ISSN (Print) : 2319-5940
ISSN (Online) : 2278-1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 2, Issue 2, February 2013

Partial Template of Human Iris Patterns Recognition and identification using Neural Networks

M. Gopikrishnan[1], Preethy Rebecca[2]

P.G Student, Dept of CSE, St. Peter's College of Engineering and Technology, Avadi, Chennai, India[1]

Assistant Professor, Dept of CSE, St. Peter's College of Engineering and Technology, Avadi, Chennai, India[2]

ABSTRACT: **Iris recognition is one of the most widely used biometric techniques for personal identification. Of all biometrics-based techniques, the iris-pattern-based systems have recently shown very high accuracies in verifying an individual's identity. Each human iris has its unique visual pattern and local image features also vary from region to region, which leads to significant differences in robustness and distinctiveness among the feature codes derived from different iris regions. However, most state-of-the-art iris recognition methods use a uniform template size (20 X 480) , where template generated from different patterns of the same person. In this paper the Iris recognition has been carried out employing a template of size 20 X 480 pixels , 10 X 480 , and 10 x 360 pixels. The results of the sizes of the templates have been compared and it has been observed that the accuracy of the results obtained with the limited template size is comparable with that of the one with the full size. The reason is the reduction of the space requirement as well as time complexity with no loss in accuracy. The results of iris recognition performed applying Hamming distance, Feed forward back propagation, Cascade forward back propagation, Elman forward back propagation and perceptron as presented in this paper. It has been established that the method suggested applying Cascade forward back propagation provides the best accuracy in respect of iris recognition with no major additional computational complexity.**

Keywords: Iris recognition, Biometric identification, Pattern recognition, Automatic segmentation

I. INTRODUCTION

Biometric is automated method of recognizing a person based on a physiological or behavioral characteristic. Among the features measured are: face, fingerprints, hand geometry, handwriting, iris, retinal, vein, and voice. Biometric technologies are becoming the foundation of an extensive array of highly secure identification and personal verification solutions. As the level of security breaches and transaction fraud increases, the need for highly secure identification and personal verification technologies is becoming apparent.

Biometric-based solutions are able to provide for confidential financial transactions and personal data privacy. The need for biometrics can be found in federal, state and local governments, in the military, and in commercial applications. Enterprise-wide network security infrastructures, government IDs, secure electronic banking, investing and other financial transactions, retail sales, law enforcement, and health and social services are already benefiting from these technologies. Biometric-based authentication applications include workstation, network, and domain access, single sign-on, application logon, data protection, remote access to resources, transaction security and Web security. Trust in these electronic transactions is essential to the healthy growth of the global economy. Utilized alone or integrated with other technologies such as smart cards, encryption keys and digital signatures, biometrics are set to nearly all aspects of the economy and our daily lives. Utilizing biometrics for personal authentication is becoming convenient and considerably more accurate than current methods (such as the utilization of passwords or PINs). This is because biometrics links the event to a particular individual (a password or token may be used by someone other than the authorized user), is convenient (nothing to carry or remember), accurate (it provides for positive authentication), can provide an audit trail and is becoming socially acceptable and cost effective..

This paper provides results of iris recognition performed on a reduced size template, applying Hamming distance, Feed forward back propagation, Cascade forward back propagation, Elman forward back propagation and perceptron. It has been established that the method suggested applying Cascade forward back propagation provides the best accuracy in respect of iris recognition with no major additional computational complexity. This

ISSN (Print) : 2319-5940
ISSN (Online) : 2278-1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 2, Issue 2, February 2013

paper uses the CASIA iris image database collected by Institute of Automation, Chinese Academy of Sciences[3].

Yingzi Du etal [4] in their paper established that the partial iris portion of the iris pattern describes the uniqueness and the pupil has no direct effect on the accuracy of the biometric recognition and identification. Using this concept, in this paper, the size of the template is reduced eliminating the pupil's portion.

II. THE HUMAN IRIS RECOGNITION

Iris recognition biometrics employs the unique characteristics and features of the human iris in order to verify the identity of an individual [1]. The iris is the area of the eye where the pigmented or coloured circle, usually brown or blue, rings the dark pupil of the eye. The iris-recognition process begins with a photograph. A specialized camera, typically very close to the subject, no more than three feet, uses an infrared imager to illuminate the eye and capture a very high-resolution photograph. This process takes only one to two seconds and provides the details of the iris that are mapped, recorded and stored for future matching/verification. Eyeglasses and contact lenses present no problems to the quality of the image and the iris-recognition systems test for a live eye by checking for the normal continuous fluctuation in pupil size. The inner edge of the iris is located by an iris-recognition algorithm which maps the iris' distinct patterns and characteristics. An algorithm is a series of directives that tell a biometric system how to interpret a specific problem. Algorithms have a number of steps and are used by the biometric system to determine if a biometric sample and record is a match.

A iris image has a circular shape when the iris is orthogonal to the sensor, iris recognition algorithms typically convert the pixels of the iris to polar coordinates for further processing. An important part of this type of algorithm is to determine which pixels are actually on the iris, effectively removing those pixels that represent the pupil, eyelids and eyelashes, as well as those pixels that are the result of reflections.

The locations of the pupil and upper and lower eyelids are determined first using edge detection. This is performed after the original iris image has been down sampled by a factor of two in each direction (to 1/4 size, in order to speed processing). The best edge results came using the Canny method [5]. The pupil clearly stands out as a circle, and the upper and lower eyelid areas above and below the pupil are also prominent. A Hough transform is then used to find the center of the pupil and its radius.

IRIS Recognition Methodology

The iris is the externally visible, colored ring around the pupil. It is a physical feature of a human being that can be measured and thus used for biometric verification or identification through the process of iris recognition [2]. The human iris is well protected, as although it is externally visible, it is an internal part of the eye. It is not genetically determined (which means that genetically identical eyes, e.g. the right and left eye of any given individual, have unrelated iris patterns) and it is believed to be stable throughout life (barring accidents and surgical operations). Iris patterns are both highly complex and unique (the chance of two irises being identical is estimated at 1 in 10 to the power of 78) making them very well-suited for biometric identification.

When a subject wishes to be identified by iris recognition system, his/her eye is first photographed, and then a template created for his/her iris region. This template is then compared with the other templates stored in a database until either a matching template is found and the subject is identified, or no match is found and the subject remains unidentified.

The first stage will be to develop an algorithm to automatically segment the iris region from an eye image. This will require research into many different techniques such as Daugmans integro-differential operator, circular Hough transform, and active contour models.

Following this, the next stage will be to normalize the iris region in order to counteract imaging inconsistencies such as pupil dilation. An implementation of Daugmans polar representation will be used for this purpose, as this is the most documented method for iris normalization.

Once a normalized iris pattern has been obtained, it will be convolved with 2DGabor wavelets in order to extract features.

Finally, matching and statistical analysis will be performed in order to test how well iris patterns can be identified against a database of preregistered iris patterns

III. ENROLLMENT

Enrollment is the process of generating some representation of the iris that is to be stored in the database for use in identification. Typically, this involves combining several images of the same iris in some manner in order to produce a representative sample that has less noise than any individual image. For this system, the normalized iris images and the result stored in the database as the template are compared for identification. The enrollment process includes image acquisition, image preprocessing and the template creation.

ISSN (Print) : 2319-5940
ISSN (Online) : 2278-1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 2, Issue 2, February 2013

IV. IDENTIFICATION

The identification process, in which a new iris image, presented to the system, undergoes the same preprocessing like that of the iris images in the enrollment database. The normalized template is then compared to each template in the enrollment database to determine a match.

V. NEURAL NETWORK DISTANCE

Artificial neural networks have been explored for iris identification. Many approaches, such as formulating the identification problem such that the neural network would identify the individual irises (i.e., the neural network contains an output class for each individual iris). This means a neural network that could identify 100 people would have 200 output nodes, each representing an individual iris. This architecture is typically useful for small databases, but requires enlarging and retraining of the neural network as the database grows.

In this paper, a neural network is used to identify the statistical pattern present when one iris template matches or does not match another. The neural network can be small (thus fast), and will contain only two output nodes representing a match or a non-match. The neural network need not be retrained as individuals are added to the database. A feed forward back propagation (FFBP) and perceptron artificial neural network, shown in Figs. [4, 5] has been used to form the match decision. The error back-propagation training algorithm is used to adjust the internal neural network weights.

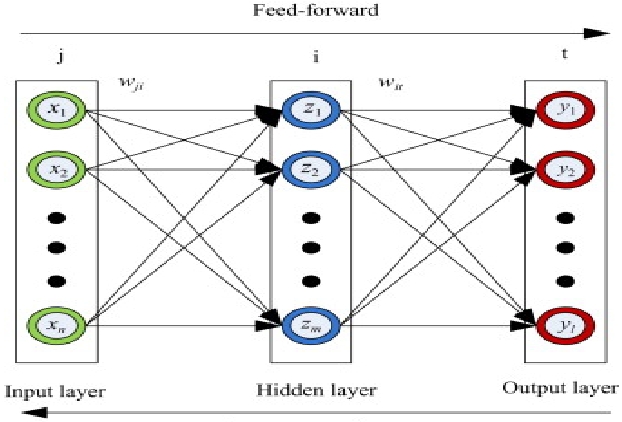

Figure 4: Feed – Forward Back propagation

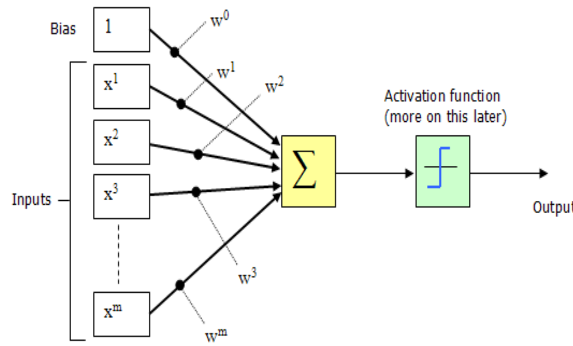

Figure 5: Perceptron

VI. EXPERIMENTAL RESULTS

The performance of the proposed optimized methodology is evaluated with CASIA database (the institute of Automation, Chinese Academy of Sciences). The CASIA data base contain nearly 4500 iris images at (320X280). The experiments were carried out in Intel i3-530 processor with 2.93 GHz with 4 GB DDR3 for all iris sample templates. This is a real world application level simulation. The experimentation is conducted in two stages:

1) Performance evaluation of the proposed improved methodology for iris recognition.

2) Comparison with the existing approaches in the field of iris recognition.

In the first stage of the experimentation, emphasis is on the performance evaluation of the current approach based on the matching accuracy. Evaluation of the proposed method is by comparing its recognition accuracy with the matching strategies. The performance of the proposed genetic process is demonstrated in Tables 1 to 5, through selection of optimum features as well as increase in the overall system accuracy. The verification performance of the proposed approach is shown in Figures 6 to 9 using a 3D Column chart. The effect of performance evaluation on different security requirements is obtained by changing the values of weightages. The experimental results measure the probability of accepting an imposter as an authorized subject, and the probability of rejecting an authorized subject incorrectly. During the second stage, through a series of experimentation, a comparative analysis of the suggested method with the existing methods is carried out, in respect of recognition accuracy and computational complexity.

ISSN (Print) : 2319-5940
ISSN (Online) : 2278-1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 2, Issue 2, February 2013

Table 1 : Comparison between experimental Results.							
Neural Network Tools	Dimension of the Template	Template 1 and 2	Template 1 and 3	Template 1 and 4	Template 1 and 5	Template 1 and 6	Template 1 and 7
Cascade forward back propagation	20 X 480 pixels	0.127	0.134	0.124	0.123	0.138	0.123
	10 X 480 pixels	0.110	0.115	0.106	0.111	0.114	0.110
	10 X 360 pixels	0.103	0.112	0.105	0.104	0.110	0.108

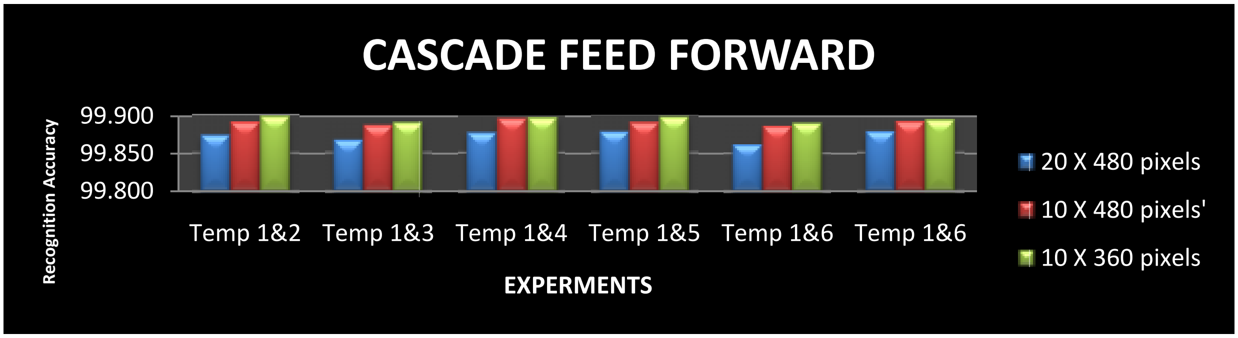

Figure 6 : Cascade forward back propagation Verification of Performance using 3D Column Chart

Table 2 : Comparison between experimental Results.							
Neural Network Tools	Dimension of the Template	Template 1 and 2	Template 1 and 3	Template 1 and 4	Template 1 and 5	Template 1 and 6	Template 1 and 7
Feed forward Back Propogation	20 X 480 pixels	0.164	0.165	0.144	0.163	0.136	0.144
	10 X 480 pixels	0.140	0.145	0.121	0.144	0.113	0.122
	10 X 360 pixels	0.138	0.142	0.118	0.136	0.108	0.111

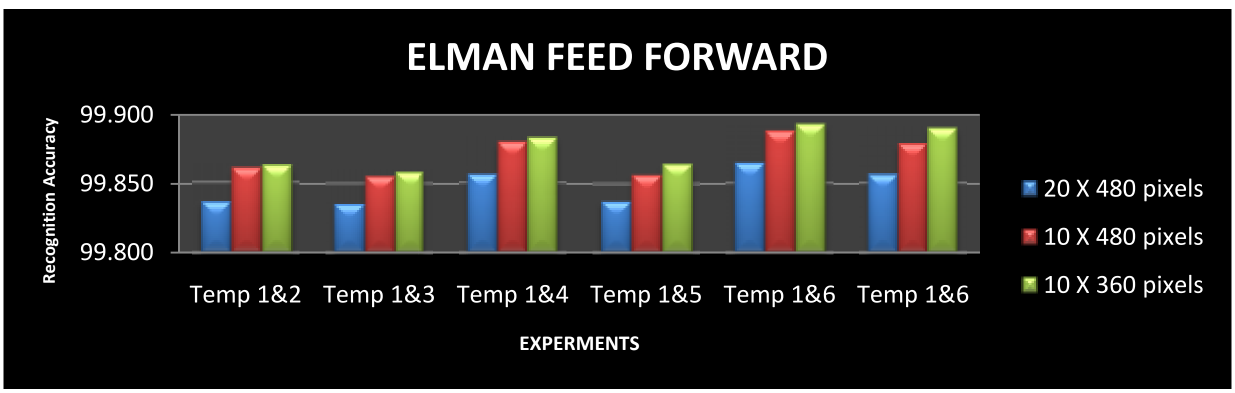

Figure 7 : Feed forward Back Propogation Verification of Performance using 3D Column Chart

Table 3 : Comparison between experimental Results.							
Neural Network Tools	Dimension of the Template	Template 1 and 2	Template 1 and 3	Template 1 and 4	Template 1 and 5	Template 1 and 6	Template 1 and 7
Elman Back propocation	20 X 480 pixels	0.163	0.165	0.147	0.164	0.140	0.144
	10 X 480 pixels	0.141	0.145	0.123	0.140	0.124	0.120
	10 X 360 pixels	0.134	0.134	0.115	0.135	0.112	0.119

ISSN (Print) : 2319-5940
ISSN (Online) : 2278-1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 2, Issue 2, February 2013

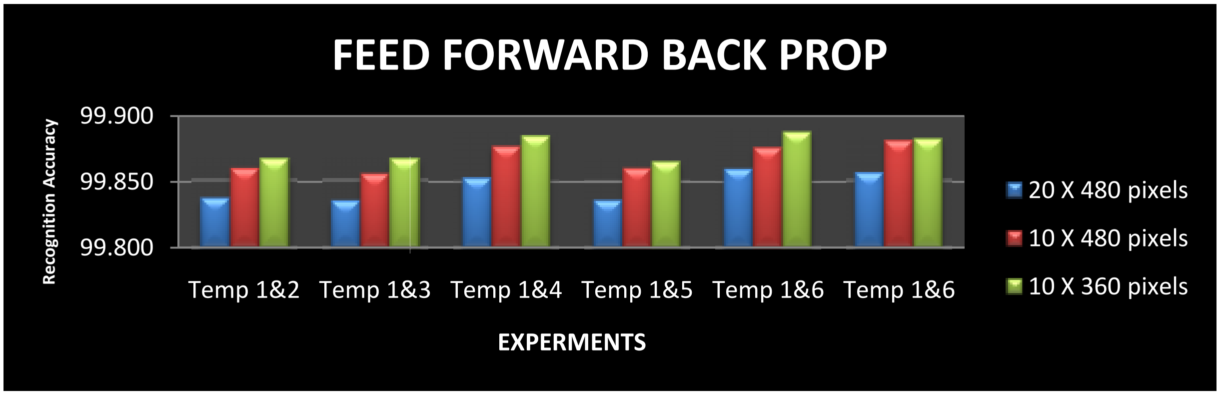

Figure 8 : Elman Back propocation Verification of Performance using 3D Column Chart

Table 4 : Comparison between experimental Results.

Neural Network Tools	Dimension of the Template	Template 1 and 2	Template 1 and 3	Template 1 and 4	Template 1 and 5	Template 1 and 6	Template 1 and 7
perceptron	20 X 480 pixels	0.278	0.286	0.260	0.278	0.240	0.252
	10 X 480 pixels	0.252	0.269	0.245	0.252	0.229	0.234
	10 X 360 pixels	0.247	0.257	0.235	0.243	0.211	0.229

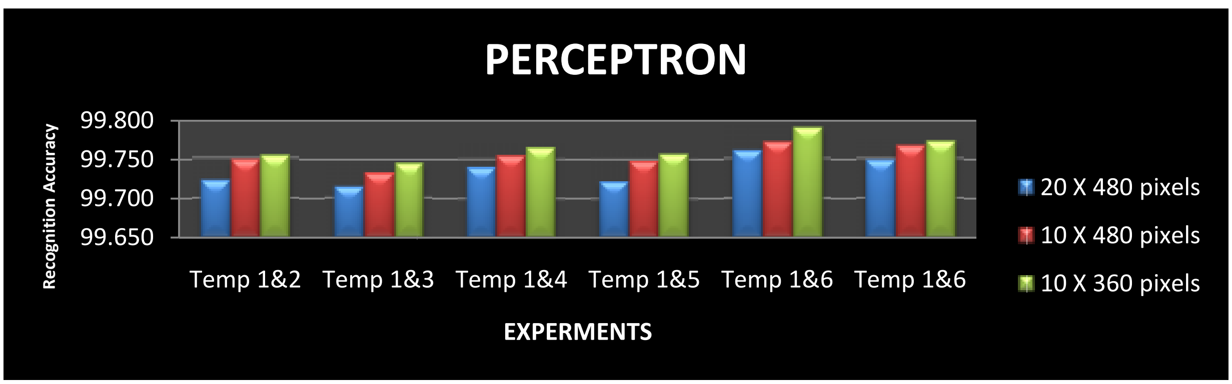

Figure 9 : perceptron Verification of Performance using 3D Column Chart

Table 5 : Comparison between experimental Results.

Neural Network Tools	Dimension of the Template	Template 1 and 2	Template 1 and 3	Template 1 and 4	Template 1 and 5	Template 1 and 6	Template 1 and 7
Hammington Distance	20 X 480 pixels	0.312	0.339	0.301	0.330	0.334	0.305
	10 X 480 pixels	0.309	0.310	0.275	0.297	0.320	0.269
	10 X 360 pixels	0.284	0.305	0.264	0.295	0.319	0.236

ISSN (Print) : 2319-5940
ISSN (Online) : 2278-1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 2, Issue 2, February 2013

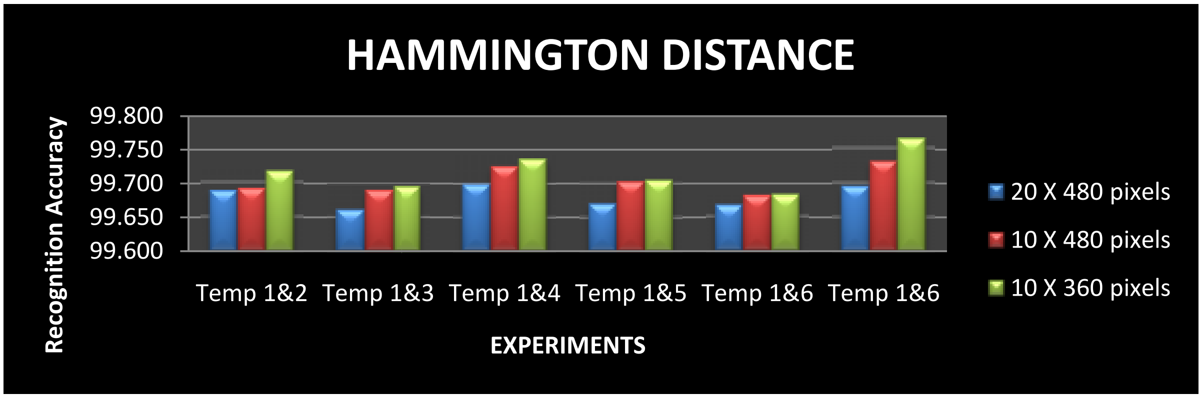

Figure 10 : Hammington Distance Verification of Performance using 3D Column Chart

VII. CONCLUSION

In this paper, an optimized iris recognition method is proposed using an efficient iris segmentation approach, based on the collarette area localization, with the incorporation of the eyelashes and the eyelids detection techniques. The 1D log-Gabor filters are used to extract the discriminating features. In order to increase the matching accuracy neural network tools have been applied. Since it has been established that the pupil has no direct effect on the accuracy of the identification, in this paper, a reduced size of template is used and the identification carried out. A comparison of results obtained for the templates namely 20 X 480 pixels, 10 X 480 and 10 x 360 pixels size has been performed. Experimental results of the improved method exhibit an encouraging performance as for as the accuracy is concerned especially on the CASIA data set. The performance evaluation and comparisons indicate that the proposed method is a viable and very efficient method for iris recognition resulting in lesser time complexity and space requirement.

ACKNOWLEDGMENT

The iris CASIA dataset is available on the web at http:// www. sinobiometrics.com / English / Iris%20Data bases.asp[3]

REFERENCES

[1] J. Daugman, "How Iris Recognition Works", IEEE Transaction on Circuits and Systems for Video Technology, Vol. 14, No. 1, pp. 21- 30, 2004.
[2] L. Flom and A. Safir, United States Patent No. 4,641,349 (issued February 3, 1987), Iris Recognition System, Washington D.C.: U.S. Government Printing Office.
[3] CASIA Iris Image Database, http:// www.sinobiometrics.com.
[4] Yingzi Du, Robert Ives, Bradford Bonney and Delores Etter, " Analysis of partial iris recognition" by spie – 2005.
[5] J. Canny, "A Computational Approach to Edge Detection", IEEE Transactions on Pattern Analysis and Machine