Improving Iris Recognition Performance using Local Binary Pattern and Combined RBFNN

Kamal Hajari

Abstract— ***Biometric is constantly evolving technology due to increased concerns in security. It exploits discriminable behavioral or physiological characteristics to identify a legitimate individual. The physiological features like DNA, Iris, Retina, Palm print, face, Ear, Fingerprint and Hand geometry etc. are being extensively used as biometric features to discriminate among different individuals. Iris recognition is a challenging problem, because iris is distinct and intrinsic organ, which is externally visible and yet secured one. It is well protected by the eyelid and the cornea from environmental damage. Our primary focus is to develop reliable system and increase the iris recognition rate on CASIA iris dataset. In this paper, a novel texture features are derived from iris images using histogram of Local Binary Pattern (LBP) and the Neural Network based classifier, namely Radial basis function networks is implemented for classification. Before feature extraction, pre-processing of iris images is performed including iris localization, Segmentation and Normalization. The proposed system give high recognition rate of 93.5% on CASIA iris dataset compared with other methods.***

Index Terms— ***Local Binary Pattern, Radial basis Neural Network Classifier, CASIA, Histograms.***

I. INTRODUCTION

In the today's information technology era, biometric recognition systems are in widespread use and are gaining more and more attention all over the world, because the iris region consist of rich texture information, which is useful for recognizing individuals [1, 2]. The two iris patterns are not similar or identical even if those of identical twins, even between the same individuals left and right eye [3]. The main goal of this research paper is to enhance the performance of iris recognition system by using Local Binary Pattern (LBP) texture features obtained from iris region. Iris recognition process is quite complex and is divided into three different steps i.e. pre-processing, feature extraction and recognition as shown in Fig. 1 [4]. It is essential to pre-process the acquired iris mask to obtain the desired region of interest for further processing [5]. The pre-processing is compartmentalized into three steps: iris localization, iris segmentation, normalization [6, 7]. In comparison with other biometric traits, iris recognition has higher accuracy [8, 9]. T. Ojala [10] introduced the concept of LBP. The 3x3 mask is applied on each pixel of iris image and center position pixel intensity value is compared with the neighborhood pixels and condition is applied as greater or less than the center pixel, that result as a binary bit stream. Due to computationally less complex in nature, hence it is widely used emerging technique for texture analysis. C. Avila et al. [11] used the Gabor wavelet transform for analyzing and extracting features of iris patterns. In the proposed work, texture of iris pattern is represented using local binary patterns (LBP). Next, the normalized LBP image histogram texture values are stored as the feature vectors. The radial basis neural network is used for classifying the individuals into different classes. The iris of human being is captured using standard digital cameras. The acquired iris depicts noise characteristics typically applied in real time [12]. CASIA is the most extensively used iris dataset. It is a Chinese Academy of Science iris database. First introduced in Biometrics Verification Competition (BVC) on fingerprint, face, and iris recognition [13]. The developed system is trained and tested on CASIA iris dataset.

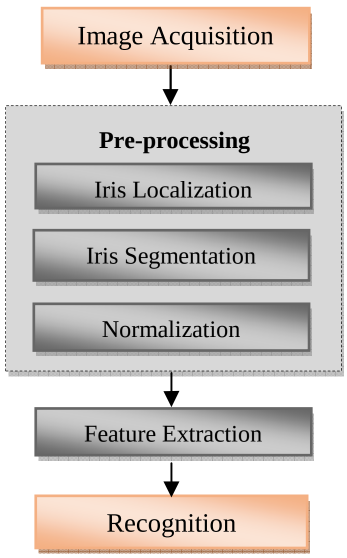

Fig. 1 General structure of iris recognition system

This paper is organized into the following sections. Section 1 gives an introductory part and importance of efficient iris recognition system. Section 2 gives review of literature. Section 3 presents a detailed discussion on iris pre-processing. Section 4 presents a detailed discussion on texture feature extraction. Section 5 presents a detailed discussion on iris classification using Neural Network classifier. Comparative analysis of experimental results are reported in Section 6. Section 7 concludes the paper.

II. REVIEW OF LITERATURE

The accuracy of iris recognition system is affected by the inaccurate pre-processing. As discuss in earlier section segmentation is one of the pre-processing step. The segmentation process used to locate limbic, pupillary, and eyelid boundaries that are elliptical or circular in shape. However, A. Ross and S. Shah [14, 15] describe a novel iris segmentation method based on active contours to extract the iris from the eye image in Ideal and Non-ideal conditions. J. Daugman [16] proposed a novel method of iris segmentation, in which iris, eyelid, eyelashes is segmented based upon the structural characteristic of eye image. L. Masek [17] proposed

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a scheme for iris recognition. After pre-processing feature extraction is the next in iris recognition. R. Thool [18] uses the wavelet transformation to extract the discriminable features from normalized iris image. In this pre-processed iris image is decomposed into multiple resolutions. U. Gawande et al. [19] proposed a combined approach of the zero-crossing 1 D wavelet with Euler number, and genetic algorithm based feature extraction method that results in normalized score values, that are fused to decide whether the user is genuine or imposter. Jin et al. [20] proposed the innovative method in which, LBP operator describe local structure information under certain conditions known as improved LBP (ILBP), which compares every pixels (including the central pixel) with the mean intensity value of all the pixels in the face image. T. Ojala et al. [21] proposed the rotation invariant texture classification approach using feature distributions. P. Manikandan et al. [22] proposed novel feature extraction method based on the Discrete Wavelet transformation and also compared it with two dimensional-discrete wavelet transform in order to increase the classification accuracy. Neural Network classifier are used for classification purpose. There are different types of classifier such as probabilistic neural network (PNN), multilayer perceptron (MLP) neural network, radial basis function (RBF) neural network and Self-organizing map (SOM) neural network. D. F. Specht [23] proposed the PNN classifier. Some algorithms for neuron selection in pattern layer have been proposed in [24, 25].

III. PROPOSED METHODOLOGY

Amongst a variety of biometric traits, iris based recognition systems are more valued due to its distinct pattern. Iris patterns are believed to be unique due to its rich, distinctive and complex pattern of crypts, furrows, arching, collarets and pigment spots. It is very precise and most stable personal identification biometric. Iris recognition consists of three main steps, (1) pre-processing, (2) extracting the feature sets, and (3) recognition.

3.1 Iris Pre-processing

The Human eye images contain sclera, iris, pupil, eyelids, and eyelashes as shown in Fig. 2a. It is mandatory to preprocess the eye image to extract the accurate features. The following are the iris per-processing steps i.e. localization, Segmentation and Normalization [7].

3.1.1 Iris Localization and Segmentation

In iris localization, we try to locate iris part in an eye Image. The two boundaries are identified Inner boundary and the outer boundary. Iris is nothing but approximated circles. However, the two circles are usually not concentric. The segmentation step consist in applying canny edge detection to generate an edge map, then using circular Hough transform to detect the iris and pupil boundaries and deduce their radius and center co-ordinates [3]. To increase the accuracy and efficiency of the circle detection process Hough transform is applied for the detection of boundaries between iris/sclera first, then for the iris/pupil within the pupil region, instead of the whole eye region as shown in Fig. 2b . Then detect and eliminate the eyelash and eyelid which is considered to be the noisy region in eye image as shown in Fig. 2c [6].

3.1.2 Normalization

The iris size of every individual is not the same, hence normalization is performed and spatial coordinated converted to polar product image. Once the iris region is successfully segmented, it is transformed into fixed dimension size rectangle of size 20 x 240 representation is modeled using Daugman's Rubber sheet model [16] as shown in Fig. 2d.

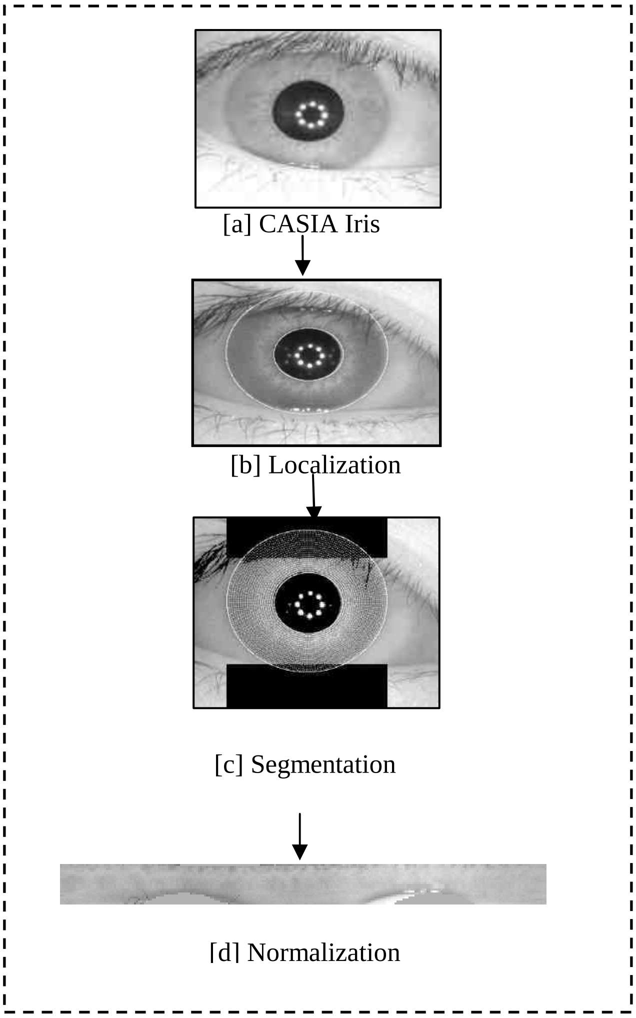

Fig. 2 Iris Pre-processing Output

IV. TEXTURE FEATURE EXTRACTION USING LOCAL BINARY PATTERN

There is abundant texture information in features of the iris that is unique to each individual. Hence Texture features are extracted using Local Binary Pattern (LBP). The original LBP operator labels the intensity of pixels in an image with decimal numbers, which are called LBP codes that encode the local structure around each pixel. It is illustrated in Fig. 3. Each pixel is compared with its eight neighbours in a 3x3 neighbourhood by subtracting the center pixel intensity value; the resulting strictly encoded with binary values as 0, and the others with 1. For each pixel, a binary number is obtained by concatenating all these binary values in a clockwise direction, which starts from the one of its top-left corner neighbor. The Corresponding decimal value of the generated from binary number is then used for labelling the given pixel. [20].

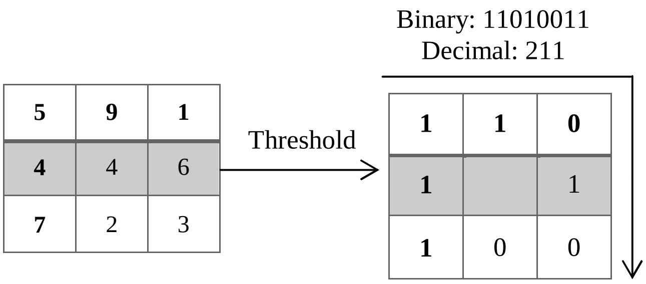

Fig. 3 Example of Local Binary Pattern (LBP)

The histogram of normalized images are shown in Fig. 4. The encoded decimal values are plotted on x-axis and on y-axis count of decimal values are plotted. Each iris image local binary pattern and histogram is different among themselves, because each iris image sample consist of discriminating texture information. The histogram values are normalized and these values are stored as feature vector.

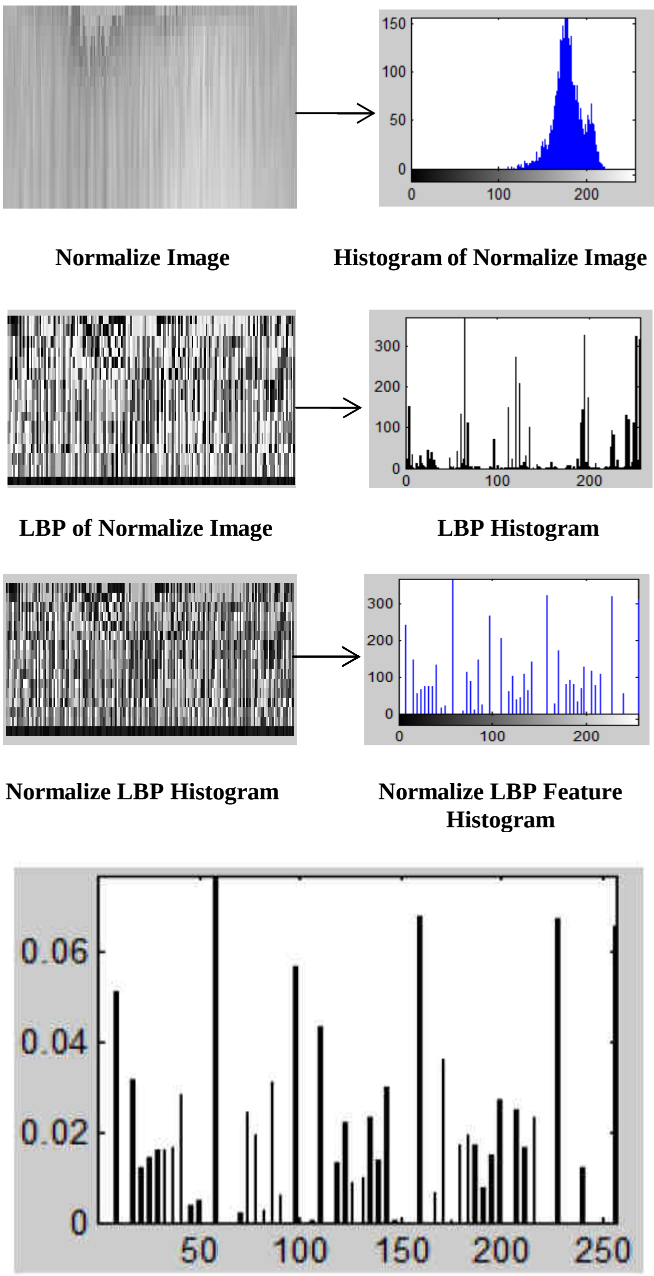

Fig. 4 Local Binary Pattern Feature Extraction Method

The size of stored feature vector is 1*256. The CASIA iris database consist of 100 subjects. Each subject has 5 images. So total features are extracted from database are 500*256. That can be used by Radial basis Neural Network for classification.

V. IRIS CLASSIFICATION USING NEURAL NETWORK

In this section, we discuss about the Neural Network classifier, which is used for classification purpose. The experiments are performed on extracted texture features from different subjects. The database consists of 500 images of 100 subjects. The pairs of iris images are obtained for each subject. Each pair of iris one subject. Out of these 300 images are stored as reference data for training purpose. Remaining 200 images are stored as two per subject, is used for testing. The obtained texture feature vectors are given as an input to RBFNN classifier. The training is performed on 300 reference feature vectors and neural network is generated. The output layer consist of 200 neurons. i.e. 100 classes. The next section discuss about the experimental results obtained by using neural network.

VI. EXPERIMENTAL RESULTS

In this section, we discuss the performance of proposed system. The experiments are performed for three parameters, namely, FMR, FNMR and TAR. The database consists of 500 images from 100 subjects. We use 100 subjects of iris from CASIA database. Three pairs of iris images are obtained for each subject. Each pair of iris one subject. So, total number of images are 500. Out of these 300 images are stored as reference data for training purpose. The CASIA iris database specification is describe in Table 3. Remaining 200 images are stored as two per subject, is used for testing. The obtained texture feature vectors are given as an input to RBFNN classifier. The most promising result of 3% False Match Rate (FMR) and 3.5% False Non Match Rate (FNMR) and recognition rate of 93.5% achieved by the PNN classifier. True Acceptance Rate (TAR) faired to 97% and required very less training time of 0.903 sec. and testing time of 0.0341sec per sample as shown in Table 1. The experiments are performed in MATLAB 2013b version and graphical user interface is created for describing visually the obtained results. The Table 2 shows the comparison of existing approaches on CASIA datasets. The proposed system performance is somehow better, if it is compare with existing approaches i.e. True Acceptance Rate (TAR) for proposed system is 97%, FNMR is 3% and highest recognition rate is achieved using RBFNN classifier is 93.5%. Comparatively existing system require more training as shown in Table 2.

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Table 1 Classification accuracy of proposed system

Type of features	Classifier	Error Rates		Recognition Rate	Training Time	Testing Time (per sample)
		FMR/FAR	FNMR/FRR			
Proposed Texture feature Extraction Method	RBFNN	3.5%	3%	93.5%	0.903	0.0341

Table 2 Comparison with existing approaches on CASIA

Algorithm	Error Rates		Recognition Rate	Time (seconds)
	FMR/FAR	FNMR/FRR		
Topological features[26]	1.81%	0.0001%	92.39	0.043
global textural features[26]	0.77%	0.0001%	96.57	1.15
2v-SVM Fusion Match score[26]	0.38%	0.0001%	97.21	1.82

Table 3 Structure of CASIA iris dataset

Datasets	Total Size
Training samples per subject for Genuine cases	3 x 100 = 300
Testing samples per subject for Genuine cases	2 x 100 = 200

VII. CONCLUSIONS

Iris recognition is a challenging problem. Hence we have successfully enhance the iris recognition system performance and also increase the iris recognition rate on CASIA iris database. The most promising result of 3.5% False Match Rate (FMR) and 3% False Non Match Rate (FNMR), recognition rate of 93.5% and True Acceptance Rate (TAR) faired to 97% is achieved using RBFNN classifier. The computation time required is very less training time of 0.903 sec. and testing time of 0.0341sec per sample. Research primary goal is to developed reliable system, but there is still a scope of improvement. This work can be extended for future research. To begin with, the experimental results can also be perform on different iris datasets such as MMU, UBIRIS, ND iris and ICE and innovative methods of image processing can be used with different Neural Network classifiers such as Probabilistic Neural Network(PNN) and Back propagation neural network(BNN). Multimodal system can also be developed, which is a combined approach of different biometric characteristics.

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