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NEXT GENERATION BIOMETRICS FOR HUMAN IDENTIFICATION

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Abstract

Biometrics provides a secure method of authentication and identification. Biometric data are difficult to replicate and steal. Unique identifiers include fingerprints, hand geometry, earlobe geometry, retina and iris patterns, voice waves, DNA, and signatures. This paper is based on Periocular biometric recognition, which is the appearance of the region around the eye. Periocular recognition may be useful in applications where it is difficult to obtain a clear picture of an iris for iris biometrics or a complete picture of a face for face biometrics. Acquisition of the Periocular biometrics does not require high user cooperation and close capture distance. This region usually encompasses the eyelids, eyelashes, eyebrows and the neighbouring skin area. Periocular biometrics encompasses the information of face recognition and iris recognition system. A record of a person's unique characteristics is captured and kept in a database. Later on, when identification verification is required, a new record is captured and compared with the previous record in the database. If the data in the new record matches that in the database record, the person's identify is confirmed. In this paper, the Local Binary Pattern (LBP) and Gray Level Co- occurrence Matrix (GLCM) are used for the feature extraction on the Periocular images. LBP is a type of feature used for classification in computer vision and a powerful feature for texture. For an effective classification and recognition of an authorized individual Back propagation neural network (BPNN) classifier is used.

Keywords: Periocular Recognition, Local Binary Pattern (LBP), Gray Level Co-occurrence Matrix (GLCM), Backpropagation Neural Network (BPNN), Biometrics

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INTRODUCTION

Biometric systems are applied for the unique identification of an individual by evaluating one or more distinguishing biological traits. Authentication plays a major role as a first line of defense against intruders. The number of systems that have been compromised is ever increasing and biometric verification is any means by which a person can be uniquely identified by evaluating one or more distinguishing biological traits. Periocular biometric recognition is based on the appearance of the region around the eye. The performance of iris recognition is affected if iris is captured at a distance, also affected for subjects who are blind or have cataracts and the performance of face recognition is affected by lighting changes, hair of the person, the age and if the person wear glasses. Periocular recognition (Karen *et al.*, 2012) is useful in applications where it is difficult to implement the iris and the face biometrics. Acquisition of the Periocular biometrics does not require high user cooperation and close capture distance.

In the existing work, After capturing the periocular region, feature extraction method is done using Local binary pattern (LBP), Gray Level Co-occurrence Matrix (GLCMs) and Scale Invariant Feature Transform (SIFT). The human and the machine performance are analyzed based on these algorithms and this not a complete automated system. In this manual intervention is required for the recognition of the features that is obtained using those algorithms. Davide Maltoni and Rafiacle Cappelli (2008) described Fingerprint Recognition using Minutiae based approach (Davide Maltoni and Rafiaele Cappelli, 2008). Fingerprints have been using for over a century. It can be used in forensic science to support criminal investigations, biometric systems such as civilian and commercial identification devices for person identification. A fingerprint is comprised of ridges and valleys. The ridges are the dark area of the fingerprint and the valleys are the white area that exists between the ridges. The fingerprint of an individual is unique and remains unchanged of over a lifetime. Minutiae are the most popular approach that is used for fingerprint representation.

Figure 1. Original Left and Right Periocular Images

Bowyer *et al.* (2008) proposed a survey of image understanding for iris biometrics (Bowyer, 2008. Biometricmethods based on the spatial pattern of the iris are believed to allow very high recognition accuracy. The iris colored annular ring that surrounds the pupil. Iris images acquired under infrared illumination consist of complex texture pattern with numerous individual attribute which allow for highly reliable personal identification Zhao et al. (2003) described a survey of face recognition in [11]. Humans have a remarkable ability to recognize fellow beings based on facial appearance. So, face is a natural human trait for automated biometric recognition. Face recognition systems typically utilize the spatial relationship among the locations of facial features such as eyes, nose, lips, chin, and the global appearance of a face. The forensic and civilian applications of face recognition technologies pose a number of technical challenges both for static mug-shot photograph matching to unconstrained video streams acquired in visible or near-infrared illumination. The problems associated with illumination, gesture, facial makeup, occlusion, and pose variations adversely affect the face recognition performance. While face recognition is non-intrusive, has high user acceptance, and provides acceptable levels of recognition performance in controlled environments.

Lyle *et al*. (2010) proposed soft biometric classification using periocular region features in (Lyle, 2010). The focus is on gender and ethnicity classification of individuals using periocular images. The core is to focus whether periocular images carry enough information to reliably obtain similarsoft biometric information to that obtained from face images. This paper describes a soft biometric classification approach using appearance based periocular features. The soft biometric information thus obtained can be effectively used for improving the performance of existing periocular based recognition approaches Woodard *et al.* (2010) describedperiocular region appearance cues for biometric identification in (Zhao *et al*., 2003). The low-level features extracted from the periocular region can be effectively used for identification. The chief novelty in this work lies in our use of only the level-two periocular features based on skin texture and color information to perform identification. To this effect, mask the eye in the periocular region thus removing the iris and various level- one features. Although removal of the eye from a periocular region image may seem like a heavy loss of discriminating information, it could be potentially advantageous as the level-one features are highly sensitive to the opening and closing of the eyes and may end up influencing the texture features adversely.

MATERIALS AND METHODS

A record of a person's unique characteristic is captured and kept in a database. Later on, when identification verification is required, a new record is captured and compared with the previous record in the database. If the data in the new record matches that in the database record, the person's identity is confirmed. After capturing the Periocular region, feature extraction methods such as Local Binary Pattern (LBP) and Gray Level Co- occurrence Matrix (GLCMs) are used on the Periocular images, to capture the texture and the gradient information.

Database

The databases are acquired with a Nikon Coolpix S70 and Nikon Coolpix S4000. The periocular images are obtained from 20 subjects, by manually cropping the periocular images with the size of 512X512 pixels. Both the left and the right periocular images are used for the experiment.

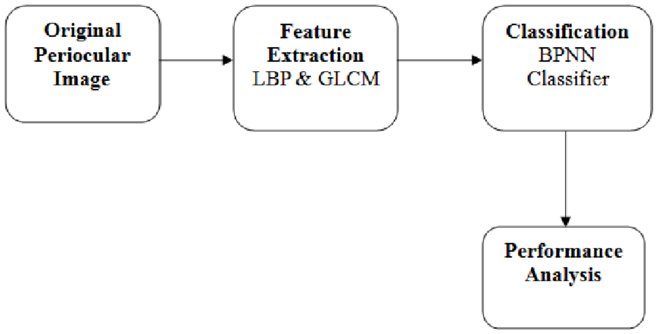


Figure 2. Block diagram of proposed biometric system

Feature Extraction

The features from the periocular region are extracted using efficient algorithms. The algorithm (Guillaume Heusch,?) which is used for feature extraction is Local Binary Patterns (LBP) and Gray Level Co-occurrence Matrix (GLCM).

Local Binary Pattern

A local binary pattern (LBP) is a type of feature used for classification in computer vision. LBP (Ahonen *et al*., 2006) is found to be a powerful feature for texture classification improves the detection performance. Before performing LBP to the input image the original periocular image is converted into grayscale image.

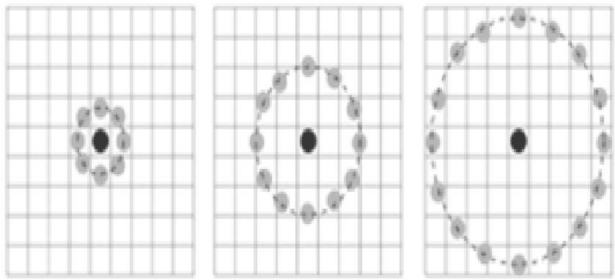


Figure 3. Three Neighborhood examples used to define a texture and calculate a local binary pattern (LBP)

The LBP feature vector is created by,

- Divide the examined window into cells.
- For each pixel in a cell, compare the pixel to each of its 8 neighbors, follow the pixels along a circle
- Where the center pixel's value is greater than the neighbor, write "1". Otherwise, write "0". This gives an 8-digit binary number and is converted into decimal code.
- Compute the histogram, over the cell, of the frequency of each "number" occurrence.
- Optionally normalize the histogram.
- Concatenate normalized histograms of all cells which give feature vector of examined window.

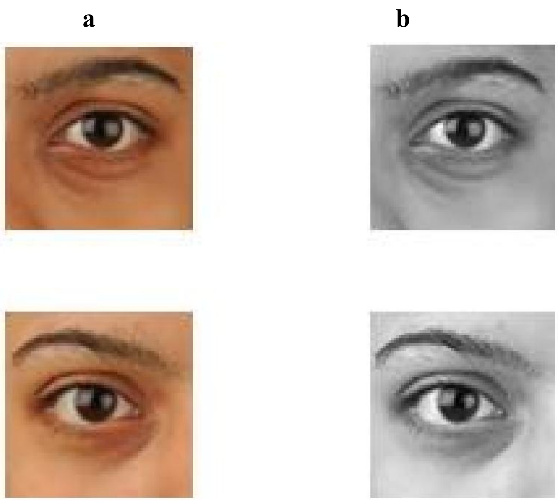


Figure 4. (a) Original Periocular Image (b) Gray Image

The decimal form of the resulting 8-bit word (LBP code) can be expressed as follows:

$$LBP(x_c, y_c) = \sum_{n=0}^{7} s(i_n - i_c)\, 2^n \qquad \text{.............................. (1)}$$

where ic corresponds to the grey value of the center pixel (xc, yc), in to the grey values of the 8 surrounding pixels. The function s(x) is defined as:

$$s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \qquad \text{.. (2)}$$

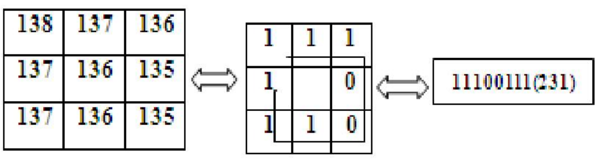
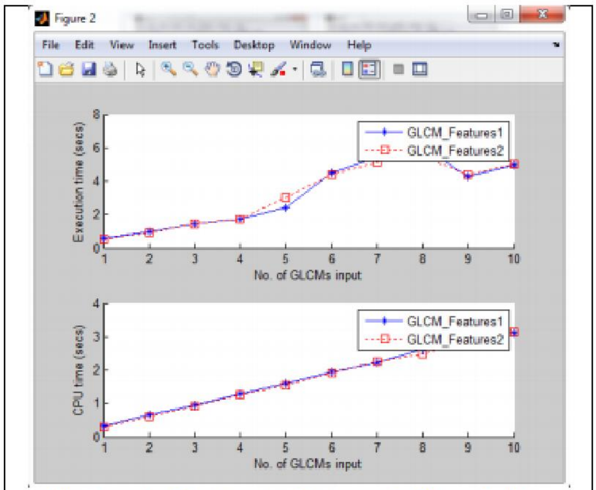


Figure 5 LBP operator

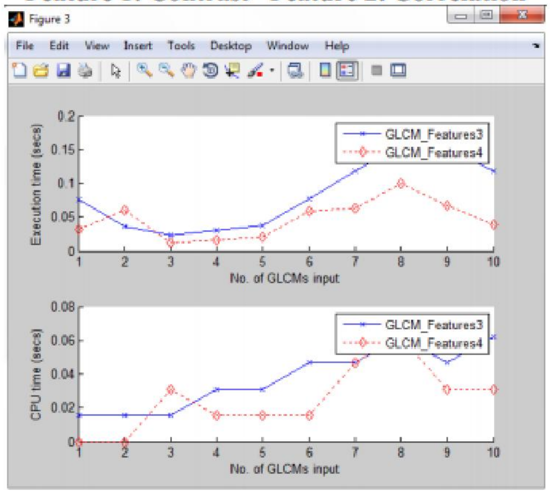
A statistical method of examining texture that considers the spatial relationship of pixels is the gray-level co- occurrence matrix (GLCM), also known as the gray-level spatial dependence matrix. The GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix.

(The texture filter functions, described in Texture Analysis cannot provide information about shape, i.e., the spatial relationships of pixels in an image.)

After you create the GLCMs, you can derive several statistics from them using the graycoprops function. These statistics provide information about the texture of an image. The following description is about the statistics. The outputs are given in (Figure 6).



Feature 1: Contrast Feature 2: Correlation



Contrast

Measures the local variations in the gray-level cooccurrence matrix.

$$\sum_{i,j} |i - j|^{2p(i,j)}$$

Correlation

Measures the joint probability occurrence of the specified pixel pairs.

$$\sum_{i,j} \frac{(i - \mu i)(j - \mu j)p(i,j)}{\sigma i \sigma j}$$

Energy

Provides the sum of squared elements in the GLCM. Also known as uniformity or the angular second moment.

$\sum_{i,j} p(i,j)^2$

Homogeneity

Measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.

$$\sum_{i,j} \frac{p(i,j)}{1+|i-j|}$$

Classification of periocular image

Once the features are extracted from the periocular images for the recognition of an individual similarity measure is used. Due to the illumination in the images an intelligent technique is needed for the effective recognition. For that purpose a neural network classifier is used. A neuralnetwork classifier based on Backpropagation training is used for the classification and the recognition of an authenticated individual.

Feed Forward Neural Network

The feed forward neural network, or perceptron, is a type of neural network first described by Warren McCulloch and Walter Pitts in the 1940s. Feedforward Neural networks can be used for classification and regression. The feed forward neural network (<u>http://en.wikipedia.org/wiki/</u> *feedforwardneuralnetwor.*,?) is trained with the Backpropagation training technique, which uses weighted connections from an input layer to zero or more hidden layers, and finally to an output layer.

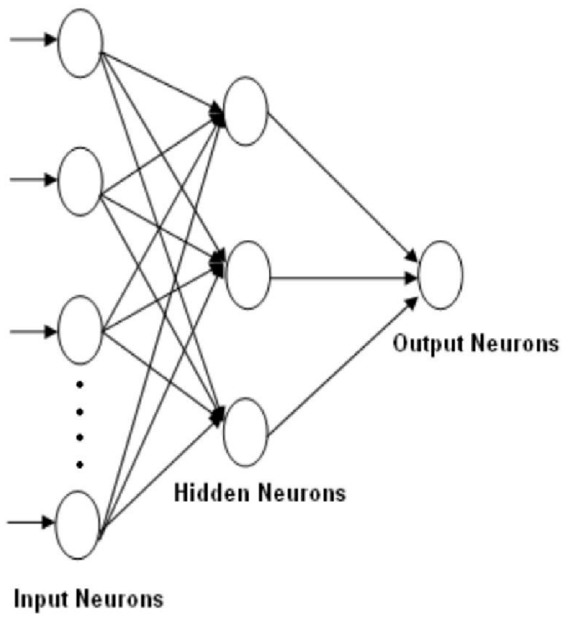


Figure 7. Architecture of Feed Forward Neural Network

Feedforward networks remember what they learn by adjusting weights between the neurons. Feedforward neural network is an interconnection of perceptrons in which data and calculations flow in a single direction, from the input data to the outputs. The number of layers in a neural network is the number of layers of perceptrons.

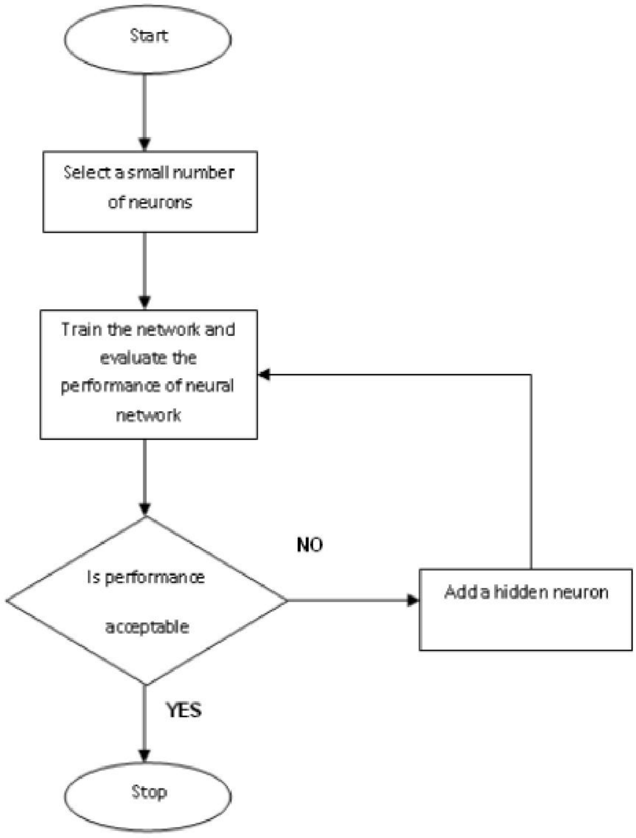


Figure 8. Flow chart for Feed Forward Neural Network

Architecture

In a feed forward neural network, data enters at the inputs and passes through the network, layer by layer, until it arrives at the outputs. During normal operation, that is when it acts as a classifier, there is no feedback between layers. This is why they are called feed forward neural networks. Figure 7 shows a typical feed forward neural network.

The number of neurons in input layer and the output layer depends on the application. The hidden layers and the neurons in the hidden layer are chosen generally by "rules of thumb" that can be used to assist making these decisions. In nearly all cases some experimentation will be required to determine the optimal structure for feed forward neural network. The input layer should represent the condition for which the neural network is trained for. Every input neuron should represent some independent variable that has an influence over the output of the neural network. The output layer determines the actual output of the application used. The neurons in the hidden layers decide the best network architecture and hence the neurons should be chosen optimally. An optimal network can be constructed if the number of hidden neurons is less than twice t he input layer size. Ultimately the selection of the architecture of the neural network will come down to trial and error.

Operation

The operation of this network can be divided into two phases.

Learning using Backpropagation

Backpropagation (Leonard *et al*., 1990) training procedure is used for feed forward neural networks. Its primary objective is to provide a mechanism for updating connected neurons based upon minimization of error. To accomplish this, gradient descent is generally used to determine the steepest path toward the minimum of

$$E(\vec{w}) = \frac{1}{2}\sum_{d\in D}((t_d - o_d)^2) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3)}$$

where d is a training instance in D, t_d is the target value, o_d is the output value, and is the weight vector.

Backpropagation requires determining an error by first feedfowarding inputs into the network and subtracting the result from some target output. This difference is then multiplied by the derivative of the neuron's activation function, in this application sigmoid function is used. After each error term is calculated, the weights are updated by the multiplication of each branch's output with the forward node's error and the learning rate.

Classification using FFNN

In the classification phase, the weights of the network are fixed. A pattern, presented at the inputs, will be transformed from layer to layer until it reaches the output layer. The classification can occur by selecting the category associated with the output unit that has the largest output alue. The periocular images are classified using the FFNN trained usingbackpropagation algorithm. The periocular images are first converted into a gray image and the local binary patterns are extracted from the gray image.

A Euclidean distance is calculated with the query image and the images in the database and the corresponding output is obtained. In certain situations, the algorithm does not recognize the accurate periocular images because of the skin aging. Hence, an intelligent classifier is needed to recognize the periocular images with much accuracy and efficiency. A neural network classifier is used to classify the authenticated persons. The number of input neurons fed to the classifier depends on the similarity measures obtained using Euclidean distance measure. One hidden layers is chosen and the number of neurons in the hidden layer is set to 70.

The output layer shows the authenticated periocular image. The hidden layer neurons is activated using a sigmoid activation function given as,

$$f(x) = \frac{1}{1+e^{-x}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(4)}$$

The output layer neuron is activated by using a linear activation function. The images in the database are separated into training and testing images. The 15 periocular images of both right and left eyes are given for training and for the purpose of testing the whole images in the database is given. The pseudocode for the periocular image classification system is given below,

Assign all network inputs and output
Initialize all weights with small random numbers, typically between -1and1
Repeat
For every pattern in the training set (x_i, y_i)
Present the pattern to the network
For each neuron in the input layer
Calculate the weight sum of the inputs to the node
Add the threshold to the sum
Calculate the activation for the node
End
For every node in the output layer
Calculate the error signal
End
For all the neurons in the hidden layer
Calculate the node's signal error
Update each node's weight in the network
End
Calculate the Error Function
End
While ((maximum number of iterations < than specified)
OR (Error Function is > than specified))

RESULTS

The images are preprocessed from various subjects and the periocular images are manually cropped and are stored in the database which is used for the recognition of an authorized person. The Query images are imported and are converted into gray scale image because the feature extraction methods are applied to the grayscale images. LBP which is an efficient algorithm and the parameters used are,

P = 8 (P->Number of Sampling Points)
R = 3 (R->Radius)

LBP preprocess the input periocular image and is represented with its texture patterns given by the LBP operator at each pixel location and the histogram of the Query Image and the LBP is given in the (Figure 9).

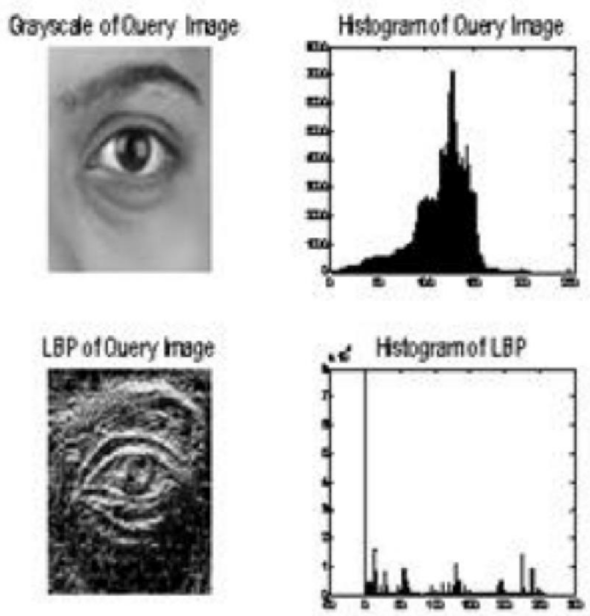


Figure 9. LBP image and its Histogram

Backpropagation method is to train neural network in which the initial system output is compared to the desired output, and the system is adjusted until the difference between the two is minimized. The error rate while training backpropagation is shown in (Figure 10)

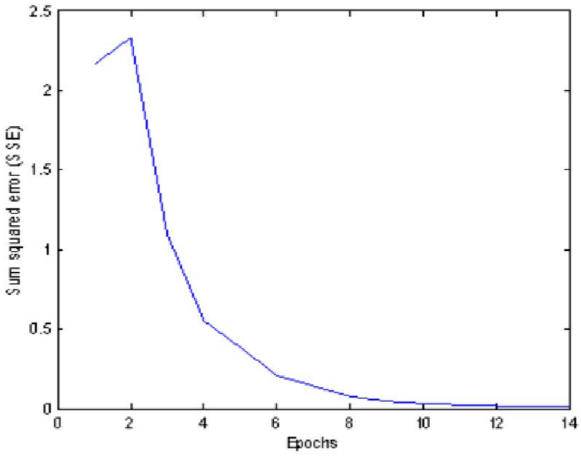


Figure 10. Error Rate of BPNN

The final output that is the given query image should be recognized as the authorized or an unauthorized image by Comparing the query image with the images that is stored in the database that is already collected and stored. The query image given is recognized as the authorized image and the recognized image given in (Figure 11)

Figure 11. Recognized Image

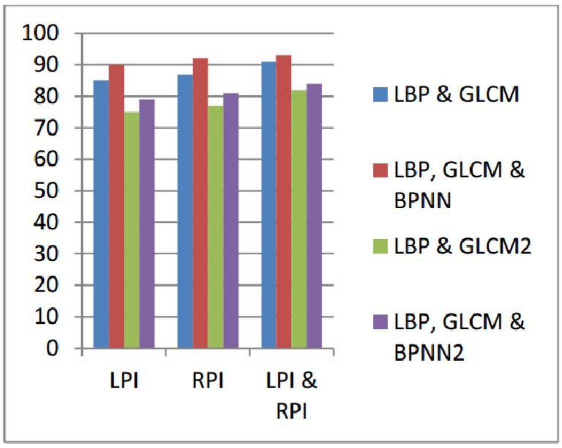


Figure 12. Performance Analysis

Table 1. Recognition Rate of the periocular images

	Recognition Rate (in%) for P=8, R=3		Recognition Rate (in%) forP=16, R=4	
	LBPand GLCM	LBP, GLCM and	LBPand GLCM	LBP, GLCM and BPNN
LPI	85	90	75	79
RPI	87	92	77	81
LPI and RPI	91	93	82	84

The recognition rate for the periocular images are tabulated in Table 1 by considering only the Left Periocular Image (LPI), only Right Periocular Image (RPI) and by combining both the LPI and RPI. The Performance chart is represented in Figure 11. By this chart it is shown that the feature extraction methods along with the similarity measure provides the better recognition. The recognition accuracy reduces due to the illumination in the images. Due to this, effective recognition training is given by the BPNN classifier which provides very high recognition accuracy. A chart is prepared based on the recognition rate with different P and R values. The recognition accuracy of Left Periocular Image (LPI), Right Periocular Image (RPI) and both PIandRPI is measured with LBP and GLCM alone and also with LBP, GLCM and BPNN.

Conclusion

In this work Periocular region which is used as the biometrics for the efficient recognition of an authenticated individual. Periocular recognition encompasses both the face and the iris biometrics. Acquisition of the Periocular image does not require high user cooperation and close capture distance. The features from the periocular region are extracted using feature extraction methods like Local Binary Pattern and Gray Level Co-occurrence Matrix. For the intelligent recognition of an authenticated individual and to make completely automated biometric system an effective classifier is used. Back propagation neural network classifier is used for effective classification and recognition of an authenticated individual. High Recognition accuracy of 93% is achieved in this proposed work when compared with the existing work.

Future research in periocular biometrics can be done by adding more features for the recognition of an individual and various classifiers can be used to increase the identificationperformance.

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