Iris Recognition Using Improved Xor-Sum Code

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1 Introduction

Biometric authentication had been used in personal identification frameworks since decades. The automated identification of persons relying upon behavioral and physical features is termed as biometric authentication [1]. Embracing innovative methods to furnish greater accuracy, extra security, and promptness, biometric authentication system has grown as a novel arena to be explored. Biometric authentication framework can be driven in two manners, i.e., identification and verification mode. DNA, ear, face, fingerprint, palmprint, iris, keystrokes, odor, retinal scan, signature, periocular, gait, ECG, EEG, palm vein, finger vein, hand geometry, and voice are some physical and behavioral traits which can be used in human authentication [2]. Biometric system is expedient in terms of validation, secrecy or data concealment, access control, and non-abandonment. The most persistent trait in biometrics is iris [3]. Iris is the shaded circle around the pupil which controls the entering of light in eye [4].

One of the most encouraging fields in biometrics is iris recognition as the attributes of iris are essentially distinctive which can be perceived even from certain distance. The false acceptance/rejection rates are perceptibly lower than the other traits that is why forgery and spoofing are a very perplexing chore in case of iris. The key stages of an iris recognition system comprise of image acquirement, pre-processing of image,

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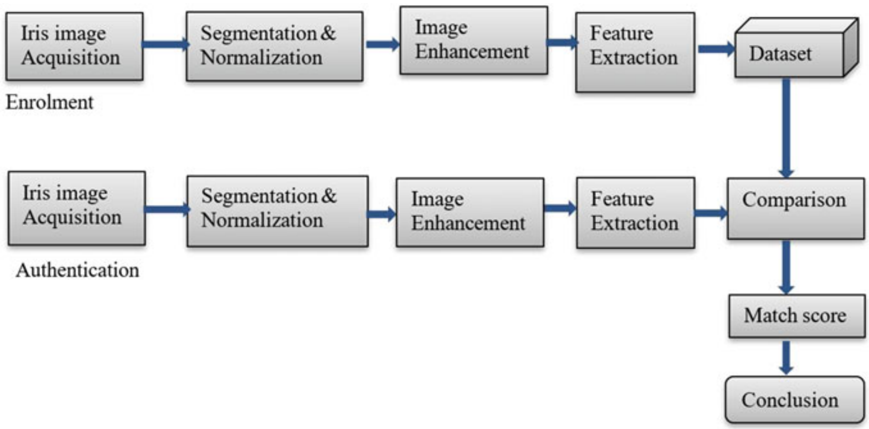

Fig. 1 A common iris recognition system

feature extraction, and classification. A general block diagram of iris recognition framework is depicted in Fig. 1.

Following are the various indispensable pluses of iris recognition system:

1. Precision: Iris is the extraordinary modality as compared to other biometric modalities regarding precision. FAR and FRR are perceptibly lesser in iris recognition system, which certifies the greater precision.
2. Adaptability: This technique is profoundly adaptable and can be utilized in both huge and little scope programs. That is why it has been deployed in many person authentication systems as well as in various governments' authentication systems.
3. Permanence: The texture of iris designs stays invariant all through a person's life.
4. Accessible: Iris recognition system is modest to utilize related to other biometric traits. The only requirement is to stand facing camera for image acquisition.
5. Contactless: Authentication: The acquisition system in iris recognition acquires the image without having any substantial contact of individual with the machine and hence this method is sterile.

2 Related Work

Firstly, Flom and Safir [5] anticipated the idea of an iris recognition system based on inimitable characteristics of iris and pupil. Subsequently, Daugman [6] developed an iris recognition system which applies Gabor filters for texture feature extraction of iris and encrypts iris data into series of 2D Gabor wavelet coefficients and then for recognition it applies Hamming distance method. Successively many outstanding research works based on iris recognition were proposed. Zhao et al. [7] proposed negative iris recognition system that was solely focused on the security of confidentiality of iris database, irrespective of augmenting the accuracy of segmentation or the efficiency of recognition. Shifting and masking strategies were applied for efficient matching in addition to matching rule. Dhage et al. [8] extracted features employing Discrete Wavelet Transform (DWT) and Discrete Cosine Transform (DCT) and swarm optimization for selecting features.

Chen et al. [9] introduced a novel iris recognition system for identification and matching of iris crypts automatically regardless of their sizes. To manage the possible topological variations in the extraction of identical crypt in dissimilar images, Earth Mover's Distance matching model has been used. Hofbauer et al. [10] proposed an experimental analysis to check the effect of segmentation and feature extraction techniques on recognition rate of the system and proved that decision for selecting segmentation and feature extraction technique must be done together as these are interdependent.

Nalla and Kumar [11] developed a novel algorithm based on Markov random field model to enhance the iris recognition rate and an EDA-NBNN-based classification structure for matching of cross-domain images. The efficacy of the proposed framework has been evaluated on two public datasets. Ahmadi and Akbarizadeh [12] introduced an effective and robust iris recognition system that uses MLPNN and PSO for classification of images. For feature extraction, it employs 2D Gabor kernel algorithm and results are validated on publicly available datasets.

Chen et al. [13] presented an innovative technique for efficiently extracting distinctive feature vectors of iris. Amalgamation of T-Center loss and traditional softmax loss functions augmented the discerning capability of CNN-based deep features. Nguyen et al. [14] suggested a novel approach on the basis of artificial intelligence. Their experimental outcomes demonstrate that even though the network was primarily trained with features of general things, it performs well in representation of iris images, and validation of proposed approach has been done on two publicly available datasets. Daugman and Downing [15] investigated the correlation of texture features amid radially scattered bits of iris codes acquired form iris images instead of correlation between raw pixels. Two-dimensional wavelet is employed to obtain iris codes. Vyas et al. [16] introduced a novel feature extractor, derived through sub-bands of curvelet transform, for better iris recognition.

Liu et al. [17] applied collaborative representation method for feature detection and categorization of iris images. Ahmadi et al. [18] suggested amalgamation of step filter, polynomial filter, and 2D Gabor filter, for extracting features of iris images and employed combination of Radial Basis Function Neural Network (RBFNN) and Genetic Algorithm (GA) for classification of images, which results in efficient iris recognition system. Sahu et al. [19] introduced a novel feature reduction technique for Phase Intensive Local Pattern (PILP) by employing Density-Based Clustering Technique (DBSCAN), which results in feature vector of five times lesser dimensionality with same recognition accuracy.

Barpanda et al. [20] proposed wavelet mel-cepstrum for extracting features of iris images and employed MFCC for classification of iris patterns. They also compared the outcome of their suggested approach with another existent approaches and proved that proposed system beats the others. Galdi and Dugelay [21] amalgamated color and texture features and proposed a novel approach for smartphones with lesser computational power. Oktiana et al. [22] employed homomorphic filters for conquering the reflection and phase-based classifier for categorizing images in order to design a cross-spectral iris recognition system with augmented recognition accuracy.

In this paper, the existing Xor-sum code is modified by including the curvature information in the 2D Gabor filters. This curvature information aids to the uniqueness of the extracted iris features, which in turn leads to the performance improvement of the overall recognition system. Further, inclusion of curvature information may prove to be effective with images acquired under visible wavelength illumination, which are otherwise more challenging to represent. Hence, this paper provides a comprehensive evaluation of iris recognition system. Rest of the paper is organized in the following manner: introduction and related works are discussed in Sects. 1 and 2, respectively. Whereas the proposed approach through curvature Gabor filter is elucidated in Sect. 3. Subsequently, discussions of database, performance metrics, and obtained results are completed in Sect. 4. Lastly, Sect. 5 concludes the paper along with specifying few future directions of work.

3 Proposed Approach

This paper presents an Improved Version of Xor-Sum Code (IXSC) [23], making it more suitable to iris recognition application both in Visible Wavelength (VW) and Near-Infrared (NIR) spectrum. As was apparent from the original approach [23] that the use of two-dimensional (2D) Gabor filters could facilitate the task of iris recognition in an effective manner. This efficacy could be attributed to the ability of Gabor filters to model the receptive fields of a simple cell in the primary visual cortex [24]. It is due to this property only that the Gabor filter could yield unprecedented performance by highlighting the micro-textures present in the normalized iris templates.

However, after carrying out the outperforming legacy of the aforementioned approach [23] into the datasets acquired through modern-era devices, we have observed that the approach could not deliver to the fullest of its capabilities. This may be happening because of the extended challenges in case of visible wavelength iris images (which are very popular in more recent datasets). Some of the common challenges are huge reflections, illumination variations, blur, and off-focus. All these challenges make it hard for the conventional Gabor filters to perform in an epochal way. Hence, there has been a need to have an efficient feature descriptor that can perform well for both NIR and VW images.

The conventional Gabor filter has been effectively used to capture the orientation of micro-textural regions present in the iris template. However, if the curvature of these regions can also be taken into account, then the recognition accuracy can be enhanced to a considerable extent. These small curvatures present in the textural edges can aid to the distinctiveness of Xor-sum code features, hence making it a more suitable descriptor for VW images as well.

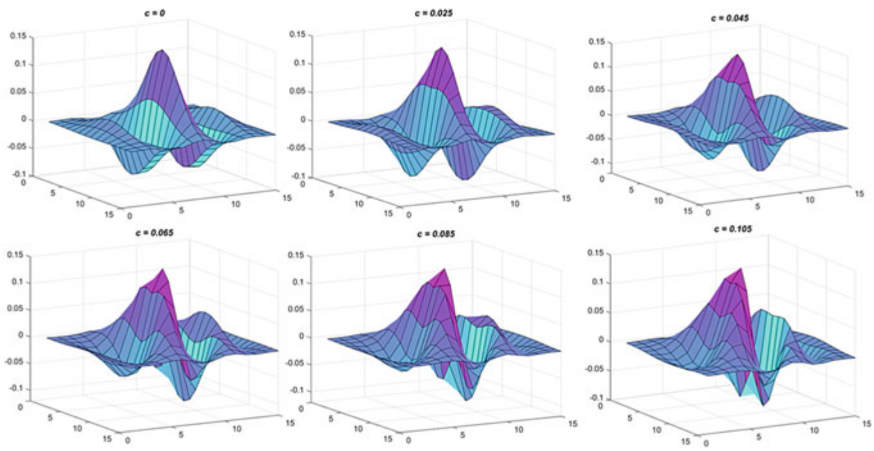

Fig. 2 Effect of curvature control parameter ("c")

3.1 *Curvature Gabor Filter (CGF)*

CGF is a modified form of the traditional 2D Gabor filter, where a curvature parameter gets included in the mathematical expression itself [25], as shown in the equation below:

$$\xi\left(x, y, \sigma, \nu, \phi, c\right) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{x^2+y^2}{2\sigma^2}\right\} \times \exp\left\{2\pi i\left(\nu\left(x\cos\left(\phi\right) + y\sin\left(\phi\right)\right) + c\sqrt{x^2+y^2}\right)\right\}. \tag{1}$$

In addition to the known parameters from [23], above equation is equipped with a curvature control parameter, "c," which usually defines the degree of curvature in the filter responses. Figure 2 illustrates the varying curvature with different values of "c," where smaller "c" tends to a smaller degree of curvature and vice versa. Notably, if curvature control parameter ("c") becomes zero, the filter turns into a conventional Gabor filter (i.e., with no curvature information). Whereas Fig. 3 illustrates the 2D surface plots of CGF, where the curvature degrees can be easily visualized.

4 Results and discussion

In this paper, two challenging databases, namely, IITD [26, 27] and CrossEyed iris databases [28, 29], are employed for the purpose of experimentation. Out of these two databases, the IITD iris database consists of eye images acquired in NIR wavelength. Furthermore, the images of this database were acquired in a constrained environment, i.e., with minimal illumination variations and nominal challenges like

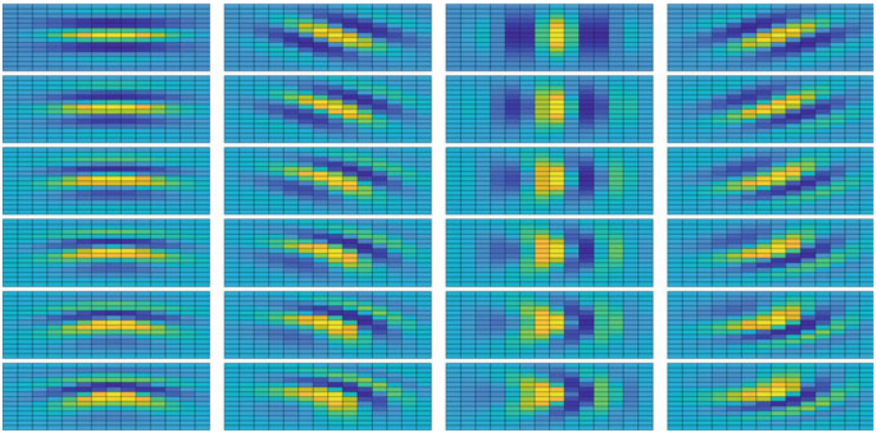

Fig. 3 2D surface plots of CGF; (rows) "*c*" = [0, 0.025, 0.045, 0.065, 0.085, 0.105]; (columns) orientations (in degrees) = [0, 45, 90, 135]

specular reflections and/or blur. Further, this database provides 2240 eye images from 224 subjects, with 5 images from each eye of the subject. On the other hand, the second employed database, the CrossEyed database is a more contemporary one, providing eye images in both NIR and VW wavelengths, that too possessing pixel-to-pixel correspondence among different wavelength images. The images in this database suffer from more real-life challenges, such as larger reflections and off-focus error. Moreover, this database consists of 960 iris images captured in NIR and VW wavelengths from both the left and right eyes of 120 subjects, respectively. However, current work employs only 500 images from 50 subjects from both the VW and NIR illuminations.

Notably, before the feature extraction stage, all the employed eye images are processed through the segmentation procedure followed by normalization of the iris regions into rectangular templates of dimensions 64×512. These constant dimensions of iris templates facilitate the invariable matching irrespective of the dilation and contraction of pupil. The sample eye images from both the employed databases and their corresponding normalized iris templates are shown in Fig. 4. Readers are advised to refer to [30] for details of the segmentation procedure. For comparison purpose, the famous performance metrics of the biometrics domain are utilized, especially the Equal Error Rate (EER), Genuine Acceptance Rate (GAR), False Acceptance Rate (FAR), and Decidability Index (DI). Notably, all the GARs are reported at FAR of 1%. The Receiver Operating Characteristics (ROC) curves are also exhibited for enhanced visualization of the recognition performance. Another vital metric is the Area Under the ROC Curve (AUC).

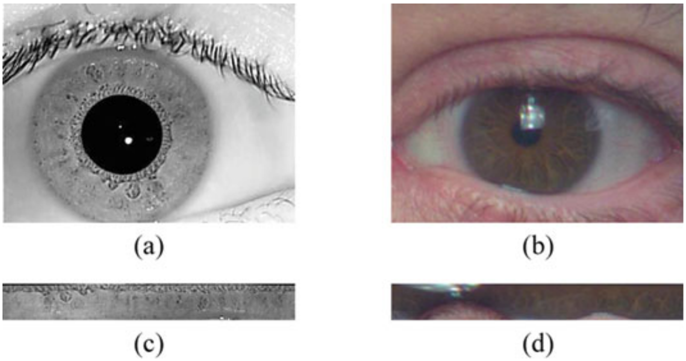

Fig. 4 Sample images; **a** eye image from IITD database, **b** Eye image from CrossEyed-VW database, **c** iris template corresponding to eye image in (**a**), (**d**) Iris template corresponding to eye image in (**b**)

4.1 IITD Iris Database

The investigations in this paper first consider the IITD iris database, where multiple values of curvature control parameters are explored to identify the best suited value. The obtained performance metrics and corresponding ROC curves are demonstrated in Table 1 and Fig. 5.

It is apparent from Table 1 that inclusion of curvature information into the Gabor filter has certainly led to improvements in all the performance metrics. However, for ascertaining the optimal degree of curvature, experiments are performed with five different values of parameter "*c*." However, larger values of "*c*" are not tested because of absence of huge curvatures in the iris texture. From the employed values, it can be noticed from the ROC curves that curvature of 0.065 proves to be suitable for the problem on hand. As is evident from Table 1, this optimal value of curvature yields approximately 37% improvement in EER when compared with that of original XSC. This huge improvement can be vital and decisive, looking at the large number

Table 1 Performance metrics for IITD database

Approach	EER (%)	DI	GAR (%)	AUC
Xor-sum code (XSC)	3.62	2.7427	95.48	0.9807
Improved XSC (c = 0.025)	2.55	2.5599	96.67	0.9907
Improved XSC (c = 0.045)	2.36	2.6882	97.00	0.9919
Improved XSC (c = 0.065)	**2.28**	**2.7326**	**97.38**	**0.9938**
Improved XSC (c = 0.085)	2.70	2.6541	96.48	0.9946
Improved XSC (c = 0.105)	2.43	2.6285	96.84	0.9945

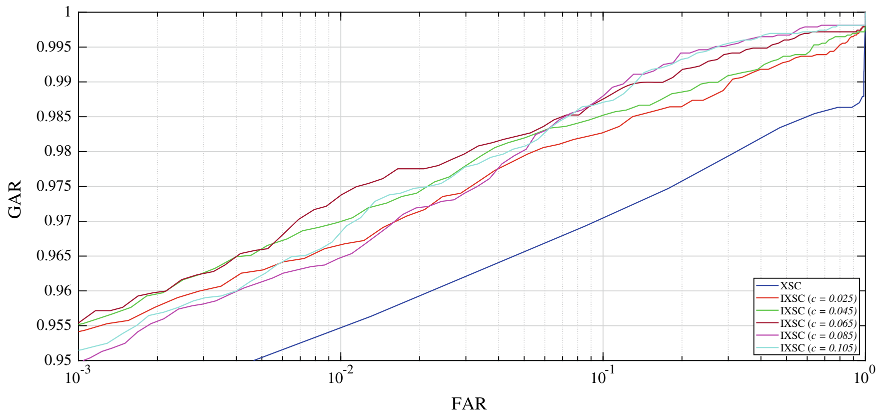

Fig. 5 ROC curves for IITD iris database using various curvature degrees

of classes of the IITD database. At the same time, incorporation of this curvature also enhances the GAR value from 95.48 to 97.38%, which is also quite significant.

In addition to EER and GAR, the other two performance metrics (DI and AUC) for CGF with "*c*" = 0.065 are reported as 2.7326 and 0.9938, respectively. This points toward improvement in AUC and almost similar DI, as compared to the original XSC. Furthermore, it is interesting to see that every degree of curvature, which is investigated in the current work, has contributed toward the improvement in almost all the performance metrics. This fact can be validated through the ROC curves shown in Fig. 5, where all the curves corresponding to the improved XSC (IXSC) lie above that of XSC. This clearly supports the hypothesis of gathering the curvature information about the textural edges of iris for improved performance.

4.2 CrossEyed Iris Database

This database has more challenging eye images, emerging from the visible wavelength as well. Moreover, this database comes up with registered NIR and VW images, which means that there is pixel-to-pixel correspondence within the NIR and VW versions of images for every eye. Hence, this database can be suitable for investigations on cross-spectral iris recognition. However, the current work is focused toward establishing the generalized capability of IXSC approach to both the NIR and VW matching scenarios individually, and not toward the cross-spectral matching framework. Hence, only individual VW results are reported here, which are subsequently reflected in the NIR counterpart as well.

After careful inspection of Table 2, it is observed that the CrossEyed database exhibits better performance with IXSC for the curvature control parameter value of 0.045, most of the other values also display improvements though. For this optimal

Table 2 Performance metrics for CrossEyed-VW database

Approach	EER (%)	DI	GAR (%)	**AUC**
Xor-sum code (XSC)	9.75	1.8581	83.16	0.9509
Improved XSC (c = 0.025)	11.79	1.5416	79.03	0.9353
Improved XSC (c = 0.045)	**7.96**	**2.0513**	**86.72**	**0.9654**
Improved XSC (c = 0.065)	8.48	2.2301	86.59	0.9619
Improved XSC (c = 0.085)	9.07	2.1900	86.08	0.9540
Improved XSC (c = 0.105)	8.82	2.3002	87.32	0.9514

curvature, the improvements in EER and GAR are counted to be approximately 18% and 4%, respectively. These improvements are clear indication of the discriminative capability of curvature Gabor filters. Concurrently, the other metrics, namely, DI and AUC also get improved substantially. Similar trends of improvements after incorporation curvature property are illustrated in the ROC curves shown in Fig. 6.

Just in order to evaluate the proposed IXSC approach on NIR images, we have conducted the experiments with the optimal value of "*c*" obtained from the experiments with VW images, i.e., 0.045. Notably, IXSC has outperformed XSC for NIR images as well. The corresponding performance metrics are tabulated in Table 3, where the IXSC has again produced better, though slightly, results as compared with XSC.

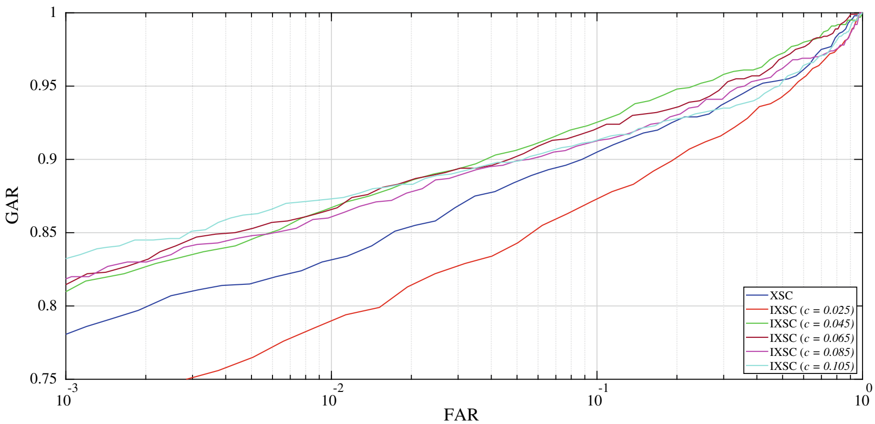

Fig. 6 ROC curves for CrossEyed-VW iris database using various curvature degrees

Table 3 Quick comparison of performance for CrossEyed NIR database

Approach	EER (%)	DI	GAR (%)	AUC
Xor-sum code (XSC)	8.74	2.2712	84.91	0.9504
Improved XSC (c = 0.045)	**8.58**	**2.3982**	**85.44**	**0.9611**

5 Conclusion

In this article, an improved Xor-sum code feature descriptor is proposed for the problem of iris recognition. Laid on the basis of original Xor-sum code, the proposed approach makes it inclusive of the curvature information along with the orientation information. Inclusion of curvature information leads to extraction of increased discriminatory features from the normalized iris templates. The proposed approach is hypothesized to work well for both types of iris images, acquired in near-infrared and visible wavelength. The same fact is validated through extensive experiments with two publicly available databases, namely, IITD and CrossEyed database. Huge improvements are reflected through the proposed approach in terms of common performance metrics, like EER, GAR, and AUC. The largest improvement achieved is in EER for IITD iris database, where the proposed approach exhibits an improvement of almost 37%. This proves the promising nature of the proposed IXSC approach. In future, the proposed approach can be tested for more challenging frameworks, like cross-spectral and smartphone-based iris recognition.

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