Comparative Study on Biometric Iris Recognition based on Hamming Distance and Multi Block Local Binary Pattern

K. Saminathan¹*, T. Chakravarthy¹ and M. Chithra Devi²

¹Department of Computer Science, A.V.V.M. Sri Pushpam College, Poondi-613503, India; arksami@gmail.com, tcvarthy@gmail.com
²Department of Software Engineering, Periyar Maniammai University, Vallam-613403, India; m.chithradevi@gmail.com

Abstract

Personal identification based on biometric is most essential to ensure security. Recognition based on iris unique texture is a reliable, simple and fast. The abundant as well as unique patterns of iris are extracted. Matrix format template is generated that contains 4800 elements for each iris. Multi block local binary pattern, hamming distance and support vector machine performs matching based on the template’s unique features of iris. The experimental results of this proposed work illustrate a better performance. The popular CASIA (Chinese Academy of Sciences – Institute of Automation) iris database with hundred users’ eye image samples are experimented to prove, that the multi block local binary pattern is comparatively better with minimal true rejection rate.

Keywords: Hamming Distance, Iris Preprocessing, Iris Template, Multi Block Local Binary Pattern

1. Introduction

Biometric identification system is a widely preferred system to make sure consistent security areas such as immigration and finance. Identification system based on iris features has been in practice for the past three decades. Biometric based recognition is still experimented, in various dimensions, to support large volume of data easily and quickly. The unique features of iris possess all the biometric characteristics. It ensures more security and not feasible to steal by impostor⁵–⁹.

Figure 1 depicted the human eye image with iris parts. It is an annular part of the eye which exists between the pupil’s (low intensity part) and sclera’s (high intensity part) in front view. It helps to controls the amount of light that enters the eye. The dilator and sphincter muscle supports to control the pupil size⁵.

*Author for correspondence

Figure 1. Human eye image.

Its abundant textures are unique from one user to another, among twins and even between the left and right eye of an individual. Some of the iris features are arching ligaments, crypts, furrows, ridges and zigzag collarettes⁵–⁸. Its uniqueness is developed from the third month of fetal to eighth month of gestation period.
There are several colors of iris such as brown, blue and hazed colors are quite common. The pupil size varies from 10 to 80 percent of 12 mm iris average diameter\(^{16}\). Iris uniqueness was first noticed by Albert Bertillon in 1880. Many researchers got patterned: Daughman in 1994, Richard P. Wildes et al. in 1998, Mit Matsushita in 1999. Several difficulties in stages such as localization of iris regions, extracting required features, data storage format, storage space and techniques to classify or matching, performance and speed are faced in iris recognition system. This paper is concerned to increasing the performance using a simple method.

1.1 Related Work

Researchers worked on this automatic recognition system using various approaches. Features in an image are classified into three types: Geometric features, Spectral features and Textural features\(^{18}\). John Daughman and Richard P. Wildes concentrate on entire automatic recognition system from image capturing to decision making\(^{5-7}\). Other researchers tried to improve the performance of iris recognition system on specific phases, such as noise removal\(^{1,20}\), dimensionality reduction\(^2\), features based\(^{3}\), classification phase\(^{4,13}\), and so on. Hamming distance was widely applied by researchers for matching phase in iris recognition system\(^5\). A number of researchers have used Local Binary Pattern (LBP) to extract feature and also for classification\(^{12,15}\). Local binary pattern can be classified into several types: transition, direction coded, modified, volume RGB, opponent color, multi resolution and multi block. The multi block local binary pattern divides the image into several blocks then a LBP histogram is calculated for each block. Finally all the histograms of each block are concatenated into a single histogram. The machine learning algorithm support vector machine was used to classify the authenticated users. It was proposed by Boser, Guyon and Vapnik. It acts as efficient classifier compared to other machine learning classifiers\(^{2-4,17,18}\).

2. Proposed Work

This work presents two experiments to support automatic iris recognition system. In general, iris preprocessing methods and template generations are common for both these two experiments. To enhance the speed and accuracy the feature dimensions are minimized by obtaining the required minimal traits from the inner boundary to middle region of iris\(^{7}\). In this work the distinctive iris traits of collarettes region, some degree of furrows and ridges are included in template generation phase. In the first experiment, the matching phase by hamming distance algorithm based on binary value of the templates result in moderate performance. In the second experiment, SVM with multi block local binary pattern algorithm based on neighbor values provides good performance with maximum true rejection and least false rejection rate at maximum speed for the given data set. The novelty of this work supports both authentication and recognition. The matching can be done on the basis of both identity and without identity, which means classification process of both one to one or among gallery. The matching speed is enhanced due to the minimal and unique features that are passed as input.

2.1 Preprocessing

The preprocessing of eye image is essential for getting the required and accurate input for further processing. Image capturing is the first step and the quality of input image helps to store the biometric distinctive feature extraction easier and faster. The input must not be in the state of close, off-angle, aniridia diseased and cataract surgery undergone eye images. Blurred images are neglected for further processing. Images can be obtained from the database or through scanners. The height and width of eye image is passed as x and y value. Grey scale image helps to find the boundaries of iris easily for localization. In this work CASIA database image of grey scale was experimented.

2.1.1 Iris Localization

Figure 3. Eye Image.
Iris localization is the process of finding the iris’ lower and upper boundary values. The input image in grey scale format is depicted in the Figure 2. The expected two concentric circles of iris boundaries are depicted in the Figure 3. To obtain the expected iris boundaries, the pupil outer boundary and sclera inner boundary are needed to compute based on the intensity value. Pupil boundary algorithm was applied over the image to retrieve the pupil boundary by setting threshold value lowest intensity 0 (black) and for limbic boundary highest intensity value 255 (white). The canny edge detection algorithm was applied to retrieve the edges and the inbuilt Gaussian filtering helps to retrieve the smooth and sharpened image edges. The Hough transform algorithm finds the possible circle. The set of edge points are accurately captured with this transformation technique. It is well supported to find the possible circle even though with the presence of noise and gap between pixels. The Figure 4 and 5 depicts the pupil boundary and limbic boundary. The Figure 6 depicts the iris boundaries as a result of differencing Figure 4 and Figure 5. In MAT lab Imoverlay function was applied to get the expected iris boundaries.

**2.1.2 Iris Normalization**

Normalization is the process of transforming cartesian format of iris into polar format. Masking was applied over the localized image of the eye to acquire the actual iris part. In this work eyelid, eyelashes and specular highlights are replaced with lowest intensity value 0 as noise. The occlusion of pupil helps to reduce the computational complexity. Daugman’s rubber sheet model was applied to get the fixed dimensions of iris by transforming cartesian into polar format\(^4\). Keeping pupil centre as reference point the iris boundaries are fixed and remapped.

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**Figure 3.** Expected eye image.

**Figure 4.** Pupil Boundary.

**Figure 5.** Limbic Boundary.

**Figure 6.** Iris Boundaries.

**Figure 7.** Unwrapped Iris.
by each point within the iris region as a pair of polar coordinates \((r, \theta)\) where \(r\) is on the interval \([0,1]\) (rows) and \(\theta\) is angle \([0,2\pi]\) (column). The outcome of Daugman's rubber sheet model was depicted in Figure 8.

2.2 Feature Extraction

In this work the unique features that are abundant in the iris template ranges from lower to middle were extracted. The iris image has the intensity ranges from 0 to 255. The iris template was generated in the form of matrix. The intensity values of unique patterns in the iris template are efficiently used for further classification. The template generated in matrix format, consists of 20 rows and 240 columns. The \(r\) radius of iris was limited to 20 rows and the \(\theta\) value to 240 columns and it is depicted in Figure 8.

![Figure 8. Matrix template of iris.](image)

The template consists of adequate unique features of iris such as collarette, crypts, certain degree of furrows and ridges in 1 to 10 rows. The value of 2400 elements with less occlusion of eyelashes as noises in the template helps to reduce the storage space and to classify rapidly\(^{21}\). The single row vector was generated to pass as inputs for further classification. Figure 9 depicts the single row vector of iris template.

### 2.2.1 Local Binary Pattern

Local binary pattern supports for feature extraction to classify efficiently. Its operator has tolerance against illumination changes. The output of LBP is the feature vectors with \(n\)-dimension used as an input to other classifiers. Figure 10 illustrates an example of the input sub-image with size 3×3, the center is threshold value such that, if the gray level of the neighboring pixel is higher or equal, the value is set to one and otherwise the value is set to zero. The normalized iris image is divided into 2400 smaller regions from which LBP histograms are calculated for every block and concatenated as the final histogram.

2.3 Matching of Iris

2.3.1 Hamming Distance

This algorithm is the simplest method of finding the sum of difference between the given and the stored templates based on XOR operation. This matching method is based on two similar iris templates have small distance and for dissimilar the hamming distance will be greater than the threshold. The XOR is a Boolean operator that gives binary value 1 if the bit at position \(i\) in \(X_i\) and \(Y_i\) are different and 0 if they are similar. The normalized hamming distance was applied as mentioned in the equation 1.

![Figure 9. Single row vector of iris.](image)
Where,

\[ HD = \frac{1}{N} \sum_{i=1}^{N} X_i \text{(XOR)} Y_i \]  

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Table 1. Time taken to classify the authorized and unauthorized users

| User                  | Hamming Distance | SVM with Local Binary Pattern |
|-----------------------|------------------|------------------------------|
| Authenticated (1 to 80) | 0.0112            | 0.0107                        |
| Non-authenticated (891 to 100) | 1.1004           | 1.0666                        |

Table 1 depicts the time taken to classify the input for authorized and unauthorized users using hamming and SVM with multi block local binary pattern. SVM with local binary pattern takes lesser time in both authorized and unauthorized compared to hamming distance.
3. Experimental Results

This proposed work was experimented with the CASIA (Chinese Academy of Science Institute of Automation) database\(^1\). It consists of human eye images in proper illumination. The images were grey scaled and the maximum radius of iris 20mm. Database was trusted as reliable and extensively used by various researchers doing their research in iris. The images are in jpeg format that supports type conversion for further process\(^16\). During training phase the 240 templates for 80 users were generated and stored in database. During testing phase the given input unique feature are extracted and template generated. After template generation, instead of being stored as authenticated template, it was compared with the available 240 (80 x 3) templates of 80 authenticated users. This work experimented with 600 eye images ((80 + 20) x 6) were passed for matching by hamming distance and SVM classifier. SVM classifier receives input vectors which are the output generated by multi block local binary pattern. During testing if the given input's template matched with stored templates then true acceptance rate would increase else false rejection rate would increase. Thus the performance results for authorized 80 users' true acceptance rate are depicted in Figure 12.

| User | HD | SVM with LBP | User | HD | SVM with LBP | User | HD | SVM with LBP |
|------|----|--------------|------|----|--------------|------|----|--------------|
| 1    | 83.3 | 100          | 28   | 100 | 100          | 55   | 83.3 | 100          |
| 2    | 100  | 100          | 29   | 100 | 56           | 100  | 66.6 | 100          |
| 3    | 30   | 100          | 30   | 100 | 57           | 100  | 100  |
| 4    | 100  | 83.3         | 31   | 100 | 58           | 100  | 100  |
| 5    | 32   | 100          | 32   | 100 | 59           | 100  | 100  |
| 6    | 100  | 100          | 33   | 100 | 60           | 100  | 100  |
| 7    | 34   | 100          | 34   | 100 | 61           | 100  | 100  |
| 8    | 100  | 100          | 35   | 100 | 62           | 100  | 66.6 |
| 9    | 83.3 | 100          | 36   | 100 | 63           | 100  | 100  |
| 10   | 100  | 100          | 37   | 100 | 64           | 100  | 100  |
| 11   | 38   | 100          | 38   | 100 | 65           | 100  | 100  |
| 12   | 100  | 100          | 39   | 100 | 66           | 100  | 100  |
| 13   | 40   | 100          | 40   | 100 | 67           | 100  | 100  |
| 14   | 41   | 100          | 41   | 100 | 68           | 100  | 100  |
| 15   | 42   | 83.3         | 42   | 100 | 69           | 100  | 100  |
| 16   | 43   | 100          | 43   | 100 | 70           | 100  | 66.6 |
| 17   | 44   | 100          | 44   | 100 | 71           | 100  | 100  |
| 18   | 45   | 100          | 45   | 100 | 72           | 100  | 100  |
| 19   | 46   | 100          | 46   | 100 | 73           | 100  | 100  |
| 20   | 47   | 100          | 47   | 100 | 74           | 100  | 100  |
| 21   | 48   | 100          | 48   | 100 | 75           | 100  | 100  |
| 22   | 49   | 100          | 49   | 100 | 76           | 100  | 83.3 |
| 23   | 50   | 100          | 50   | 100 | 77           | 100  | 100  |
| 24   | 51   | 100          | 51   | 100 | 78           | 100  | 100  |
| 25   | 52   | 100          | 52   | 100 | 79           | 100  | 83.3 |
| 26   | 53   | 100          | 53   | 100 | 80           | 100  | 100  |
| 27   | 54   | 100          | 54   | 100 | 83.3         | 100  | 100  |
These results indicate that the SVM with multi block local binary pattern results 97.5 percent of performance compared to the hamming distance method. Therefore, the true positive or true accept rate is high and good for authorized users. It is likely to have zero percent of false negative or false rejection for unauthorized users. Thus from the two series of experiments multi block local binary pattern results better and ensures that imposter cannot tamper the data.

4. Comparative Analysis

Comparative study of few existing and proposed work performance is depicted in table 3. Comparison among various matching and classifications based on overall performance was provided.

![Figure 12. Performance of True Acceptance Rate for Authenticated users.](image)

### Table 3. Comparative analysis of existing and proposed method for iris recognition system

| S. No. | Classification Techniques | Input (Iris) | Accuracy % |
|-------|---------------------------|--------------|------------|
| 1.    | Hamming Distance⁵         | Iris Image (All possible features) | 100        |
| 2.    | Euclidean Distance⁶       |              | 95.0       |
| 3.    | Hamming Distance x Fragile Bit Distance¹¹ | | 92.1       |
| 4.    | Local Binary Pattern + LVQ¹² | | 91.4       |
| 5.    | Local Binary Pattern + Histogram + LVQ ¹² | | 93.6       |
|       | Proposed Method           | Iris Image (Collarette, crypts, Furrows among lower to middle region) | 94.9       |
|       |                            |              | 97.4       |
5. Conclusion

The proposed work supports for automatic recognition based on iris spectral features. This paper examined with two series of experiments using hamming distance and SVM with multiblock local binary pattern were applied and verified. 600 samples of eye images from CASIA database were applied for experimental study and the effectiveness of this proposed system was evaluated. The obtained results proved that the multi block local binary pattern algorithm combined with SVM results in a high performance of 97.5 percent of accuracy especially with zero percentage of false acceptance rates. Therefore this proposed work is suitable for both identification and verification.

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