

## Automatic Segmentation and Recognition of Iris Images: With Special Reference to Twins

**Abstract:** This paper describes an automatic approach for iris segmentation and recognition with focus on twins. The technique entails localizing and segmenting the iris, followed by iris normalization and obtaining distinctive features. Lastly, iris templates are matched to realize one to one and one to much recognition in twins. Further, effect of various template sizes on the accuracy and memory requirement are studied. To our knowledge, this is the first iris based authentication with special emphasis on twins.

**Keywords:** Iris segmentation; iris recognition; twins; feature extraction.

### INTRODUCTION

Iris recognition is an important facet of biometric based authentication. This is because the patterns in human irises are unique, stable and thus reliable for secure user verification. Specifically, the iris patterns are different even in genetically similar sources such as the right and left eyes of a single person and the eyes of twins. So, iris recognition is valuable in discriminating between the true user and impostor. Considering this, various researchers have concentrated on accurate segmentation and recognition of human iris images. Notably, Daugman advocated iris recognition based on identifying the pupillary and limbic boundaries, followed by iris segmentation, wavelet-based feature encoding and similarity testing. Further, Daugman has emphasized that iris-based identification is more arduous compared to simple verification. Besides, Liu et al. involved orientation matching to recognize iris boundaries and circle fitting to remove outliers. Additionally, eyelid and eyelashes are delineated to improve segmentation efficacy. Moreover, Frucci et al. devised watershed based recognition in noisy images. This technique also entailed circle fitting coupled with contour refinement and pupil identification. Similarly, Chen et al. necessitated scale invariant feature transform along with weighted matching for authentication. Further, Krishnamoorthi and Poorani put forth variable and fixed size models for iris normalization. They have indicated that variable size representation is more appropriate to lighting changes. Besides, Vatsa et al. utilized global textural and local topological aspects to augment segmentation. In addition, similarity scores are integrated by support vector machine (SVM), followed by iris indexing which shortens recognition time. Likewise, Pirasteh et al. involved edge detection and Hough transform in localization, feature encoding with Zernike Moments and classification by SVM. Moreover, Umer et al. incorporated restricted Hough transform in iris segmentation and feature encoding by multiscale morphology. The merits of this technique are its speed and usage of portions of iris. Besides, Song et al. entailed sparse error correction and dictionary learning coupled with sparsity index dependent validation. Notably, this technique efficiently handles interferences from eyelid, eyelash and reflections. Similarly, Bhateja et al. advocated sparse representation and knearest subspace in segmentation. Subsequently, three classifiers weighted by genetic algorithm are incorporated. Further, Liu et al. propounded Mahalanobis distance dependent technique in poor quality images. This boosted

efficacy by intertwining local as well as global information. Moreover, Haindl and Krupicka devised unsupervised practice for eliminating defects. For this, they integrated multispectral and spatial knowledge. In addition, Abate et al. utilized watersheds, followed by limbus and pupil delineation to attain iris recognition, primarily at mobile sets. Furthermore, Othman et al. put forth OSIRIS package with modules for segmentation, normalization, feature encoding and matching. Thus, the review of recent literature emphasizes that though various iris recognition techniques are commonly available, there is a paucity of studies focusing on iris recognition in twins. This is an important aspect that necessitates special research attention as twins connote genetically similar people and their correct identification is crucial in validating the tested biometric system. This is especially true because some biometrics like face recognition cannot be applied to identical twins. However, other biometrics such as fingerprint and iris authentication systems are extensible even to identical twins considering their unique patterns and variability between twins. Although published works on fingerprint and palmprint recognition in identical twins are available, to our knowledge, there are no dedicated studies for iris authentication in twin images. This is the motivation for the current work that deals with iris recognition in twins. The manuscript contents are as below: methodology, results and discussion, and conclusion.

#### **METHODOLOGY**

Iris images from CASIA Iris Twins of CASIA IrisV4 are used as input. To our knowledge, this is the only comprehensive source for twin images. It houses image sets from 100 twins. Sample twins' images are portrayed by Fig. 1. Further, the proposed method for iris segmentation and authentication is given by Fig. 2. This entails preprocessing through histogram equalization for enhancing image contrast and elimination of specular reflections in iris using morphological operations. Subsequently, iris localization is performed i.e. iris region is demarcated in the preprocessed image. For this, the limbic boundary at iris-sclera interface and pupillary boundary at iris-pupil interface are delineated. The pupillary boundary is found inner to limbic boundary, as depicted by Fig. 3. These boundaries are demarcated based on the integrodifferential operator. This operator obtains the boundaries by looking for maximum variation in pixels by altering the radius and center positions. This is done repetitively accompanied by gradual decrease in smoothing to accomplish accurate localization. Next, the iris is segmented based on the localized boundaries. Following this, iris normalization is carried out to facilitate comparability and eliminate potential inconsistencies arising from varying illuminations, camera positioning, etc. This entails transforming the segmented irises into uniform rectangular blocks. Subsequently, the characteristic aspects of iris are obtained by Gabor filters. This is called feature extraction and is crucial in creating iris template for authentication. The features comprise of amplitude as well as phase information. While amplitude is discarded, the phase information is quantized and represented in binary. The noise mask that connotes zero-amplitude locations is obtained alongside binary template. The binary form ensures compression and memory management. Besides, the proposed work investigates the effect of various template sizes on accuracy and memory requirements of system.

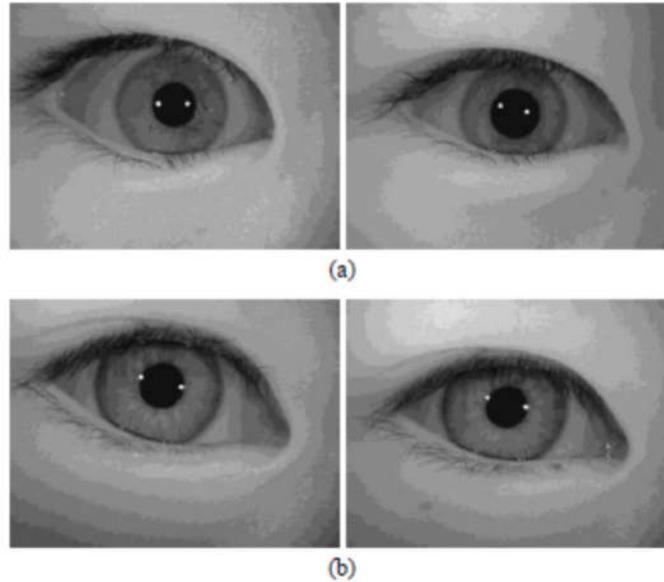


Fig. 1. (a) and (b) Sample images of twins

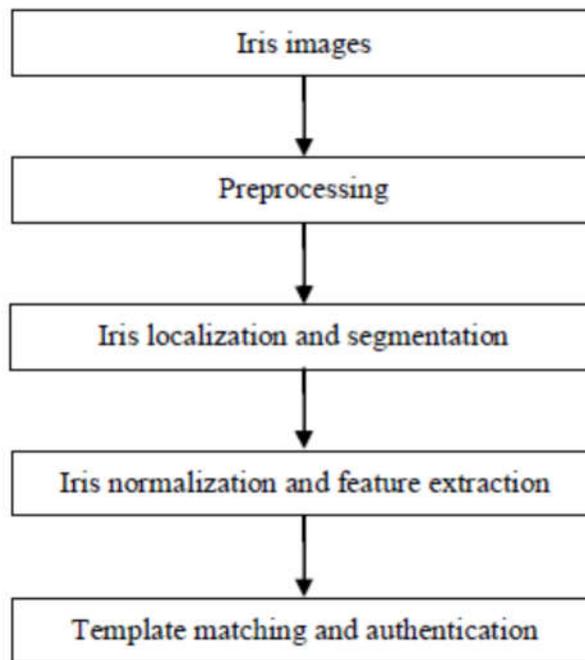


Fig. 2. Proposed technique

Further, template matching is effected by Hamming distance. This is denoted by

$$\text{Ham dist} = (\sum_1 TA_1 \text{ (XOR) } TB_1) / N$$

Here, TA and TB indicate the templates while N symbolizes number of bits. In addition, noise masks are entailed in distance computation for appropriate matching. Moreover, template shifting helps overcome errors stemming from rotational discrepancies. Ultimately, template matching is utilized to authenticate genuine users from imposters. This encompasses one to one recognition between a pair of twins and one to many recognition among all twins. Its efficacy is

quantified through False Acceptance Rate (FAR) and False Rejection Rate (FRR). Here, FAR implies imposters being falsely accepted whereas FRR connotes genuine clients being falsely denied.

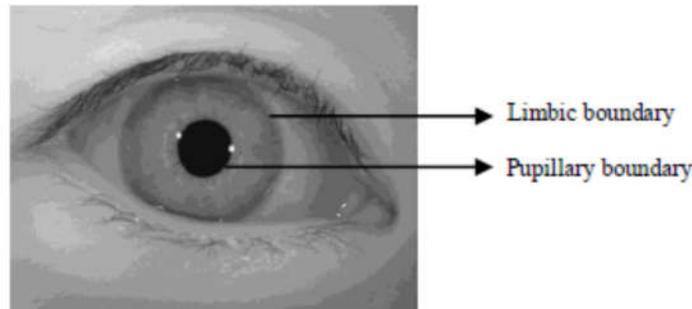


Fig. 3. Iris boundaries

**RESULTS AND DISCUSSION**

The results of iris segmentation and representation in a pair of twins are portrayed by Figs. 4 and 5. Further, Table I indicates the obtained FAR and FRR metrics for one to one and one to many recognition. While one to one recognition signifies matching between a single pair of twins, one to many recognition denotes authentication based on all twins. Additionally, the effect of different template sizes, namely, (10\*40), (50\*200) and (100\*400) on the FAR, FRR and memory requirements is also given by Table I. As observed from Table I, the FAR for one to one and one to many recognition decreases as template size increases. Besides, a constant FRR of 0% is accomplished for one to many recognition at all template sizes whereas the 0% FRR is realized only at (100\*400) template size in one to one recognition. Nevertheless, the memory requirement also rises with template size; it is 1.6 kb/template for size (10\*40) and reaches 160 kb/template at size (100\*400). The optimal template size is chosen at (100\*400) considering the good FAR and FRR realized at this size. Moreover, it is observed from Table I that the accuracy for one to many recognition is higher than one to one recognition in twins. This is attributable to the genetic identity within a single pair of twins that gives rise to larger FAR in one to one recognition relative to one to many recognition that deals with all twins images put together. To exemplify the contribution of proposed work, the FAR and FRR of other techniques are mentioned here. Bhateja et al. recorded FRR of 13.3% and FAR of 0.56% while Masek tabulated the FAR and FRR at various thresholds. It is 0% FRR and 7.599% FAR when threshold is 0.45. To interpret the reported FAR and FRR, it is noted that they exhibit an inverse relationship i.e. smaller FRR implies larger FAR.

Table.1: EFFECT OF TEMPLATE SIZE ON ACCURACY AND MEMORY REQUIREMENT

Template Size	One to one recognition		One to many recognition		Memory requirement
	FAR	FRR	FAR	FRR	
10*40	53%	4%	70%	0%	1.6 kb
50*200	42%	4%	25%	0%	40 kb
100*400	12%	0%	5%	0%	160 kb

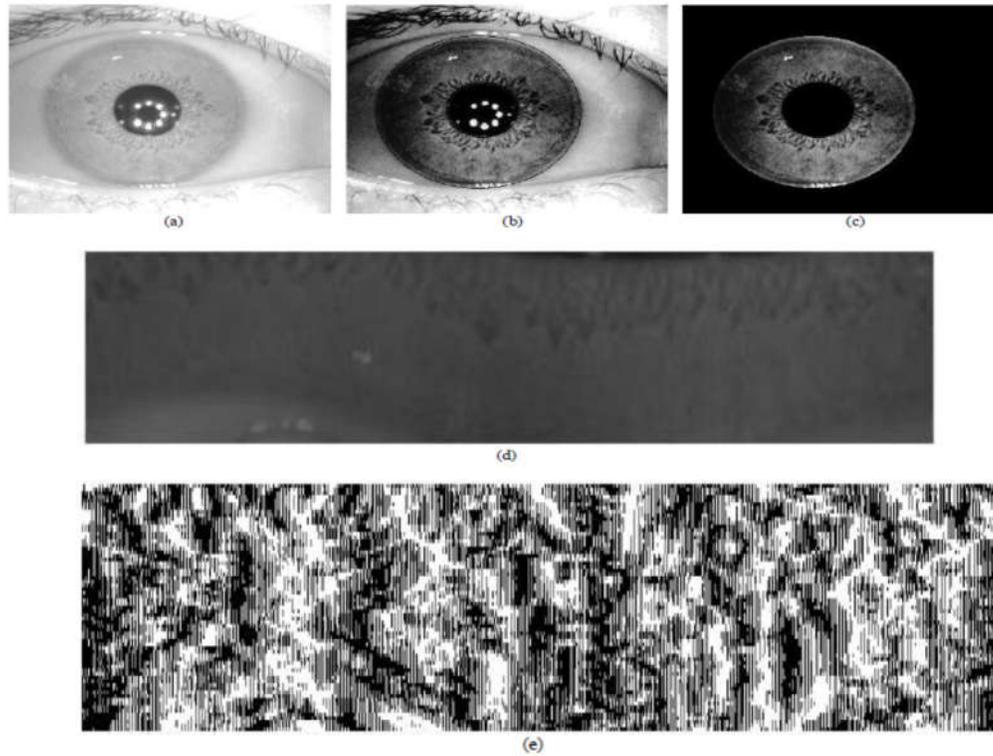


Fig.4. (a) Input image; (b) preprocessed image with iris boundaries marked; (c) segmented iris; (d) iris normalization; (e) iris representation as template for Twin A

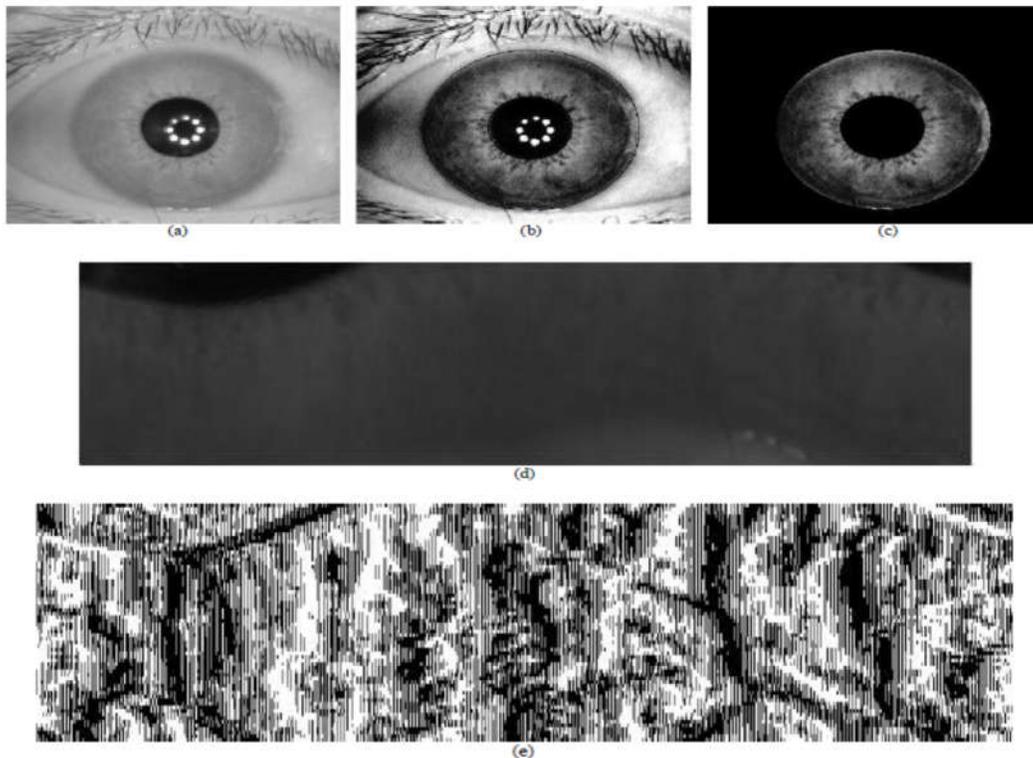


Fig.5. (a) Input image; (b) preprocessed image with iris boundaries marked; (c) segmented iris; (d) iris normalization; (e) iris representation as template for Twin B

## CONCLUSION

Thus, this work concentrates on iris segmentation and recognition in twins. To our knowledge, this is the first approach focused entirely on iris recognition in twins. It involves one to one recognition within a pair of twins as well as one to many recognition based on all twins. In future, the iris recognition framework can be extended to singleton siblings and its efficacy compared to twins.

## REFERENCES

- [1] J. Daugman, "How iris recognition works," IEEE Trans. Circ. Syst.Video Technol., vol. 14(1), pp. 21-30, January 2004.
- [2] C.C. Liu, P.C. Chung, C.M. Lyu, J. Liu, and S.S. Yu, "A novel iris segmentation scheme," Math. Probl. Eng., vol. 684212, pp. 1-14, 2014.
- [3] M. Frucci, M. Nappi, D. Riccio, and G.S. Baja, "WIRE: watershed based iris recognition," Pattern Recogn., vol. 52, pp. 148-159, 2016.
- [4] Y. Chen, Y. Liu, X. Zhu, F. He, H. Wang, and N. Deng, "Efficient iris recognition based on optimal subfeature selection and weighted subregion fusion," Scientific World J., vol. 157173, pp. 1-19, 2014.
- [5] R. Krishnamoorthi and G.A. Poorani, "Tradeoff between variable and fixed size normalization in orthogonal polynomials based iris recognition system," SpringerPlus, vol. 5(367), pp. 1-21, 2016.
- [6] M. Vatsa, R. Singh, and A. Noore, "Improving iris recognition performance using segmentation, quality enhancement, match score fusion, and indexing," IEEE Trans. Syst. Man Cybern. B. Cybern., vol. 38(4), pp. 1021-1035, August 2008.
- [7] A. Pirasteh, K. Maghooli, and S. Mousavizadeh, "Iris recognition using localized Zernike's feature and SVM," Int. Arab J. Inf. Technol., vol. 13(5), pp. 552-558, September 2016.
- [8] S. Umer, B.C. Dhara, and B. Chanda, "Iris recognition using multiscale morphologic features," Pattern Recogn. Lett., vol. 65, pp. 67-74, 2015.
- [9] Y. Song, W. Cao, and Z. He, "Robust iris recognition using sparse error correction model and discriminative dictionary learning," Neurocomputing, vol. 137, pp. 198-204, 2014.



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