A Framework for Iris Partial Recognition based on Legendre Wavelet Filter

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***Abstract*—An increasing need for biometrics recognition system has grown substantially to address the issues of recognition and identification especially in highly dense areas such as airport, train stations and for financial transaction. Evidences of these can be seen in some airports and also the implementation of these technologies in our mobile phones. Among the most popular biometric technologies include facial, fingerprints and iris recognition. The iris recognition is considered by many researchers to be the most accurate and reliable form of biometric recognition, because iris can neither be surgically operated with a chance of losing slight nor change due to ageing. However, presently most iris recognition system available can only recognize iris image with frontal-looking and high-quality images. Angular image and partially capture image cannot be authenticated with existing method of iris recognition. This research investigates the possibility of developing a framework for recognition partially captured iris image. The research also adopts the Legendre wavelet filter for the iris feature extraction. Selected iris images from CASIA, UBIRIS and MMU database were used to test the accuracy of the introduced framework. A threshold for the minimum iris image required was established.**

Keywords—Iris recognition; partial recognition; wavelet; Legendre wavelet filter; biometric

I. Introduction

The increasing need for a reliable means for an identification and verification system cannot be over emphases [1]. The world population and the need for identifying or verifying people in highly dense areas force the evolution of the use of biometric technologies as alternative and more effective means of access control [2].

The word biometrics is a two combine word of the Greek words bio and metric, which is “life meaning bio and measurement meaning metric”. Biometric technology is defined as any technique that can use measurable physiological or behavioral characteristics to discriminate one person from another [3]. Common physiological biometric traits include iris, fingerprints, facial, hand geometry, and retina images. Whereas, common behavioral biometric traits include: voice recording, signature, and keystroke rhythms. It is noted that behavioral biometrics, in general, include a physiological component as well [4].

Although all biometric systems work in the same manner, the first process is enrollment in which each new user is registered into the database. Information about a specific characteristic of the individual is captured. This information is usually passed through an algorithm that turns the information into a template that the database stores. Note that it is the template that is maintained in the system, but not the original biometric measurement as many people may suspect. Compared with the original measurement of the biometric trait, the template has a tiny amount of information; it is no more than a collection of numbers with little meaning except to the biometric system that produced them. When a person needs to be recognized, the system will take the appropriate measurement, translate this information into a template using the same algorithm that the original template was computed with, and then compare the new template with the database to determine if there is a match, and hence, either verification or identification [5].

Today fingerprint and facial recognition system are one of the most used biometric recognition system. Both the fingerprint biometric and the facial recognition system are used in the public domains such as airport, train station and also our financial institution such as banks and Automated Teller Machine (ATM) [6]. However, both the fingerprint and the facial recognition are facing some setbacks. For the fingerprint recognition, the system users need to scan their finger on a fingerprint scanning device, this makes it difficult to authenticate someone with his knowledge and also frequent use of the scanning device often makes the scanning device dirty thus fails during recognition.

Iris recognition has been verified to be one of the most accurate and reliable biometrics authentications, unlike facial recognition, and fingerprint. The facial recognition has great problem due to the fact that the human faces changes over time due to growth development in human nature. The fingerprint unlike the facial recognition does not change for as long as we leave however face setback such as the need for the authenticated individual to scan his or her hand to the scanning device, this make it difficult to authenticate an individual without his or her knowledge, sometimes the scanning device maybe dirty [7]. The identified problems make iris recognition an alternative as the best biometric authentication; iris is neither affected by age nor requires an individual to have a contact with its scanning device

Presently, iris recognition methods can work very well with frontal-looking and high-quality images. Daugman’s 2D Gabor wavelet approach has been tested and evaluated using huge databases, such as the CASIA database, UBIRIS database, and MMU database among others, with over 600,000 iris images with over 200 billion comparisons [8]. However, most existing methods are not designed for non-cooperative users and cannot work with off-angle or partially captured iris images. Recognition can be quite good if canonical poses and simple backgrounds are employed, but changes in illumination and angle create challenges. Recognizing an individual with incomplete or partially captured images in biometric technology continues to be an important challenge today. Despite the advancement made in fingerprint identification techniques, little or not much have been achieved for that of iris recognition. Partially captured image or images with noise or occlusion is a well-known research problem, and many researchers have tried to address the problems in a different capacity.

II. Databases

We selected four different databases to test our method, namely; Chinese Academy of Sciences Institute of Automation (CASIA) [9], University Beira IRIS (UBIRIS) [10], and Multimedia University (MMU) database. The selected database was based on the most frequently used database for the iris recognition algorithm. However, to show the effect of partial recognition, there is a need for the dataset to be carefully selected. We only selected images that are partially captured. However, for registering the iris images to the database, here, we also selected best-captured images. For each subject or eye image, 2-10 images are selected, depending on the availability of the partially captured image of the particular subject or eye.

The iris recognition was implemented with the selected database. The selected databases include CASIA v4 database, UBIRIS v2 database, MMU v2 database, and IITD database. The CASIA v4 database consist of subset namely, CASIA-IRIS-interval, CASIA-IRIS-twins, CASIA-IRIS-distance, CASIA-IRIS-thousand, CASIA-IRIS-syn, however only the CASIA-IRIS-interval and CASIA-IRIS-distance were used. The CASIA-IRIS-interval consists of 249 subjects with a total of 2639 number of iris images, but only 994 images were used from 249 subject. The CASIA-IRIS-distance consists of 142 subjects with a total of 2567 number of images, but only 710 images were used from 142 subject. The UBIRIS v2 database consists of 261subjects and 522 irises with a total of 11102 images, but only 783 were used from 261 subject. The MMU database consists of 100 subjects and 200 irises with a total of 10000 number of image, but only 300 images were selected from 100 subjects as in Table I.

Fig. 1 is a sample of some best-captured eye image from the MMU database; we roundly select then to show how they look. While Fig. 2, is a sample of some partially captured eye image from the MMU database. They are partially captured because either the subject eyes are partially closed or the subject is looking sideway, or the eyelashes of the subject partially closed the eye image.

TABLE I. Information of the Selected Dataset

s/n	Database	Subject	Images
1	CASIA-IRIS-interval	249	994
2	CASIA-IRIS-distance	142	710
3	UBIRIS v2	261	783
4	MMUv2	100	300

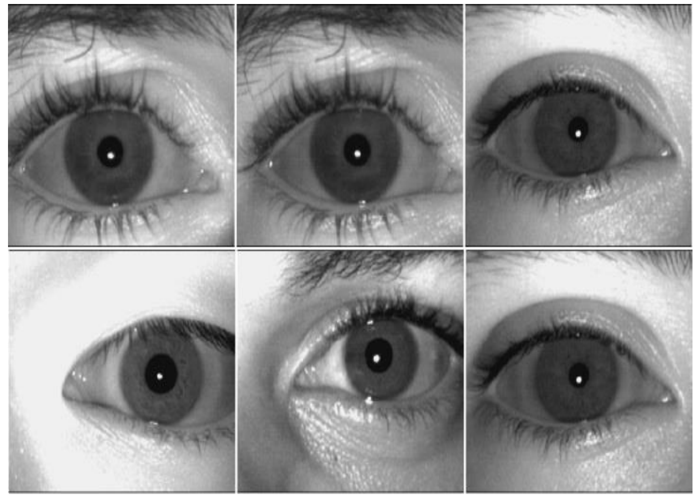

Fig 1. Best-Captured Image from MMU Iris Database.

Fig 2. Partially-Captured/Noisy Iris Images from MMU Database.

Fig 3. Some Partially-Captured/Noisy Iris Images from UBIRIS Database.

Fig 4. Some Best-Captured Image from UBIRIS Iris Database.

Fig. 4 is sample of the best-captured eye image from the UBIRIS database; we roundly select them to show how they look. While Fig. 3 are the partial captured eye image from the UBIRIS database. They are partially captured because either the subject eyes are partially closed or the subject is looking sideway, or the eyelashes of the subject partially closed the eye image.

III. Methodology

The idea here is to find a threshold for which iris can be recognized partially. That is, to find the smallest among of size of iris required to authenticate the subject. The research will consider the normalized iris image at for different percentage; 50 percent, when the normalized iris image is divided into two parts, 25 per cent, when the normalized iris image is divided into four parts, 16.5 per cent, when the normalized iris image is divided into six parts, and 12.5 per cent when the iris image is divided into eight equal parts. With this for different sizes, we find the minimum size of normalized iris required for the recognition process. The processes for the recognition include segmentation, normalization, feature extraction and matching as in Fig. 5.

The first stage of the recognition is the acquisition of the image, for the stage we intend to use the available database online. Some of the databases need some adjusting. Also, the iris images are in different resolution and there is need for a standard size of resolution across the database images. The UBIRIS database images, for example, need to be converted into greyscale image, for others such as CASIA and MMU are all in greyscale. Fig. 6 shows the converted UBIRIS image from colored to a greyscale image.

A. Segmentation

For most of the database, the conversion of the image from colored to greyscale is not needed. The process usually starts with segmentation. The iris image is selected from the eye image as in Fig. 7.

B. Normalization

Next is to normalized the segmented iris image, here, the rubber sheet mode was used to achieve this function. This is shown in Fig. 8.

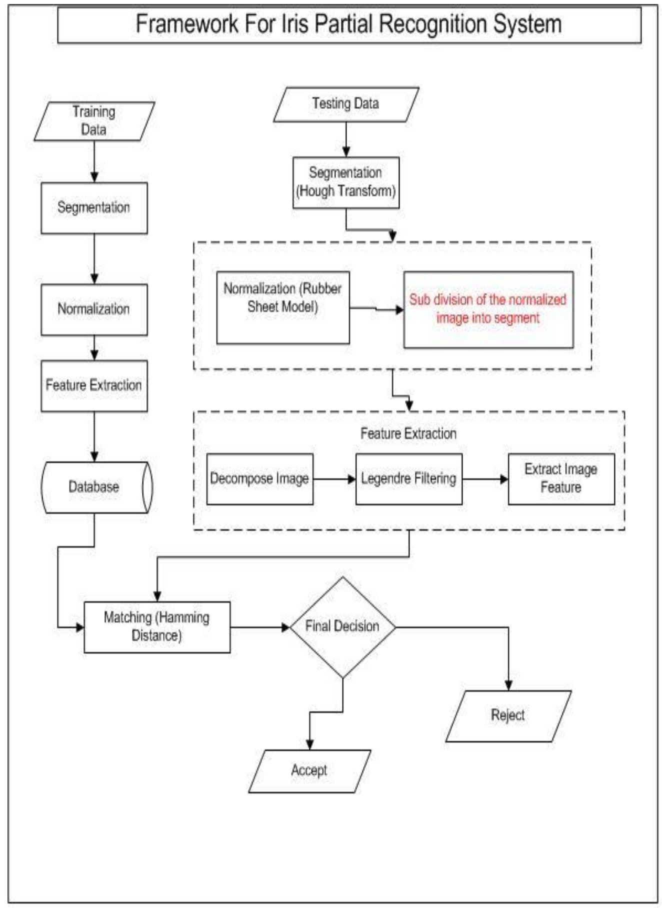

Fig 5. Framework for Partial Iris Recognition.

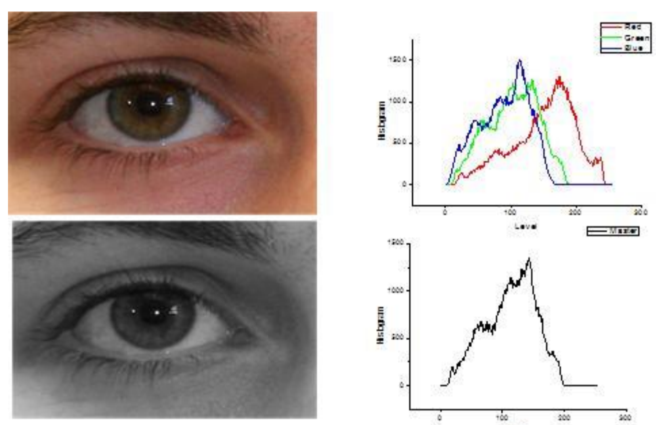

Fig 6. Iris Image from UBIRIS Database Converted to Greyscale.

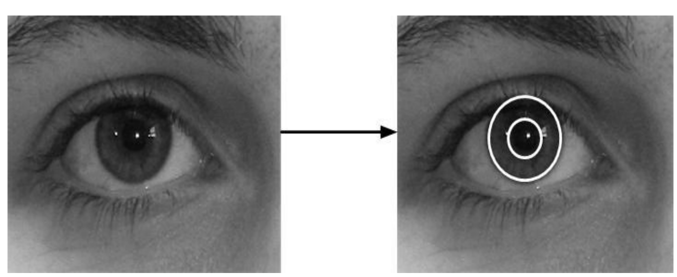

Fig 7. Iris Segmentation of the Eye Image.

Fig 8. Iris Normalization.

C. Feature Extraction

The feature extraction follows after the normalization. Feature that distinguish the iris image are enhance using the Legendre wavelet filter. Following the approach of [11], the Legendre wavelet filter can be define as in Equation (1).

$$\Psi_{n_1,m_1,n_2,m_2}(x,y) = \Psi_{e,n_1,m_1,n_2,m_2}(x,y) = \sqrt{\left(m_1+\frac{1}{2}\right)\left(m_2+\frac{1}{2}\right)2^{\frac{(k_1+k_2)}{2}}} \times P_{m_1}(2^{k_1}x-\hat{n}_1)P_{m_2}(2^{k_2}y-\hat{n}_2)e^{j2\pi(u_1x+v_1y)} \quad (1)$$

where

$$e^{j2\pi(u_1x+v_1y)} = \cos[2\pi(u_1x+v_1y)] + j\sin[2\pi(u_1x+v_1y)] \quad (2)$$

u_1 and v_1 are the fundamental frequencies in X and Y direction m = 0,1,…M and n = 0,1,…2^{k-1}, the coefficient $\sqrt{\left(m_1+\frac{1}{2}\right)\left(m_2+\frac{1}{2}\right)}$ is for the orthonomality and the Pm is Legendre polynomial

Generally, image features are pieces of information that describes an image or a part of an image as in Fig. 9. However, in pattern recognition feature is a piece of information which is relevant for solving the computational task related to a certain application. Feature extraction begins from an initial set of measured data and builds derived values feature intended to be informative and non-redundant, helping the subsequent learning and generalizing steps, and in some cases leading to better human interpretations.

Fig 9. Iris Feature Extraction.

D. Matching

Lastly the recognition is concluded by the matching, were the unique feature extracted from the iris image is been compare with the corresponding iris image in the database for verification or the unique feature are searched across the saved feature in the database until a match is found for identification.

IV. Evaluation Parameter

False Acceptance Rate (FAR): FAR is the frequency of fraudulent access to imposter claiming identity. This statistic is used to measure biometric performance when operating in the verification mode. A false accepts occurs when the query template of an individual is incorrectly matched to existing biometric template of another individual.

False Rejection Rate (FRR): FRR is the frequency of rejections relative to people who should be correctly verified. This statistics is used to measure biometric performance when operating in the verification mode. A false reject occurs when an individual is not matched correctly to his/her own existing biometric template.

Genuine Acceptance Rate (GAR): GAR is the frequency of genuine access with respect to overall number of attempts.

V. Result and Discussion

The Legendre wavelet filter was implemented using Matlab R2015 installed on a Window 7 professional desktop computer, Intel core i7. We considered the Legendre wavelet filter at three different orders. The experimental setting is introduced, including the selected database, parameter setting and performance evaluation. Then, to study the effect of the proposed partial method of the iris code production, comparisons are made between the performances of the iris codes produced by an implementation of traditional iris code generation method.

The iris code generated was tested with the selected images in CASIA-IRIS-interval and the result is as in Table II. The lowest accuracy was achieved at 50% and the highest was achieved at 16.5%. The FAR has its lowest at 50% and its highest at 12.5% while the FRR has its highest at 50% and its lowest at 16.25%. The graphical representation of the accuracy of the CASIA-IRIS-interval is shown in Fig. 10.

TABLE II. Result of the Partial Recognition with CASIA-Iris-Interval

PERCENTAGE OF THE IRIS IMAGE	FAR %	FRR %	GAR %	ACURACY %
50%	5.48	15.89	87.05	87.05
25%	6.45	14.26	88.26	88.26
16.5%	6.75	13.25	92.25	92.25
12.5%	6.82	13.56	91.95	91.95

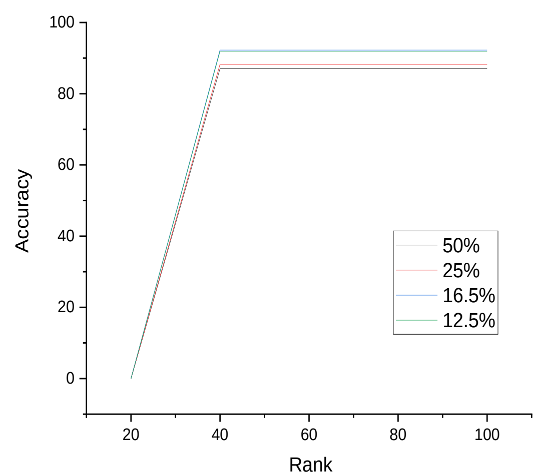

Fig 10. Accuracy Result of the Partial Recognition with CASIA-IRIS-Interval.

TABLE III. RESULT OF THE PARTIAL RECOGNITION WITH CASIA-IRIS-DISTANCE

PERCENTAGE OF THE IRIS IMAGE	FAR %	FRR %	GAR %	ACURACY %
50%	7.59	16.49	84.05	84.05
25%	8.95	15.36	85.26	85.26
16.5%	7.95	14.28	86.25	86.25
12.5%	6.42	18.59	84.95	84.95

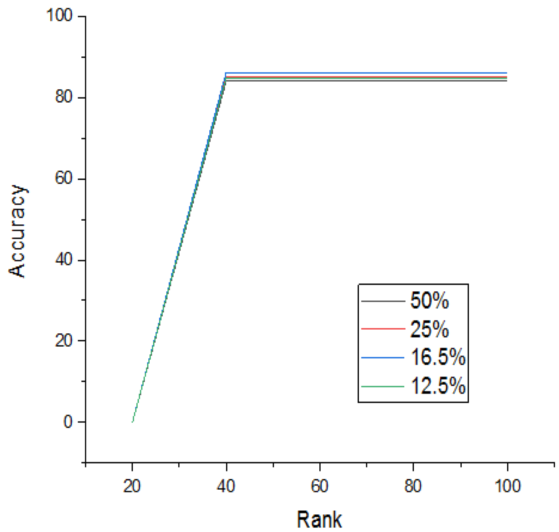

Fig 11. Accuracy Result of the Partial Recognition with CASIA-IRIS-Distance.

The iris code generated was tested with the selected images in CASIA-IRIS-distance and the result is as in Table III. The lowest accuracy was achieved at 50% and the highest was achieved at 16.5%. The FAR have lowest at 50% and highest at 12.5% while the FRR has highest at 12.5% and lowest at 16.25%. The graphical representation of the recognition accuracy is in Fig. 11.

The iris code generated was tested with the selected images in UBIRISv2 and the result is as in Table IV. The lowest accuracy was achieved at 12.5% and the highest was achieved at 16.5%. The FAR have lowest at 12.5% and highest at 16.5% while the FRR has highest at 12.5% and lowest at 25%. The graphical representation of the recognition accuracy is in Fig. 12.

TABLE IV. RESULT OF THE PARTIAL RECOGNITION WITH UBIRISV2

PERCENTAGE OF THE IRIS IMAGE	FAR %	FRR %	GAR %	ACURACY %
50%	4.59	20.69	74.05	74.05
25%	3.95	19.86	74.36	74.36
16.5%	4.95	24.48	74.95	74.95
12.5%	1.42	25.19	73.55	73.55

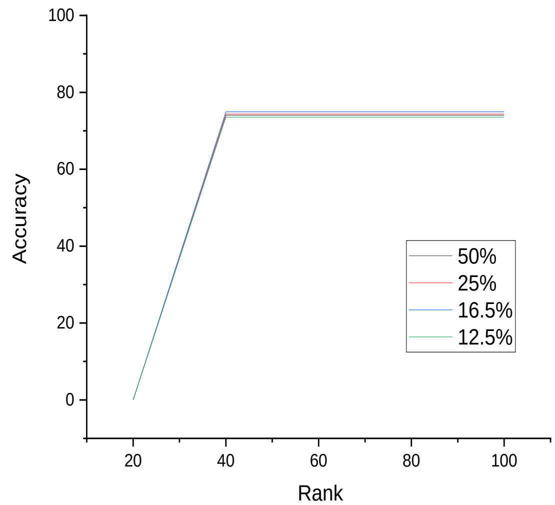

Fig 12. Accuracy Result of the Partial Recognition with UBIRISv2.

The iris code generated was tested with the selected images in MMUv2 and the result is as in Table V. The lowest accuracy was achieved at 50% and the highest was achieved at 16.5%. The FAR have lowest at 12.5% and highest at 50% while the FRR has highest at 50% and lowest at 12.5%. The graphical representation of the recognition accuracy is in Fig. 13.

TABLE V. RESULT OF THE PARTIAL RECOGNITION WITH MMUV2

PERCENTAGE OF THE IRIS IMAGE	FAR %	FRR %	GAR %	ACURACY %
50%	3.50	13.69	92.05	92.05
25%	3.25	12.86	92.96	92.96
16.5%	2.50	10.48	94.45	94.45
12.5%	1.50	11.19	93.55	93.55

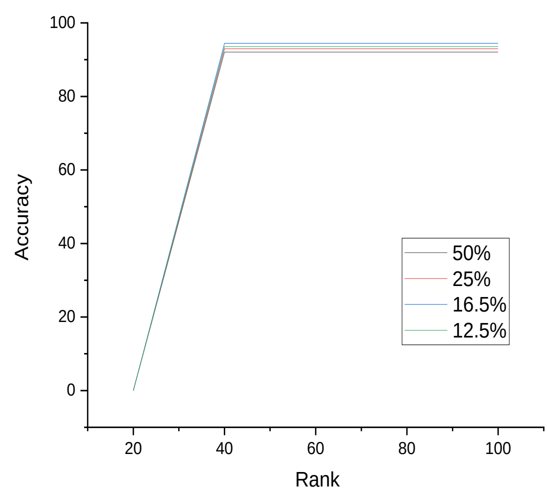

Fig 13. Accuracy Result of the Partial Recognition with MMUv2.

VI. Conclusion and Future Work

The main focus of the research was to try the iris recognition with a partially capture image and to also do the recognition partially. So the idea was to find a threshold that can determine the minimum amount of iris region required to identify an individual. Presently the method of partial recognition is applied in fingerprint recognition especially with fingerprint integrated with the mobile hand phone, whereby any part of your fingerprint can be used for the recognition.

Based on the experiment that was carried out, it shows that the partial recognition can also be applied with the iris. Substantially the iris can be recognition with as low as only 12.5% of the iris image. However, best results were achieved with the iris image at 16.5%.

Some of the future work of the research is to create a database that will have only iris images that are partially captured. Providing the database will help standardize the process of the proposed framework evaluation.

Secondly more feature extraction technique can be introduced for better extraction of the iris feature.

References

[1] K. S. Kumar, K. N. N. S. Ram, K. Kiranmai, and S. S. Harsha, “Denoising of Iris Image Using Stationary Wavelet Transform,” in 2018 Second International Conference on Inventive Communication and Computational Technologies (ICICCT), 2018, pp. 1232–1237.

[2] K. Muralidharan, P. Niehaus, and S. Sukhtankar, “Building state capacity: Evidence from biometric smartcards in India,” Am. Econ. Rev., vol. 106, no. 10, pp. 2895–2929, 2016.

[3] M. Nabti and A. Bouridane, “An effective and fast iris recognition system based on a combined multiscale feature extraction technique,” Pattern Recognit., vol. 41, no. 3, pp. 868–879, 2008.

[4] S. Patil, S. Gudasalamani, and N. C. Iyer, “A survey on Iris recognition system,” in International Conference on Electrical, Electronics, and Optimization Techniques, ICEEOT 2016, 2016, pp. 2207–2210.

[5] W. W. Boles and B. Boashash, “A Human Identification Technique Using Images of the Iris and Wavelet Transform,” IEEE Trans. Signal Process., vol. 46, no. 4, pp. 1185–1188, 1998.

[6] B. Mary Reni, “Iris recognition based age estimation in security systems using Canny edge detection,” Res. J. Pharm. Biol. Chem. Sci., vol. 6, no. 5, pp. 349–357, 2015.

[7] A. Khatun, A. K. M. F. Haque, S. Ahmed, and M. M. Rahman, “Design and implementation of iris recognition based attendance management system,” in 2nd International Conference on Electrical Engineering and Information and Communication Technology, iCEEiCT 2015, 2015.

[8] J. Daugman, “New methods in iris recognition,” IEEE Trans. Syst. Man, Cybern. Part B Cybern., vol. 37, no. 5, pp. 1167–1175, 2007.

[9] T. Tan, Z. He, and Z. Sun, “Efficient and robust segmentation of noisy iris images for non-cooperative iris recognition,” Image Vis. Comput., vol. 28, no. 2, pp. 223–230, 2010.

[10] H. Proenc, “Iris Recognition : On the Segmentation of Degraded Images Acquired in the Visible Wavelength,” vol. 32, no. 8, pp. 1502–1516, 2010.

[11] D. Muktar, S. Jamel, S. N. Ramli, and M. M. Deris, “2D legendre wavelet filter for iris recognition feature extraction,” in Proceedings of the 3rd International Conference on Cryptography, Security and Privacy, 2019, pp. 174–178.