. The feature extraction is done either by using Gabor Wavelet [14][15], Local Binary Pattern or Histogram of Orientation Gradient. Data sets will be prepared using features obtained by the feature extraction techniques. These obtained features are fed to the back propagation neural network [10] for the classification.

2.1 IRIS images
The images from MMU Iris image database are taken. Experiments are conducted on 600 images, which is divided into 120 classes and each of them has 5 images. The first three Iris images of each person are chosen to build a template and the other Iris images for testing.

2.2 Structure of Iris Recognition
The architecture of the Iris feature extraction system is given in fig 1. During Iris acquisition, the Iris image in the input sequence must be clear and sharp. Clarity of the Iris minute characteristics and sharpness of the boundary between the pupil and the pupil and the Iris and the boundary between the Iris and the sclera affects the quality of the Iris image. A high quality image must be selected for Iris recognition.

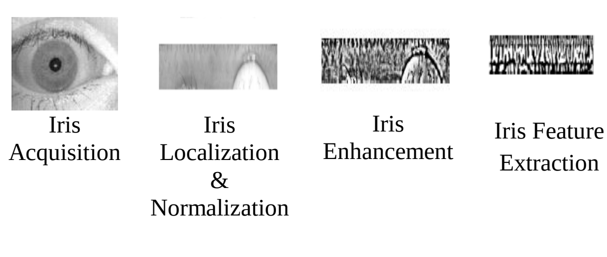

Figure 1: Structure of Iris Feature Extraction

In Iris preprocessing stage, the Iris region can be approximated by two circles one that separates the Iris and the sclera and another inside the first circle that separates the Iris and the pupil. At this stage, circle detection algorithm is used. Daugman's integro-differential operator is used for locating the inner and outer boundaries of Iris as well as the upper and lower eyelids [1][2]. Once the Iris region has been duly segmented from a given image, it becomes important to organize its information. The normalization process is responsible for generating images with fixed dimensions and so images from the same Iris captured under different conditions will have characteristic features at the same spatial location. For the purpose of achieving more accurate recognition results, the homogenous rubber sheet model devised by Daugman [1] used to remap each point within the Iris region to a pair of polar co-ordinates (r, θ) where r is on the interval [0, 1], upper half portion of the Iris takes the angle [0, π] and lower half portion takes the angle [π, 2π].

The center vectors pass through the Iris region. A number of data points are selected along each radial line. This number of points represents the radial resolution and defines the vertical dimension of the rectangular representation. The number of radial lines represents the angular resolution and defines the horizontal dimension of the rectangular representation. The rubber sheet model which takes into account pupil dilation and size inconsistencies in order to produce a normalized representation with constant dimensions. The normalized Iris image has low contrast and non-uniform illumination caused by the light source position. The image needs to be enhanced to compensate for these factors. Local histogram analysis is applied to the normalized Iris image to reduce the effect of non-uniform illumination and obtain well distributed texture image [7][8].

2.3 Feature Extraction

The Iris is a thin circular part which lies between the pupil and sclera. The features of the Iris can be extracted by different approaches for Iris recognition such as internal region, external region, lower region and upper region [16][17] are used to generate the rectangular representation.

2.3.1 Gabor Wavelet

Gabor wavelet transform used for analyzing the Iris patterns and extracting feature points from them. In order to extract the discriminating features from the normalized collarets region, the normalized pattern is convolved with one dimensional Gabor wavelet [4]. Thus feature encoding is implemented by breaking the two-dimensional normalized Iris pattern into one-dimensional wavelets and then these signals are convolved with one-dimensional Gabor wavelet.

2.3.2 Local Binary Pattern

LBP texture analysis [6][7] operator is defined as a gray scale invariant texture measure derived from a general definition of texture in a local neighborhood. A LBP code for an eight neighborhood of a pixel is produced by multiplying the threshold values with weights given to the corresponding pixels and summing up the result. The average of the gray levels below the center pixel is subtracted from that of the gray levels above the center pixel. Two dimensional distributions of the LBP and local contrast measures are used as features.

2.3.3 Histogram of Oriented Gradient

Histograms of Oriented Gradient (HOG) feature vectors [5] for the detecting window are computed as feature based on appearance. Each detection window is divided into cells of size 8x8 pixels and each group of 2x2 cells is integrated into a block in a sliding fashion, so the blocks overlap. Each cells consisting of 9-bin Histogram of Oriented gradients, each block contains a concatenated vector of all its cells. HOG features are invariant to illumination and local geometrical changes. Once the features are extracted using any one of the following techniques Gabor, LBP and HOG an Iris image is transformed into a unique representation within the feature space. In order to make the decision of acceptance or refusal, the extracted features of the Iris are fed to the BPNN.

3. BPNN BASED IRIS PATTERN RECOGNITION

Back Propagation Neural Network (BPNN) is a systematic method for training multi-layer artificial neural network [10]. It is a multi-layer forward network using extend gradient descent based delta-learning rule known as back propagation (of errors) rule. Back propagation provides a computationally efficient method for changing the weights in a feed-forward network, with differentiable activation function units, to learn a training set of input output being a gradient descent method it minimizes the total squared error of the output computed by the network.

The network is trained by supervised learning method. The basic structure of the BPNN includes one input layer, at least one hidden layer (single layer / multiple layers), followed by output layer. Neural network works by adjusting the weight values during training in order to reduce the error between the actual and desire output pattern [4]. The aim of this network is to train the net to achieve a balance between the ability to respond correctly to the input patterns that are used for training and the ability to provide good responses to the input that are similar.

In this work, we used three layers BPNN as the classifier, the number of node in the input layer is equal to dimension of the feature vector that characterizes the Iris image. The number of the node in the hidden layer is set by trail and error during training. The number of node in the output layer is equal to the number of the subjects in the database.

The algorithm for Iris recognition using BPNN [11] is as follows:

(i) Load normalized Iris data set (contains feature vector values ranges from 0 to 1 for different subjects).

(ii) Use this normalized data for training set and testing set by randomly drawing out the data for training and testing.

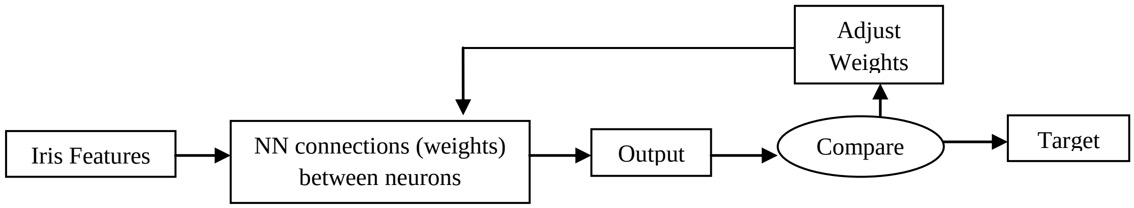

Figure 2: Back Propagation Neural Network

(iii) Create an initial NN architecture consisting of three layers, an input, an output and a hidden layer. The number of nodes in the input layer is equal to dimension of the feature vector that characterizes the iris image information. Randomly initialize the nodes of the hidden layer. The output layer contains one node. Randomly initialize all connection weights within a certain range.

(iv) Train the network on the training set by using Back Propagation algorithm until the error is minimum for a certain number of training epochs specified by the user.

(v) Present the test data to the trained network and evaluate the performance.

4. EXPERIMENTAL RESULT

Experiments have been conducted to evaluate the effectiveness of the system by using Matlab 7.0 on an Intel Pentium IV 3.0 GHz processor with 512 MB memory. Back Propagation Neural Network is designed for this particular application with the following details.

No. of neurons in first layer =600
No. of neurons in hidden layer=23
No. of neurons in output layer=1
No. of epochs=10000
Learning Rate=0.001
Activation Function=Sigmoid

4.1 Iris Recognition Analysis

The recognition method showed that it is possible to improve the reliability of the system by choosing only half portion of the iris region using artificial neural network. Three feature extraction techniques such as Gabor Wavelet, Local Binary Pattern and Histogram of Oriented Gradient on iris recognition by two different methods, first by taking internal region, which is near to the pupil and external region. The internal region gives high recognition rate than external region. The second methods divide the iris as upper half and lower half portion to identify individuals. Here, lower portion gives good recognition rate than upper portion of the iris. Experiments are conducted on MMU Iris database. The feature vectors of Gabor wavelet, Local Binary Pattern and Histogram of Gradient are shown in the Table 1.

Table 1: Feature Vectors on Gabor, LBP and HOG in length

Method	IRIS Region	External/Internal Region	Upper/Lower Region
Gabor	240X20	240X10	120X20
LBP	238X18	238X8	118X18
HOG	3X47	1X47	3X23

4.2 Neural Network Recognition Response

Gabor Wavelet features, Local Binary Pattern features and Histogram of Oriented Gradient features [17] are applied to the input layer separately. The network is then trained using the above details. After the training, the network is used for identification. In this system images of 60 persons are considered. Ten images per person are taken (5 images from left eye and 5 images from right eye). Gabor Wavelet, Local Binary Pattern and HOG features are calculated and stored in the database. From these, some images of every person is used to train the neural network and others are used for test image. Sample training and test results of Gabor Wavelet, Local Binary Pattern and Histogram of Oriented Gradients are shown in the Table 2, Table 3 and Table 4 respectively.

5. CONCLUSION

In this paper experimental results have shown that using BPNN for Iris recognition is a very promising approach. The Iris features are extracted using GW, LBP and HOG either by entire Iris template or half portion of the Iris. These inputs are fed to neural network for classification. The comparative analysis is displayed in Table 5. It is concluded that the method proposed using BPNN is higher in comparison with other previous method proposed [16][17] is shown in fig 3. The results show that the proposed method, lower and inner region approach has 100% success rate of classification in all the three feature extraction techniques.

Table 2: Gabor Wavelet

Training Vectors	Testing Vectors	Full Iris Template		Inner Region		Outer Region		Lower Region		Upper Region	
		RV	**Effy**	**RV**	**Effy**	**RV**	**Effy**	**RV**	**Effy**	**RV**	**Effy**
120(20%)	480(80%)	400	83.33	404	84.17	399	83.13	408	85	398	82.92
240(40%)	360(60%)	330	91.67	335	93.05	332	92.22	337	93.61	328	91.11
360(60%)	240(40%)	220	91.67	227	94.58	215	89.58	227	94.58	222	92.5
480(80%)	120(20%)	113	94.17	115	95.83	111	92.5	117	97.5	112	93.33
540(90%)	60(10%)	58	96.67	60	100	58	96.67	60	100	56	93.33

Table 3: Local Binary Pattern

Training Vectors	Testing Vectors	Full Iris Template		Inner Region		Outer Region		Lower Region		Upper Region	
		RV	**Effy**	**RV**	**Effy**	**RV**	**Effy**	**RV**	**Effy**	**RV**	**Effy**
120(20%)	480(80%)	420	87.5	424	88.33	418	87.08	428	89.17	401	83.54
240(40%)	360(60%)	333	92.5	338	93.88	332	92.22	337	93.61	328	91.11
360(60%)	240(40%)	224	93.33	227	94.58	224	93.33	226	94.17	223	92.92
480(80%)	120(20%)	115	95.83	115	95.83	110	91.67	117	97.5	112	93.33
540(90%)	60(10%)	59	98.33	60	100	57	95	60	100	57	95

Table 4: Histogram of Orientation Gradient

Training Vectors	Testing Vectors	Full Iris Template		Inner Region		Outer Region		Lower Region		Upper Region	
		RV	**Effy**	**RV**	**Effy**	**RV**	**Effy**	**RV**	**Effy**	**RV**	**Effy**
120(20%)	480(80%)	390	81.25	400	83.33	400	83.33	480	100	480	100
240(40%)	360(60%)	303	84.17	306	85	302	83.89	360	100	360	100
360(60%)	240(40%)	202	84.17	205	85.42	201	83.57	240	100	240	100
480(80%)	120(20%)	118	98.33	119	99.17	115	95.83	120	100	120	100
540(90%)	60(10%)	60	100	60	100	59	98.33	60	100	60	100

(Note RV- Recognized Vectors; Effy-Efficiency)

Table 5: Comparative Analysis IR using BPNN with previous methods

Methodology	Full Iris Template	Inner Region	Outer Region	Lower Region	Upper Region
GW[16]	99.94	99.84	99.8	99.73	99.85
GW with BPNN	96.67	100	96.67	100	93.33
LBP[17]	99.9	99.83	99.77	99.68	99.82
LBP with BPNN	98.33	100	95	100	95
HOG[17]	99.95	99.94	99.93	99.82	99.92
HOG with BPNN	100	98.33	98.33	100	100

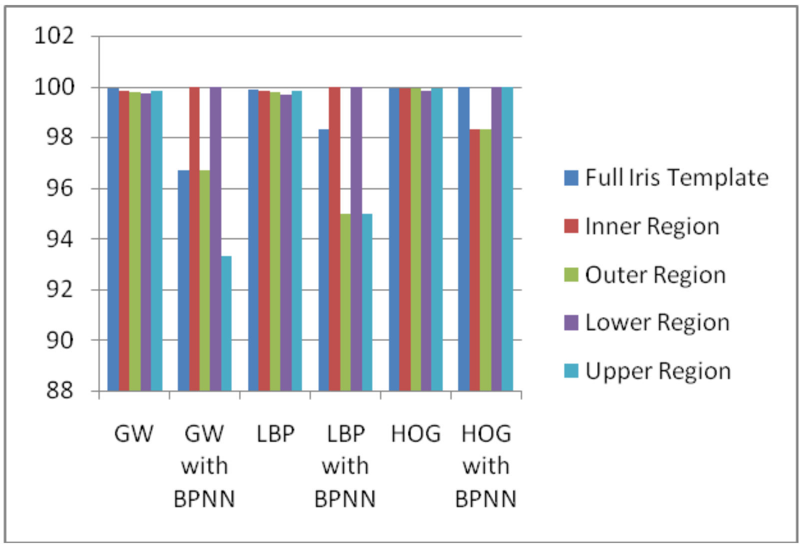

Figure 3: Performance Comparison of GW, LBP and HOG with BPNN

6. REFERENCES

[1] Daugman J, "Complete Discrete 2-D Gabor Transforms by Neural Networks for Image Analysis and Compression", IEEE Transactions on Acoustics, Speech, and Signal Processing, Vol. 36, no. 7, July 1988, pp. 1169-1179.

[2] Daugman, J. "How Iris Recognition Works", available at http://www.ncits.org/tc_home/m1htm/docs/m1020044.pdf.

[3] Daugman. J, "Biometric Personal Identification System Based on Iris Analysis", U.S. Patent No. 5,291,560, March 1, 1994.

[4] Daugman. J, "High Confidence visual Recognition of Persons by a Test of Statistical Independence", IEEE transactions on Pattern Analysis and Machine Intelligence, Vol. 15, No. 11, pp. 1148-1161, 1993.

[5] N. Dala and B.Tiggs, "Histograms of oriented gradients for human detection", IEEE CS Conference on Computer Vision and Pattern Recognition, pp.886-893, 2005.

[6] T.Ojala, M.Pietikainen and D.Harwood. "A comparative study of texture measures with classification based on feature distributions". Pattern Recognition, January 1996.

[7] Maheswari, P.Anbalagan and T.Priya, "Efficient Iris Recognition through Improvement in Iris Segmentation Algorithm", ICGST-GVIP Journal, ISSN: 1687-398X, Vol 8, Issue 2, pp. 29-35, 2008.

[8] Leila Fallah Araghi, Hamed Shahhossseini and Farbod Setoudeh, "IRIS Recognition Using Neural Network", Proceedings of the International Multi Conference of Engineers and Computer Scientists 2010 (IMECS), Vol I, March 2010.

[9] Sameul Adebayo Daramoal and Daniel ,"Automatic Ear Recognition System using Back Propagation Neural Network", International Journal of Video &

Image Processing and Network Security (IJVIPNS-IJENS), Vol. 11 No.01.pp 28-32, Feb 2011.

[10] Shylaja S S & et.al. ”Feed Forward Neural Network Based Eye Localization and Recognition Using Hough Transform”, International Journal of Advance Computer Science and Applications, Vol.2, No.3, pp.104-108, March 2011.

[11] Mohammod Abul Kashem & et. al, ”Face Recognition System Based on Principal Component Analysis with Back Propagation Neural Networks”, International Journal of Scientific & Engineering Research, Vol. 2, Issue 6, pp 1-10, June 2011.

[12] S.R. Ganorkar and J.A. Deshpande, “Person Identification Using Iris Recognition”, International Journal of Engineering and Technology, Vol.3, No. 1, pp 40-43, Feb 2011.

[13] G. Savithiri and A. Murugan, ”Performance Analysis of Iris Recognition Algorithms”, Proceedings of the International Conference on Millennium Development Goals (MDGICT) pp. 294-299, Dec. 2009.

[14] G. Savithiri and A. Murugan, “Iris Recognition Technique using Gaussian Pyramid”, Proceedings of the International Conference on Recent Trends in Business Administration and Information Processing, (BAIP), CCIS 70, pp-325-331, Springer-Verleg Berlin Heidelberg , March 2010.

[15] G. Savithiri and A. Murugan, “Iris Recognition Technique using Gaussian Pyramid Compression and Modified Distance Measures”, Journal of Computational Intelligence in Bioinformatics, Vol 3, No. 1, pp 101-110, July 2010.

[16] A. Murugan and G. Savithiri, “Feature Extraction on Half Iris for Personal Identification”, Proc. IEEE International Conference on Signal and Image Processing (ICSIP), pp 197-200, Dec 2010.

[17] G. Savithiri and A. Murugan, ”Performance Analysis on Half Iris Feature Extraction using GW, LBP and HOG”, International Journal of Computer Applications (IJCA), Vol.22, No.2, pp 27-32, May 2011.