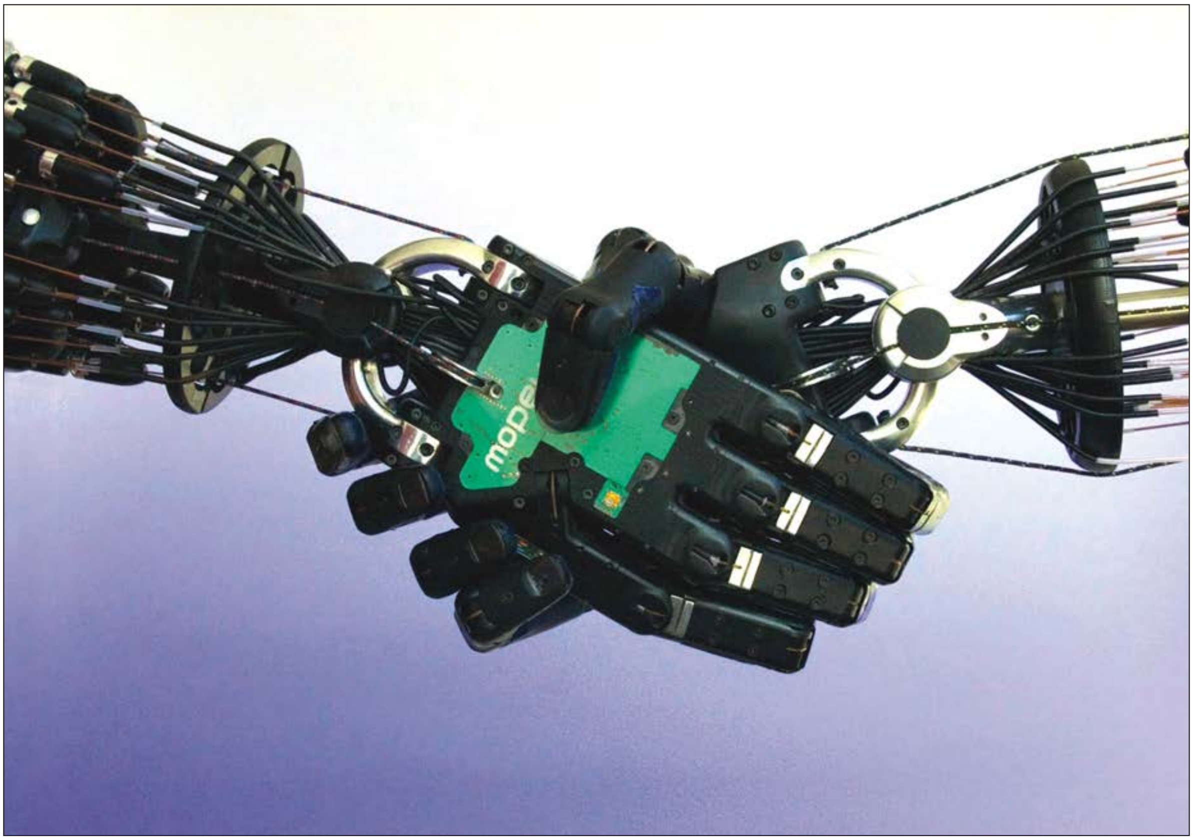

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Research Article

Towards Enhancing Non-Cooperative Iris Recognition using Improved Segmentation Methodology for Noisy Images

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Abstract

Background and Objective: Iris recognition is one of the popular winning biometric frameworks, giving promising outcomes in the identity authentication and access control systems. In this study, an efficient, fast and robust segmentation methodology suitable for non-cooperative and noisy iris images is proposed. **Materials and Methods:** This proposed methodology considers both shape and spatial feature properties of iris images taken from both the visible spectrum and near infrared spectrum. Circular hough transform is applied to the input image and iris outer boundary is identified. A minimum rectangular bounding box, MRB is defined using the obtained radius and center coordinates. High intensity valued, specular reflections and low intensity valued, pupil region, eyelids and eyelashes are identified using iterative thresholding and removed to reduce processing time. Scale invariant feature transform (SIFT) is directly applied on the segmented iris ROI, without performing normalization stage and system accuracy is tested. **Results:** By narrowing down the searching space to 65 times, this methodology provides robustness to noise as well as ensures faster segmentation of 0.34, 0.35 and 0.29 sec for CASIA V1.0, V3.0-interval and UBIRIS V1.0 datasets, respectively. **Conclusions:** The results obtained using improved segmentation methodology performs with improved recognition accuracy and reduced computational time and mislocalization count.

Key words: Circular hough transform, iterative thresholding, iris segmentation, occlusions, specular reflections, scale invariant feature transform

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Data Availability: All relevant data are within the paper and its supporting information files.

INTRODUCTION

Understanding images and extracting meaningful information for processing like identification or authentication is an important aspect of a biometric-based system[1-3]. Biometrics is classified into two broad categories: Physiological (fingerprint, face, palm print, hand geometry, iris, etc.) and behavioral (typing rhythm, gait and voice)[4]. Iris recognition has drawn the considerable attention of scientists and is gaining preference over other identifiers[5,6].

Iris is the colored portion of a human eye, residing securely between the sclera and the pupil. Pattern variability among the irises of different persons possesses a high degree of randomness, uniqueness and stability giving it an enormous mathematical advantage over other identifiers[7-9]. In today's commercial world, developing iris-based biometric systems for the unconstrained environment is a challenge[10]. Iris images captured in unconstrained environment results in more noise effects[11]. Typical noise sources are occlusions caused due to anatomical features of eye and poor image Quality.

Traditional iris segmentation algorithms were not able to remove these noises[12]. Since results of segmentation are found to help in improving the recognition rate of a biometric system, segmenting iris images taken under unconstrained environment is one of the biggest challenges[13].

Many iris segmentation algorithms including edge detection techniques, thresholding techniques, region-oriented segmentation techniques, active contour models, graph-based models and clustering based segmentation techniques are in use today[14]. There has also been an increasing interest in applying soft segmentation algorithms is also found[15].

Researchers followed different methodologies to increase iris segmentation algorithm accuracy. They are:

- Depending on starting region of segmentation
- According to the operators or methods used to describe the shapes in all eyes

In segmentation depending on starting region, researchers considered iris to be non-circular or pupil region to be darker or sclera area to have less saturated pixel values and performed further processing to segment iris region of interest.

Ross and Shah[16], Labati *et al.*[17] and Vatsa *et al.*[18] started segmentation stage by either identifying pupil region or estimating its center point and then used various techniques like thresholding, geodesic active contours, etc., to localize iris region of interest. Similarly, Chen *et al.*[19] and Proenca and Alexandre[20] started segmentation process from sclera portion considering it to be the most distinct region in non-ideal images followed by iris region of interest identification.

In the second approach, researchers considered iris to be in circular shape and used either circle defining algorithms or operators to detect the circle coordinates. Liu *et al.*[21] and Dobes *et al.*[22] considered iris to be circular and applied an edge detector followed by CHT to exactly identify the shape of iris and pupil. Schuckers *et al.*[23] worked on off-angle iris images employing integro-differential operator (IDO).

It is observed from these two approaches that even by considering iris to be circular; researchers were able to get accurate segmentation results. In literature, very few algorithms are there that do not consider the circular or elliptical property of iris[24-27].

Thus in segmentation depending on starting region approach search space involved is increased with increase in accuracy. Similarly algorithms considering the circular property results in increased segmentation accuracy but with huge mathematical computations resulting in increased computational time.

To overcome the drawbacks aforementioned, an improved iris segmentation methodology taking the advantages of both global and local feature is proposed. In this work, iris segmentation starts by considering the circular property of iris outer boundary and uses circular hough transform[28] (CHT) to identify iris outer boundary. Then by defining a minimum rectangular bounding box, MRB processing space is limited only to this region, reducing 50% of space involved. Specular reflections are removed using threshold values followed by binary morphological operators to reduce the effect of noise in this MRB. Finally, pupil region is localized by applying a simple statistical based iterative thresholding technique[1] considering the spatial feature property of pupil, eyelashes and eyelids. This solved the issue of pupil dilation effects affecting segmentation accuracy.

Using this proposed ISM, getting relatively less computational time, as the search space of the entire image is reduced by 65%. Iris segmentation accuracy regarding mislocalization count is also compared with Masek's method and found to give good results.

Iris recognition system accuracy is verified by extracting features using SIFT descriptor from the segmented iris ROI without performing normalization. Since SIFT provides scale, rotation and translation invariant features, intermediate normalization stage of iris recognition process is avoided, which further helps in reducing the time required for processing the entire system. In this paper, a novel iris segmentation methodology for non-cooperative iris images is proposed.

MATERIALS AND METHODS

Segmentation of a digital image entails the division of the input image into regions of similar attributes[14]. Iris segmentation is the process of extracting the iris region of interest from the eye image, by finding the pupil-iris boundary (inner) and iris-sclera boundary[3]. The annular region lying between the two boundaries is considered for further processing. In this improved segmentation methodology (ISM), an input eye image is taken and applies a traditional CHT algorithm[28] to identify the annular iris region. High intensity valued, specular reflections are removed using simple thresholding and morphological binarization operators. Low intensity valued, pupil boundary is obtained using simple statistical based iterative thresholding technique[1]. This study was analyzed and conducted in SRM University Kattankulathur during March-May, 2017. Figure 1 shows the flow chart for proposed ISM.

Iris-Sclera (Outer) boundary to pupil region detection: In this ISM, segmentation of iris ROI starts by determining the outer iris-sclera (limbic) boundary, i.e., from inside the limbic boundary to the outside of the pupil using Canny edge detection followed by CHT[28], considering the shape property of iris. The CHT is used to determine the parameters required to construct a circle, by knowing the number of points that fall on the perimeter. The speed of the algorithm will be computationally faster when these parameters are known. Canny edge detection operator is first applied to the eye image to identify these parameters. Based on the dataset being used, approximate radius ranges should be given as additional input to the algorithm to increase its speed. By performing trial and error methods for UBIRIS V1.0 database, radius range has been determined by experimentation as lower radius range to be 25 and upper iris radius range to be 55. Similarly, for CASIA dataset, it is found to be between 80 and 130, respectively. A circle with center coordinate $[x^{new}, y^{new}]$ and radius are identified by using the parametric Eq. 1 and 2:

$$x^{new} = x+r*\cos(\theta) \quad (1)$$

$$y^{new} = y+r*\sin(\theta) \quad (2)$$

After identifying the exact center location and new radius, a binary circular mask is created. This circular mask is then subtracted from the original eye image to isolate the iris region from the outer sclera and periocular region. By performing this step, unwanted search regions present in the eye region are eliminated and help in speeding up the entire process. As a post-processing step to eliminate the effect of occlusions or shadows or lenses overlapping in the upper and lower portion of non-ideal images, a minimum rectangular bounding box (MRB) of size 20$\times$N is created and applied on the isolated iris of size [M$\times$N]. Algorithm 1 explains the steps involved. Steps 6-9 are included to reduce the search space required and to remove noise effects like specular reflections, shadows and occlusions. By reducing the search space, a computationally faster segmentation process could be achieved when compared to other iris segmentation methods using CHT in literature[28], where they use the entire eye image for further processing and accuracy is improved by eliminating noise in the early stage itself. Figure 2 shows the results of Algorithm 1:

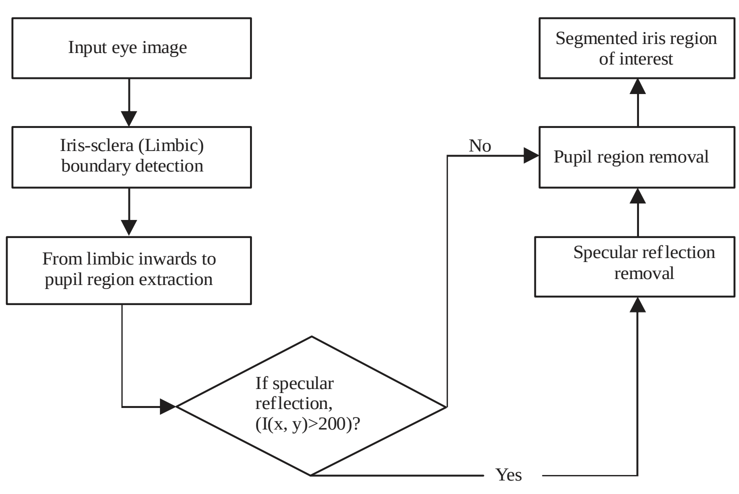

Fig. 1: Proposed ISM flow chart

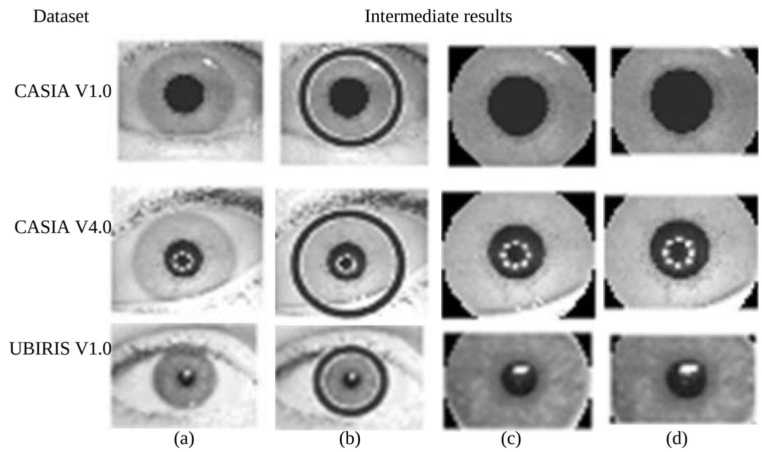

Fig. 2(a-d): Iris-sclera (outer) boundary detection and iris region isolation (a) Input Image, (b) Iris Annular region identified, (c) After applying circular mask and(d) After applying MRB mask

Algorithm 1: Iris-Sclera (outer) boundary detection and iris annular region isolation

function $iris_{MRB}$ (I, radius range)
    [Iiris, radius] ← Hough transform(I, radius range)
    BL ← Box (I(Iiris, radius))
    C_{mask} ← getnhood (strel (0 ball0 , radius, radius))
    IBL ← BL-C_{mask}
    MRB_{mask} ← IBL (20 : m-21, 1 : n),(where [m, n] = size (IBL))
    $iris_{MRB}$ ← IBL-MRB_{mask}
end function

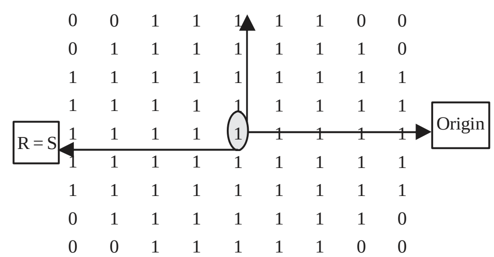

Fig. 3: Disk shaped structuring element, se

Specular reflection removal: Specular reflection removal method is usually performed as a pre-processing step in the eye image or a portion of pupil region[12,27]. Removal of the reflections in the entire image requires more processing time. However, when searched in pupil region alone, possible reflections occurred in iris regions are not taken into consideration and could lead to inaccurate results.

To overcome these drawbacks, in this approach, specular reflections are searched over the identified annular iris region alone. By only searching in the iris region, search space and computational times are reduced. The assumption here is that specular reflections are bright light spots and hence they will occupy high pixel values in an image. Hence, in this work, top 20% of the pixel values of the total pixel population is regarded as a threshold value to identify the specular reflection associated regions. Researchers considered top 5% and 10% of the pixel values of the total population[12,27]. Based on trial and error method, it has been set to top 20% in this paper.

Morphological dilation operation is included in this procedure, to find the immediate neighbors of specular reflection affected regions, as they will also have some impact. To get a normal variation, a structuring element, se, as shown in Fig. 3, is defined and used to perform morphological dilation operation on the binary reflection mask BW. The pixels identified as reflections are then equated to zero in the IBL. This process further reduces the number of pixel values involved in the search process of pupil region and thus reduces computational time of the entire process.

Steps involved in identifying and removing the specular reflections are shown in Algorithm 2 and Fig. 4 shows the results of Algorithm 2.

Algorithm 2: Specular_Reflection_Removal

function SRR ($Iris_{MRB}$, τh)
    m_{val} ← max ($iris_{MRB}$)
    $\tau h \leftarrow m_{val} - m_{val} * (20/100)$
    BW ← Binarize ($iris_{MRB}$, τh)
    se ← strel (disk, 5)
    sr_{mask} ← BW ⊕ se, where ⊕ denotes dilation of the image BW with se.)
    srr ← $iris_{MRB}$ (sr_{mask})
end function

Pupil region removal: In traditional iris segmentation algorithms, both pupil and iris boundaries are detected using

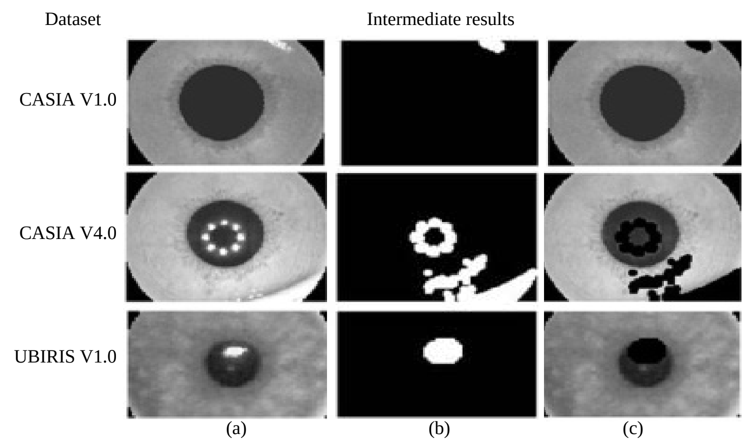

Fig. 4(a-c): Specular reflection removal (a) Iris MRB region, (b) Specular reflection mask and (c) $Iris_{MRB}$ after reflection removal

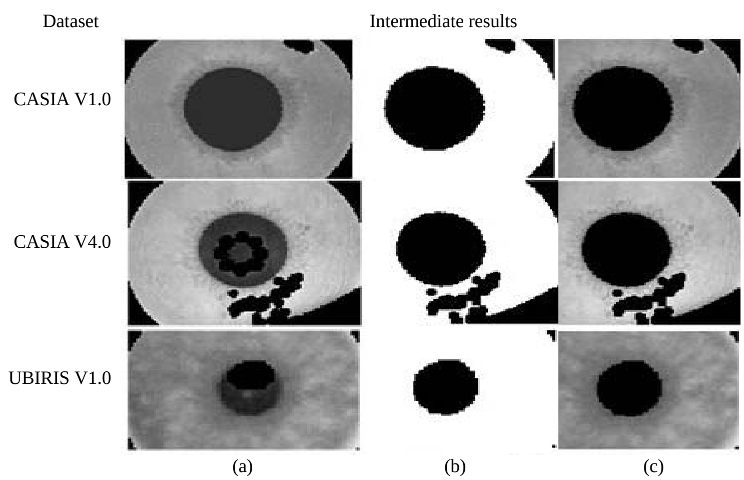

Fig. 5(a-c): Pupil region removal, (a) $Iris_{MRB}$ after Reflection Removal, (b) Pupil Region Mask and (c) Segmented Iris, IROI

the same method, i.e., Canny edge detection technique followed by CHT[28,29]. One of the drawbacks in using CHT is that it assumes that circular shaped objects will be present in the image and requires a range of radius values as input from the user. Though there were few abnormalities in the outer iris boundary shape, with experimental radius range, CHT was able to identify the outer boundary accurately. Noises like specular reflections, variation in illumination, pupil dilation effects, result in wrong localization of pupil boundary with CHT for about 50% of input images and increase computational time.

A simple statistical based thresholding technique is used to identify pupil region helping in reducing the time taken and increasing the accuracy rate. In an eye image, the pupil is the darkest region except for certain dark colored iris images[12]. In this approach, thresholding based segmentation methods followed by binary morphological operations are applied to find and isolate the pupil region. Initially, a threshold value is set to say bottom 30% of pixel values in the total population (concluded to 30% based on trial and error method). Pupil region is the total number of pixels or black holes that fall under this threshold limit within the total population[12]. Pupil region is isolated using a simple statistical based iterative thresholding technique. τl identified threshold value is used to partition SRR into two subregions. The mean of these subregions are calculated and their average is taken as a new threshold value, τ_{new}. The algorithm runs iteratively until the threshold values τl and τ_{new} in successive iterations do not change. By using a simple statistical based thresholding technique, computational time is reduced as well the pupil region if affected by dilation is also identified accurately.

Steps involved in this method are as shown in Algorithm 3 and Fig. 5 shows the implementation results.

Algorithm 3: Pupil_Region_Removal

```
function IROI(SRR, τl)
    m_high ← max(srr)
    τl ← m_high* (30/100)
    if srr > τl then: R1 ← srr
    else: R2 ← srr
    end if
    μ1 ← mean (R1)
    μ2 ← mean (R2)
    τ_new ← (μ1 + μ2)\2
    Repeat steps until τl ← τ_new in successive iterations
    BW_1 ← Binarize(srr, τ_new)
    IROI ← srr(BW_1)
end function
```

Feature extraction and matching: The SIFT[30] is a novel local feature extraction algorithm for iris recognition, providing advantages like scale, rotation and translation invariance. Normalization stages required to transform segmented iris ROI to a scale and rotation invariant block is avoided and helps in reducing the processing time required by the entire process. The first stage of SIFT is identifying and constructing a scale space that can repeatedly be assigned to the same image with Eq. 3[30]:

$$L(x, y, \sigma) = G(x, y, \sigma)*I(x,y) \tag{3}$$

where, $G(x, y, \sigma)$ is a Gaussian function, with varied 'σ' value and $I(x, y)$ is the segmented iris, ROI and '*' is the convolution operator.

Next step is to compute $D(x, y, \sigma)$ from the scale-spaces created using the difference of Gaussian (DOG) using Eq. 4[30]:

$$D(x, y, \sigma) = L(x, y, k\sigma)-L(x, y, \sigma) \tag{4}$$

where, k is a constant multiplier required to obtain different scale spaces.

From the DOG images, stable key points are extracted by comparing with two adjacent scale spaces. Key points found are either local maxima/minima of the DOG images. For each of the key points created, gradient and orientation/directions are computed which makes SIFT rotational invariant. For the assigned orientations, key point descriptors with 128 dimensions are created.

In the matching stage, key points are extracted from two segmented iris ROI images to be matched with SIFT, respectively. Based on the key points extracted from each image, matching pairs are identified and the number of matching pairs is used to measure the similarity between them. Then the suitable threshold T is selected after testing the matching score of the entire iris image data set. For example, these two iris images will be classified as the same class if the similarity score is below T, otherwise, will be classified as different classes.

RESULTS AND DISCUSSION

The proposed methodology was tested on iris images taken from UBIRIS V1.0[31] acquired in the visible wavelength and CASIA V1.0[32] and V3.0 iris interval (V3-I)[32] acquired in near IR spectrum. CASIA V1.0[32] has 756 images taken from 108 subjects. CASIA V3-I[32] has 2639 images taken from 249 subjects and UBIRIS V1.0[31] has 1877 images taken from 246 subjects. Datasets CASIA V3-I[32] and UBIRIS V1.0[31] both incorporate several non-cooperative iris images with distinct noise factors like reflections, occlusions, half-closed, off-axis and blurred images. Thus the use of these datasets permits the evaluation of the robustness of proposed segmentation methodology.

From the experimental analysis, it was observed that the proposed iris segmentation methodology was capable of handling non-cooperative iris images as well as unconstrained situations. For example, noisy instances like reflections, occlusions, half-closed, off-axis, at a distant and blurred image were presented to this proposed methodology and found to give good results. Performance accuracy was supported by identifying the mislocalization count for segmentation accuracy and by calculating iris recognition accuracy. Segmented iris ROI was given as input to SIFT[30] feature extraction algorithm and matching technique.

Proposed segmentation methodology results for a set of sample images of the three datasets are shown in Fig. 6.

These algorithms were implemented using Matlab R2015a installed on a 1.80 GHz system running Windows 8.1 and with Intel(R) Core(TM) i5-processor and 4 GB RAM. It was found that the proposed method takes the least time for segmentation when compared to some of the state-of-the-art methods. Average time taken for UBIRIS V1[31], CASIA V1[32] and V3-I[32] were calculated in seconds.

In this study, segmentation accuracy was measured in terms of mislocalization count and compared with Masek's method[33]. Similarly, average segmentation time taken per image was also compared Masek's method[33]. Mislocalization count and average time taken per image in terms of seconds comparison results were given in Table 1.

In this current methodology, a significantly low computational time when compared to other methods was achieved with reduced mislocalization count. Average time taken is reduced by reducing the search space required to localize the iris region of interest. In circle detection methods,

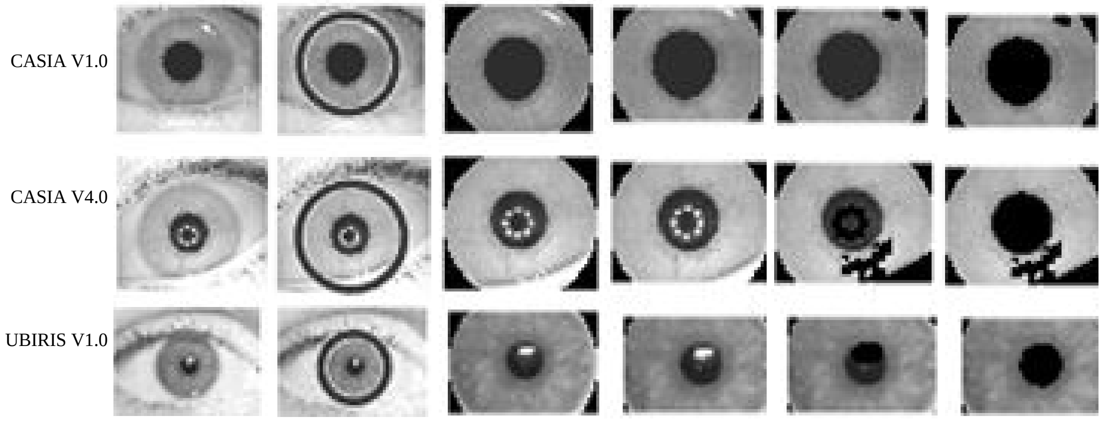

Fig. 6: Illustrations of proposed methodology for various dataset

Table 1: Mis-localization percentages of masek's, average segmentation time taken (sec) for the masek's and proposed methodology

	Databases		
Methods	CASIA V1.0	CASIA V3-I	UBIRIS V1.0
Mis-localization percentages			
Masek's	10.3175	13.2322	26.5676
Proposed	6.8783	8.9717	8.0858
Average segmentation time taken (sec)			
Masek's	11.1009	9.3962	12.2159
Proposed	0.3497	0.35524	0.2969

Table 2: Comparison of average time taken (sec) for different segmentation techniques

	Databases		
Methods	CASIA V1.0	CASIA V3-I	UBIRIS V1.0
Shah and Ross[34]	-	-	6.2
Radman *et al.*[35]	-	-	1.09
Hilal *et al.*[36]	-	-	5.8
Abdullah *et al.*[37]	-	-	0.77
Jan *et al.*[38]	7.2	7.75	1.14
Jan[10]	-	-	0.92
Soliman *et al.*[11]	2.4	-	-
Proposed	0.34	0.35	0.2969

Table 3: Iris recognition accuracy for proposed approach using SIFT

	Methods	
Databases	SIFT (without normalization)	SIFT (with normalization)
CASIA V1.0[32]	89.95	94.50
CASIA V3-I[32]	88.0	93.0
UBIRIS V1.0[31]	87.5	92.275

CHT was one of the most time-consuming techniques. By providing possible radius ranges, the number of iterations required to identify outer boundary was reduced.

Reducing the number of pixel values in pupil localization process reduced the number of iterations required by the statistical based iterative thresholding technique.

Table 2 gives comparison of average time taken per image (sec) for different segmentation techniques. Though similar findings were reported by researchers[10,11,34-38], in this work, pixel reduction rate is achieved to be nearly 65% by reducing the search space involved in every intermediate step.

Iris recognition accuracy was calculated by using SIFT and results were shown in Table 3. Though segmentation technique proposed by Masek[33], performs equally well, segmentation time for the proposed system is relatively low. It was also made clear that the segmentation had taken place accurately despite the non-cooperative nature of the image instances and helped in improving overall system efficiency.

From the experimental results given in Table 1 and 2, it was evident that the proposed method was capable of segmenting non-cooperative iris images taken in the visible spectrum as well as NIR spectrum in significantly lesser computational time with appreciable accuracy rate.

CONCLUSION

Initially, CHT is used to find iris outer boundary followed by iterative thresholding techniques to identify specular reflections, pupil region, eye lids region and eyelashes. This approach has been tested on CASIA V1, V3 (Interval) and UBIRIS V1 datasets. It has been observed that by reducing search space and working with local features, average segmentation time taken per image is highly reduced and gives comparatively good recognition accuracy when tested with SIFT technique. The experimental results on the datasets showed that the proposed scheme achieves state-of-the-art iris results while being computationally more efficient. However, there is still much space for improvement. As a future work, mislocalization count percentage obtained in this work could be reduced further by using other outer boundary identification techniques.

SIGNIFICANCE STATEMENTS

This study discovers the possibility of enhancing iris recognition for non-cooperative noisy images by improving segmentation stage. This study will help the researchers to uncover the critical area of search space reduction even in the pre-processing stage, which many researchers have not explored yet. An improved iris segmentation methodology to reduce computational time and search space with improved recognition rate has been proposed and implemented.

REFERENCES

1. Gonzalez, R.C. and R.E. Woods, 2007. Digital Image Processing. 3rd Edn., Prentice Hall, USA., ISBN-13: 9780131687288, Pages: 976.
2. Nithya, A.A., C. Lakshmi, J. Anand and N. Sekar, 2016. Multi-unit feature level fusion approach using PPCA. Indian J. Sci. Technol., Vol. 9, No. 38. 10.17485/ijst/2016/v9i35/101936.
3. Nithya, A.A and C. Lakshmi, 2015. Iris recognition techniques: A literature survey. Int. J. Applied Eng. Res., 10: 32525-32546.
4. Sahmoud, S.A., 2011. Enhancing iris recognition. M.Sc. Thesis, Computer Engineering Department, Faculty of Engineering, Deanery of Higher Studies, Islamic University, Gaza, Palestine.
5. Zafar, M.F., Z. Zaheer and J. Khurshid, 2013. Novel iris segmentation and recognition system for human identification. Proceedings of the 10th International Bhurban Conference on Applied Sciences and Technology, January 15-19, 2013, Islamabad, Pakistan, pp: 128-131.
6. Jain, A.K., A. Ross and S. Prabhakar, 2004. An introduction to biometric recognition. IEEE Trans. Circuits Syst. Video Technol., 14: 4-20.
7. Daugman, J., 2007. New methods in iris recognition. IEEE Trans. Syst. Man Cybern. Part B: Cybern., 37: 1167-1175.
8. Daugman, J., 2004. How iris recognition works. IEEE Trans. Circuits Syst. Video Technol., 14: 21-30.
9. Flom, L. and A. Safir, 1987. Iris recognition system. U.S. Patent 4,641,349, February 3, 1987. https://www.google.com/patents/US4641349
10. Jan, F., 2017. Segmentation and localization schemes for non-ideal iris biometric systems. Signal Process., 133: 192-212.
11. Soliman, N.F., E. Mohamed, F. Magdi, F.E. Abd El-Samie and M. AbdElnaby, 2017. Efficient iris localization and recognition. Optik-Int. J. Light Electron Opt., 140: 469-475.
12. He, Z., T. Tan, Z. Sun and X. Qiu, 2009. Toward accurate and fast iris segmentation for iris biometrics. IEEE Trans. Pattern Anal. Mach. Intell., 31: 1670-1684.
13. Bakshi, S., H. Mehrotra and B. Majhi, 2011. Real-time iris segmentation based on image morphology. Proceedings of the International Conference on Communication, Computing and Security, February 12-14, 2011, Rourkela, Odisha, India, pp: 335-338.
14. Mishra, A.K., Y. Aloimonos, L.F. Cheong and A. Kassim, 2012. Active visual segmentation. IEEE Trans. Pattern Anal. Mach. Intell., 34: 639-653.
15. Yogamangalam, R. and B. Karthikeyan, 2013. Segmentation techniques comparison in image processing. Intl. J. Eng. Technol., 5: 307-313.
16. Ross, A. and S. Shah, 2006. Segmenting non-ideal irises using geodesic active contours. Proceedings of the Biometrics Symposium: Special Session on Research at the Biometric Consortium Conference, September 19-August 21, 2006, Baltimore, MD., USA., pp: 1-6.
17. Labati, R.D., V. Piuri and F. Scotti, 2009. Agent-based image iris segmentation and multiple views boundary refining. Proceedings of the IEEE 3rd International Conference on Biometrics: Theory, Applications and Systems, September 28-30, 2009, Washington, DC., USA., pp: 1-7.
18. Vatsa, M., R. Singh and A. Noore, 2008. Improving Iris recognition performance using segmentation, quality enhancement, match score fusion and indexing. IEEE Trans. Syst. Man Cybernet. Part B: Cybernet., 38: 1021-1035.
19. Chen, Y., M. Adjouadi, C. Han, J. Wang, A. Barreto, N. Rishe and J. Andrian, 2010. A highly accurate and computationally efficient approach for unconstrained iris segmentation. Image Vision Comput., 28: 261-269.
20. Proenca, H. and L.A. Alexandre, 2006. Iris segmentation methodology for non-cooperative recognition. IEE Proc. Vis. Image Signal Process., 153: 199-205.
21. Liu, X., K.W. Bowyer and P.J. Flynn, 2005. Experiments with an improved iris segmentation algorithm. Proceedings of the 4th IEEE Workshop on Automatic Identification Advanced Technologies, October 17-18, 2005, Buffalo, NY., USA., pp: 118-123.
22. Dobes, M., J. Martinek, D. Skoupil, Z. Dobesova and J. Pospisil, 2006. Human eye localization using the modified Hough transform. Optik-Int. J. Light Electron Opt., 117: 468-473.
23. Schuckers, S.A.C., N.A. Schmid, A. Abhyankar, V. Dorairaj, C.K. Boyce and L.A. Hornak, 2007. On techniques for angle compensation in nonideal Iris recognition. IEEE Trans. Syst. Man Cybernet. Part B: Cybernet., 37: 1176-1190.
24. Tan, T., Z. He and Z. Sun, 2010. Efficient and robust segmentation of noisy iris images for non-cooperative iris recognition. Image Vision Comput., 28: 223-230.

25. Zuo, J., N.D. Kalka and N.A. Schmid, 2006. A robust iris segmentation procedure for unconstrained subject presentation. Proceedings of the Biometrics Symposium: Special Session on Research at the Biometric Consortium Conference, September 19-August 21, 2006, Baltimore, MD., USA., pp: 1-6.
26. Camus, T. and R. Wildes, 2002. Reliable and fast eye finding in close-up images. Proceedings of the 16th International Conference on Pattern Recognition, Volume 1, August 11-15, 2002, Quebec City, Canada, pp: 389-394.
27. Han, Y.L., T.H. Min and R.H. Park, 2014. Efficient iris localisation using a guided filter. IET Image Process., 9: 405-412.
28. Djekoune, A.O., K. Messaoudi and K. Amara, 2017. Incremental circle hough transform: An improved method for circle detection. Optik-Int. J. Light Electron Opt., 133: 17-31.
29. Wildes, R.P., 1997. Iris recognition: An emerging biometric technology. IEEE Proc., 85: 1348-1363.
30. Lowe, D.G., 2004. Distinctive image features from scale-invariant keypoints. Int. J. Comput. Vision, 60: 91-110.
31. Proenca, H. and L.A. Alexandre, 2005. UBIRIS: A noisy iris image database. Proceedings of the International Conference on Image Analysis and Processing, September 6-8, 2005, Italy, pp: 970-977.
32. CASIA., 2016. CASIA iris image database version 1.0, version 4.0 (iris-interval). http://biometrics.idealtest.org/dbDetailForUser.do?id=4
33. Masek, L., 2003. Recognition of human iris patterns for biometric identification. Bachelor Thesis, School of Computer Science and Software Engineering, The University of Western Australia.
34. Shah, S. and A. Ross, 2009. Iris segmentation using geodesic active contours. IEEE Trans. Inform. Forensics Secur., 4: 824-836.
35. Radman, A., K. Jumari and N. Zainal, 2013. Fast and reliable iris segmentation algorithm. IET Image Process., 7: 42-49.
36. Hilal, A., B. Daya and P. Beauseroy, 2012. Hough transform and active contour for enhanced iris segmentation. Int. J. Comput. Sci. Issues, 9: 1-10.
37. Abdullah, M.A.M., S.S. Dlay, W.L. Woo and J.A. Chambers, 2016. Robust iris segmentation method based on a new active contour force with a noncircular normalization. IEEE Trans. Syst. Man Cybern.: Syst., 99: 1-14.
38. Jan, F., I. Usman and S. Agha, 2012. Iris localization in frontal eye images for less constrained iris recognition systems. Digital Signal Process., 22: 971-986.