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Neural Network Approach to Iris Recognition in Noisy Environment

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Abstract

Iris recognition is a challenging problem in the noisy environment. Our primary focus is to develop the reliable iris recognition system that can work in a noisy imaging environment and to increase the iris recognition rate on CASIA and MMUiris datasets. This research paper proposes two algorithms, first, a novel method for removing noise from the iris image and second, a texture feature extraction method using a combined approach of Local Binary Pattern (LBP) and Gray Level Co-occurrence Matrix (GLCM). Our proposed approach give highest recognition rate of 96.5% and low error rate and requires less execution time.

Keywords: Noisy environment, Noisy Artifacts, Occlusion, Local Binary Pattern, Iris Recognition, Neural Networks

1. Introduction

In the modern society, most advanced security system uses biometric all over the world[1] and are used in many places such as corporate offices, criminal investigation, identification, border control, security zones, airports, hospitals, banks, autonomous and non-autonomous institutions, etc. Nowadays biometric based systems are in widespread use and it plays a vital role in human identification. Among all different biometric traits iris is a most reliable and unique organ[2]. It is well protected from environmental and physical damage by the eyelid and the eyelashes[3]. In comparison with other biometric traits, iris features are more discriminating due to non-uniform texture available in iris[4] but at the same time iris recognition process is quite complex. Hence it is divided into four different steps, i.e. 1) Iris image acquisition 2) Preprocessing 3) Texture feature extraction and 4) Classification[3]. Efficiency of iris recognition system is fully determined by correct preprocessing and feature extraction technique[5]. Existing algorithms works

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well but still there is a scope of improvement in performance of existing preprocessing and feature extraction algorithms[6]. A Major issue arises due to the presence of various artifacts, while capturing iris images. These artifacts are present in existing public databases in literature [7, 8, 9] as shown in Fig 1. Due to these artifacts the most well-known challenges faced is the iris segmentation. For example, occlusions by eyelids are caused by biological characteristics of the eye. In such cases,the boundary of the eye is not circular in shape and boundaries around the pupil and iris region is difficult to identify as shown in Fig 1 (a). Similarly occlusion by eyelashes plays the important role to determine the quality of an iris image. This also affects the iris boundary detection process. The occlusion with eyelash presence in iris image is depicted in Fig 1 (b). Segmentation accuracy is also affected by the high-intensity pixels present in pupil region in iris images, characterized as specular reflections as shown in Fig 1(c). This occurs due to improper focus of light source. Iris images may have artifacts due to motion blurriness, such as shown in Fig 1(d). The off-angled iris images artifacts is caused, when angle of orientation of sensor used for acquiring iris is improper as depicted in Fig 1(e). In such non-ideal situation the length of iris is reduced and the boundary detection becomes tedious. The large standoff distance also affect quality of iris image. It refers to the distance between the camera and subject. The pixel resolution is depend upon the distance. The number of pixel is less in acquired image, if the distance is large. In such situations, the texture information is not captured accurately as shown Fig 1(f).The more noise may be added in the acquired iris images due to presence of contact lens on the pupil region as shown in Fig 1(g). Similarly, less information is captured due to poor illumination. In such situation texture features extraction process becomes difficult and due to which recognition rate is reduced. Fig 1(h) shows the image with poor illumination. The reflection component present due to eye glasses, while capturing an iris image is also considered as noise as shown in Fig 1(i).

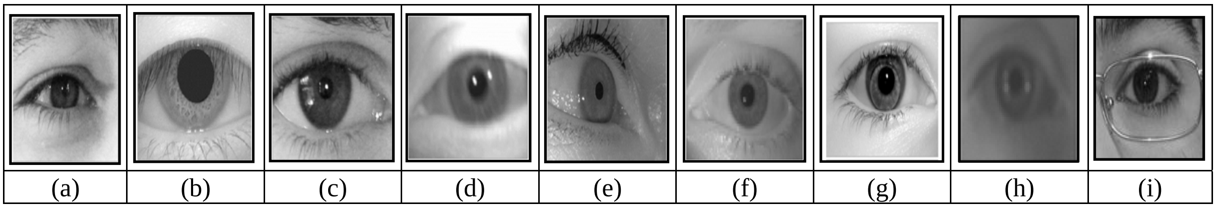


Fig. 1. (a) Occlusion by eyelids, (b) Occlusion by eyelashes (c) Specular reflections (d) Motion blur (e) Off-angle (f) large standoff distance captured iris images (g) Contact lenses (h) Poor illumination (i) Person with spec.

In such non-ideal situation the length of iris is reduced and the boundary detection becomes tedious. The large standoff distance also affect quality of iris image. It refers to the distance between the camera and subject. The pixel resolution is depend upon the distance. The number of pixel is less in acquired image, if the distance is large. In such situations, the texture information is not captured accurately as shown Fig 1(f).The more noise may be added in the acquired iris images due to presence of contact lens on the pupil region as shown in Fig 1(g). Similarly, less information is captured due to poor illumination. In such situation texture features extraction process becomes difficult and due to which recognition rate is reduced. Fig 1(h) shows the image with poor illumination. The reflection component present due to eye glasses, while capturing iris image is also considered as noise as shown in Fig 1(i).Apart from these artifacts, there are other factors like faked iris images, camera diffusion, head rotation, camera angle, reflection and contrast which may also cause improper segmentation of iris and ultimately degrades the performance of recognition[10]. Amongst all these challenges, we have addressed reflection issue in this paper, which is always present while capturing iris image. The preprocessing algorithm proposed in this work is having the capability to remove the reflection, which results in better recognition. The remainder of this research paper is described as follows: Section 2 describes proposed system architecture of iris recognition in noisy environment. Section 3 describes the noise detection and removal algorithm along with iris pre-processing. Section 4 describes texture feature extraction algorithm. Section 5 discuss about neural network classifiers. Simulation results are presented in section 6 along with the comparison of the proposed approach with existing iris recognition system available in literature. Finally, Section 7 concludes this research paper.

2. Proposed system architecture of iris recognition in noisy environment

As discussed earlier, it is difficult to develop the iris recognition system in noisy environment. The propose system architecture is shown in Fig 2. Proposed framework is divided into four main steps, 1) Image acquisition (standard iris databases CASIA [9] and MMU[10] are used). 2) Iris preprocessing, here different steps has been performed such as noise detection and removal, iris localization, eye lid and eye lashes removal and iris normalisation. 3) Feature extraction, here linear rectangular transformed image (output of step 2) has been given as input and texture features has been extracted using combined approach of LBP[11] and GLCM[12] based texture properties. 4) Classification is the last step, in this two neural network based classifier i.e. radial basis kernel and probabilistic neural network has been implemented for human identification. The two classifiers are used to find which classifier gives better performance in terms of recognition rate, for the proposed approach of noise reduction and feature extraction.

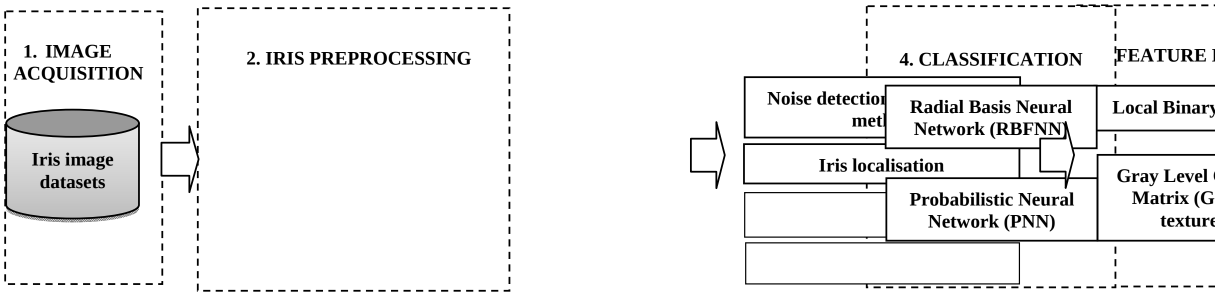


Fig. 2. System architecture of iris recognition system

3. Irisreprocessing

In this section, proposed iris preprocessing algorithm has been discussed in detail. There are four different steps include in preprocessing, i.e. 1) Noise detection and removal method, 2) Localisation, 3) Segmentation and 4) Normalisation. Each of these steps is explained in brief as follows.

3.1 Noise detection and removal

A novel algorithm called noise detection and removal of a camera reflection (noise) present in the pupil has been proposed here. This algorithm aims to remove corneal reflectional present in the iris image and to improve the accuracy of localisation and segmentation steps of pre-processing. Usually, specular or camera reflections appear as the brightest region in the iris image. This is more specific for CASIA and MMU database. From these images it is observed that pupil region consist of reflection pixels. To remove those reflections the proposed algorithm is divided into two parts 1) Camera reflection pixel identification and 2) Camera reflection pixel removal. This approach is described in detail below.

3.1.1 Camera reflection pixel identification

It consists of following steps:

1. Iris image is acquired from iris image database (i.e. reference database). Say it is 'F (x_i, y_j)', where 'i' varies from 1 to 'K' and 'j' varies from 1 to 'L'. These size may vary for images in CASIA and MMU database.
2. Compute the threshold for identification of reflection pixel. Threshold has been represented as 'T' and camera reflection pixel by 'R (x_i, y_j)'. Non-reflection pixel has been represented as 'NR (x_i, y_j)'. The threshold is computed using combined approach of global thresholding algorithm [13] and image analysis tool in MATLAB. The global thresholding is preferred because of its ability to find the single threshold for complete image 'F (x_i, y_j)'. It is expected that the combination of these two approaches would result in better identification of reflective and non-reflective pixels. The resultant image after thresholding is represented as 'F2 (x_i, y_j)' and calculated as:

$$F_2(x_{i,}y_j) = \begin{cases} \mathrm{R}(x_{i,}y_j)\mathrm{F}(x_{i,}y_j) > T \\ \mathrm{NR}(x_{i,}y_j)\mathrm{F}(x_{i,}y_j) < T \end{cases} \quad (1)$$

Were, $1 \le i \le K, 1 \le j \le L$
K→ Number of rows
L→ Number of columns

The output of this step has been identified pixels of reflection and non-reflection.

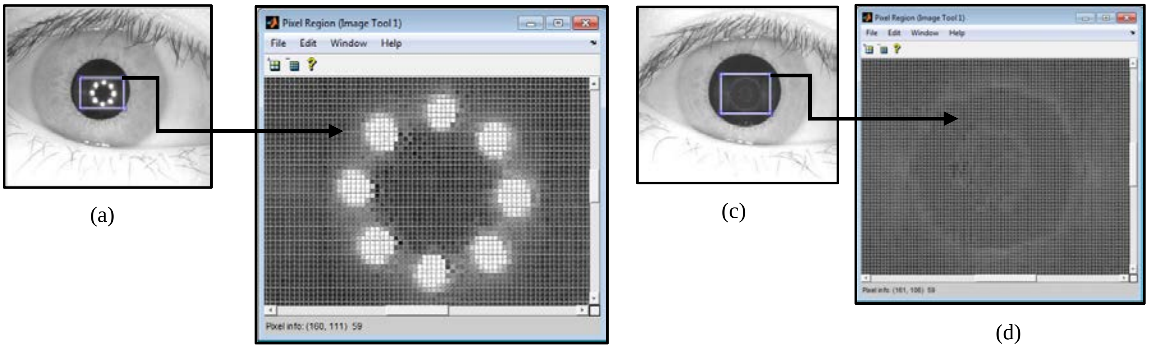
3.1.2 Camera reflection pixel removal

1. These reflection pixels are filled with the neighbourhood pixels in step 2. The neighborhood pixel location represented by 'O (x_i, y_j)' is found as :

$$\mathrm{O}(x_{i,}y_j) = \begin{cases} \mathrm{R}(x_{i,}y_j) \leftarrow \mathrm{R}(x_{i-1,}y_j)\mathrm{R}(x_{i,}y_j) > T \\ \mathrm{NR}(x_{i,}y_j) \leftarrow \mathrm{NR}(x_{i,}y_j),\ \mathrm{F}(x_{i,}y_j) < T \end{cases} \quad (2)$$

2. Repeat until $\mathrm{R}(x_{i-1}, y_j) \neq \mathrm{R}(x_i, y_j)$:
Were, $1 \le i \le K, 1 \le j \le L$

The output of this algorithm is shown in Fig. 3 for CASIA database. It represents the images before and after noise removal. The pupil analysis using imtool is represented in Fig 3(b). The rectangular box in Fig 3(a) is located in the pupil region, which consist of camera reflection pixels that affect the accuracy of localisation and segmentation process. The refilling of reflexive pixels with the neighbouring pixels is shown in Fig 3(c). Also pupil analysis after noise removal is depicted in Fig 3(d).The main advantage of this algorithm is that there is no loss of structural and textural information present in iris image. This results in more accurate texture features, which ultimately increases the recognition rate. Experiments have been performed on CASIA and MMU databases. After removal of noise the next step is the iris localisation.



(b)

Fig. 3. Pupil analysis using imtool before and after noise removal for CASIA database sample image (a) CASIA iris image (b) Image analysis tool output before noise removal (c) CASIA iris image after noise removal (d) Image analysis tool output after noise removal

3.2 Iris localisation

The iris image without noise needs to be pre-process to detect the region of interest. Here the two boundaries of iris i.e. inner boundary (pupil) and the outer boundary (sclera), which is in ring shape portion has been detected using standard algorithm of Hough transform [3]. Two circles parameters are computed separately using Hough transform [3], because circular shape boundaries are not co-centric. Here is the benefit of the proposed noise removal algorithm as it helps to locate the boundaries of iris accurately. It is tedious task to determine accurate boundaries for the acquired iris image containing noise[14]. This step is followed by iris segmentation.

3.3 Iris segmentation

Segmentation is the next step after localisation to separate sclera, eyelashes and eyelid area from eye [15]. The efficiency of segmentation algorithm depends on the quality of eye images. Noisy imaging environment makes segmentation process more difficult. The inaccurate segmentation results in poor recognition rate [16.]

3.4 Normalisation

Normalisation transforms the detected circular region into rectangular shape image [17]. This step is necessary because the iris of individuals is not of same size[15]. To convert these images into standard size, iris normalisation is required. This help to extract accurate features. In noisy conditions the process of normalisation is more imprecise due to false identification of region of interest. The inaccurate normalisation again results in poor recognition rate.

4. Texture feature extraction algorithm

After the pre-processing steps, the next important task is the extraction of relevant texture features. We propose a novel texture feature extraction algorithm. It is based on combined approach of LBP and GLCM. GLCM is use for extracting texture information from image. The feature extraction algorithm is explained in following steps:

1. Pre-processed normalise image of size 20x240 is obtained. Say it is ‘G (x_i, y_j)’, where the value of ‘i’ varies from 1 to 20 and the value of ‘j’ varies from 1 to 240
2. LBP algorithm works on thresholding approach. Image is threshold using 3x3 mask. The 3x3 mask is applied in eight directional neighbourhood in clockwise direction as follows:
   Initial value of ‘i’ and ‘j’ is declared as step 2. Due to this 3x3 mask does not extend image dimensions. Hear, ‘K’ stores the pixel information of the location ‘G (2, 2)’.
   Let, K is initialized with the pixel intensity value of the location ‘G (i, j)’ as shown in Fig 4.

   O(i-1,j-1) ← G(i-1,j-1) is greater than ‘K

   O(i-1,j) ←G(i-1,j) is greater than ‘K’

   O(i-1,j+1) ← G(i-1,j+1) is greater than ‘K’

   O(i,j+1) ← G(i,j+1) is greater than ‘K’

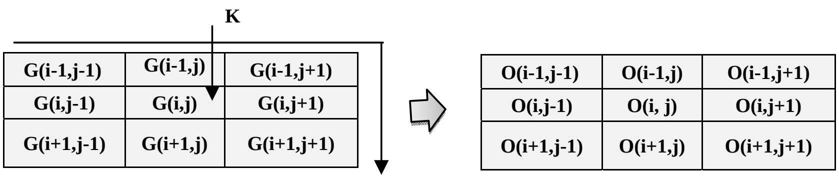
   O(i+1,j+1) ←G(i+1,j+1) is greater than ‘K

   O(i+1,j) ← G(i+1,j) is greater than ‘K’

   O(i+1,j-1) ← G(i+1,j-1) is greater than ‘K’

   O(i,j-1) ← G(i,j-1) is greater than ‘K’

   Were, $2 \geq i \leq w-1$, $2 \geq i \leq h-1$



(a) (b)

Fig.4. (a) 3X3 LBP mask coordinate location (b) Output image segment coordinate location

3. The resultant image is represented as ‘O (x_i, y_j)’. Now texture value for location ‘K’ is obtained by converting this 8 directional pixel information in decimal, which represent a unique texture feature for that image segment. Similarly, this process is recursively applied on complete image to extract texture features of size 1*256.

4. This step extracts texture features from GLCM. For that, properties of GLCM are as follows:

Entropy = $-\sum_{i,j} G(i,j) log\, G(i,j)^2$ (3)

Variance = $\sum_{i,j}(i-\mu)^2 G(i,j)$ (4)

Inertia = $\sum_{i,j}(i,j)^2 G(i,j)$ (5)

IDM = $\sum_{i,j} \frac{1}{1+(i,j)^2} * G(i,j)$ (6)

Energy = $\sum_{i,j} G(i,j)^2$ (7)

The output of this step is the feature vector with five elements.

5. Finally, the combination of LBP and GLCM texture information are stored as feature vector of size 1*261, with the expectation of better performance. This feature vector is given as an input to the neural network for further training and testing purpose.

5. Neural network classifiers for iris recognition

The architecture of the four-layer probabilistic neural network classifier used for iris pattern classification is shown in Fig 5. It consists of two hundred neurons in input layer, three hundred neurons in pattern layer and two hundred neurons in output layer.

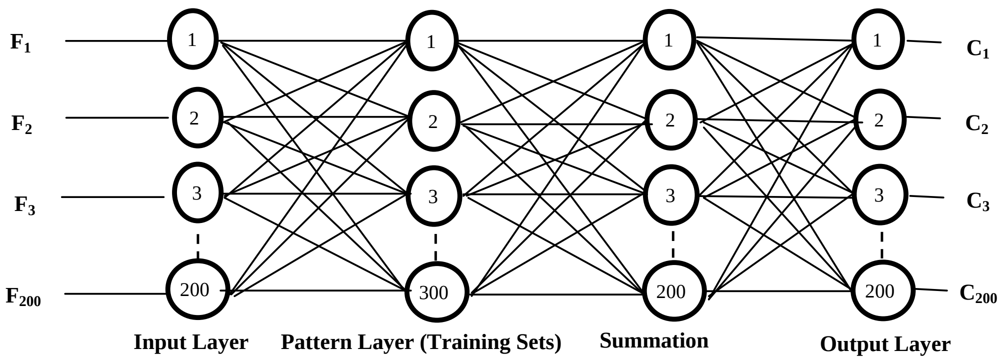


Fig. 5. Probabilistic neural network classifier for iris recognition

The pattern layer is required, as the training patterns belonging to various classes. Radial basis function [18] is used for all the neurons in the network. The network is trained by using PNN algorithm. Output layer consist of two-hundred classes for hundred legitimate users for the database. It means two classes for each individual.

6. Experimental results

In this section, we discuss the performance of presented work. The experiments are performed on three parameters, namely, False Match Rate (FMR), False Non Match Rate (FNMR), True Acceptance Rate (TAR) and response time. The database consists of 1000 images from 200 subjects. We use 100 subjects of iris from CASIA and MMU databases. For each subject, three pairs of iris images are obtained. These 300 images are used for training and remaining 200 images per subject for testing. So, total number of images in database is 1000. The texture feature vectors obtained by proposed algorithm are given as an input to PNN and RBFNN classifier. Both the classifier is trained by 600 reference feature vectors. 400 query images are tested for observing the performance of recognition rates and for finding the error rates of proposed work.

Table 1. Comparison of proposed system using different classifiers

Type of features	Database	Classifier	Error Rates		Recognition rate (%)	Training time(sec's)	Testing time(per sample)
			FNMR/FRR	FMR/FAR			
Proposed texture feature extraction method	CASIA	PNN	5.5%	0%	94.5%	0.794	0.0245
		RBFNN	3.5%	3%	93.5%	0.903	0.0341
	MMU	PNN	3.5%	0%	96.5%	0.124	0.2445
		RBFNN	5%	0%	95.5%	0.903	0.0349

Table 2. Comparison with existing approaches in [13] on CASIA and MMU datasets

Algorithm	Error Rates		Recognition rate (%)	Testing time (sec's)
	FNMR/FRR	FMR/FAR		
Topological features	1.81%	0.0001%	92.39	0.043
Global textural features	0.77%	0.0001%	96.57	1.15
2v-SVM fusion match score	0.38%	0.0001%	97.21	1.82

As observed from Table 1, the most promising result of 3.5% FRR, 0% FAR and recognition rate of 96.5% is achieved by the PNN classifier for our proposed approach on MMU database. TAR faired to 100%. We also tested it for RBFNN classifier that results in 5% of FRR, 0% FAR, recognition rate of 95.5% and TAR faired to 97%. From all these results it can be observed that the proposed system performance is somehow better in terms of FRR, FAR and TAR and highest recognition rate is achieved using PNN classifier is 96.5% for MMU dataset. Apart from these excellent results, our approach also requires very less training and testing time.

7. Conclusion

Iris recognition is a challenging problem in noisy imaging environment. Hence we have proposed a framework to enhance the iris recognition system performance in noisy imaging environment and also increase the iris recognition rate on CASIA and MMU dataset. The most promising result of 3.5% of FMR, 0% of FNMR and recognition rate of 96.5% is achieved by the PNN classifier. TAR faired to 100%. We also tested it for RBFNN classifier that results in 5% of FMR and 0% FNMR, recognition rate of 95.5% and TAR faired to 97%. These results are improved one due to the effective noise removal algorithm and feature extraction proposed in this paper. Overall it is concluded that the proposed system performance is better in terms of recognition rate, error rates and execution time. This work can be further extended by removing other noisy artifactspresent on different databases such as PHOENIX, UBIRIS, ICE, etc.

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