IMPROVING IRIS RECOGNITION ACCURACY USING GABOR KERNELS WITH NEAR-HORIZONTAL ORIENTATIONS

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Abstract: Gabor filter has proven to be one of the most successful techniques for the extraction of iris features. However, the selection of Gabor kernel orientations remains an important key for an optimum performance. In this paper, Gabor kernels with horizontal and two near-horizontal orientations (0°, 15°, 165°) are used for extracting iris features, as an attempt to improve the performance of iris recognition rate. The three iris features are cascaded into one image for the purpose of image matching. To this end, an iris recognition system is developed using methods of iris localization, eyelid removal and iris matching by Hamming Distance (HD) that have been developed previously by the same authors. The system is implemented on three standard datasets, CASIA-1, CASIA-Lamp-4 and SDUMLA-HMT. The results have shown that the overall accuracy (Accu), the True Positive Rate (TPR) and the Equal Error Rate (EER) EER are (98.85%, 99.42% and 0.58%) for CASIA-1 database, (96.56%, 98.25% and 1.75%) for CASIA-Lamp-4 database and (96%, 98% and 2.0%) for SDUMLA-HMT database. These results outrage the results of most of the previous works that have used the same databases.

Keywords: Biometrics, iris recognition, Gabor filter, iris coding, iris matching.

I. INTRODUCTION

Nowadays, person identification by human biometric recognition is becoming an essential tool for security applications such as border control, airport security, building access, financial duties and many forensic applications, [1, 2].Biometric data is a privacy information that associates with a person and unlike the traditional methods, it cannot be forgotten or stolen, [3-6].

Many biometric recognition systems have already been developed using various types of human traits such as iris, finger vein, face, fingerprints, palmprint, gait, etc., [7-15]. However, human iris has brought great attention because it has a unique texture for each person. Even the two eyes of the same person have different patterns. In addition, iris patterns are not subject to the effects of aging, therefore it remains stable throughout the life and impossible to be modified without risk, [16].

The two earliest approaches for developing iris recognition system were introduced by Daugman in 1993 and Wildes in 1997, [17,18]. These two approaches later became foundations for the development of many other systems. In these two approaches different methods were used for iris localization, iris normalization, iris coding and matching. In Daugman's approach integro-differential operator was used for iris localization and a rubber-sheet model transform was used for normalization, 1D and 2D Gabor filters were used for iris coding and Hamming Distance (HD) was used for iris matching. In Wildes' approach, Canny edge detection and Hough Transform were used for iris localization, image registration was used for iris normalization and the normalized correlation measure for iris matching. The performance of iris recognition system depends on the efficiency of the methods used for implementing the various stages of the system. In particular, image coding has great influence on the performance of the system. Many image coding methods have been used, e.g., Gabor filters, Log-Gabor filters, the Local Binary Pattern (LBP), Principal Component Analysis (PCA), Discrete Wavelet Transform (DWT) and Fourier Transform (FT), etc. Amongst these, Gabor filter has proven good success, [19]. However, the orientation of Gabor filter has always been the issue.

Many researchers used more than one orientation and different wavelengths with the algorithms of selecting the optimum orientations. In this paper, an iris recognition system, which is based on Gabor kernel with three near-horizontal orientations for iris coding is developed. Other stages of the system were implemented using methods of iris localization and eyelid detection, which were developed previously by [7,20]. Hamming Distance (HD) is used for image matching. The system is evaluated using three different databases, CASIA-V1.0, CASIA-V4.0-Lamp and SDUMLA-HMT. The remaining parts of the paper are organized as follows: A review of the related works is given in section II. A theoretical background for Gabor filter is given in section III. The proposed method of iris coding is given in section IV. Results and discussions are given in section V. Comparisons between the proposed method and the previous methods are given in section VI and finally the conclusions are given in section VII.

II. RELATED WORKS

Many iris recognition systems that have used Gabor filters for image coding have been developed. Sanchez-Avila and Sanchez-Reill, [21] used Gabor filter with four different orientations (0°, 45°, 90°, and 135°). They generated feature vectors of four different sizes, (256-bit, 512-bit, 992-bit, and 1860-bit). They achieved accuracies ranging from 95.3 for the feature size 256 bit to 98.3% for the feature size 1860 bit using Hamming distance as a matching measure. NG and others, [22] used the local Log Gabor filter for iris coding. They achieved 98.62% accuracy using CASIA-V1.0 database. Ibrahim, [23] used a bank of Gabor filters with eight different orientations of Gabor kernel (0°, 22.5°,45°, 67.5°,90°, 112.5°, 135°, and 157.5°). The eight filtered images were combined using the average absolute deviation for generating the feature vector. However, in Ibrahim's system only 50 images were used and no measurements were made for evaluating the performance of the system.

Minhas and Javed, [19] used multichannel Gabor filters globally and locally by dividing the image into four sub-images. They used a number of banks for Gabor filters (15, 20, 25, 30, 35) using six different wavelength (3, 5, 7, 9, 11) and five different orientations (0°, 30°, 60°, 90°, 120°). They achieved the best accuracy of 98.99% when Gabor filter is applied locally with 35 filters using CASIA-1 dataset. Shanthi and Dinesh, [24], used Wildes' approach for iris localization, Gabor filter for iris coding and Hamming distance for matching. They achieved an accuracy of 94.3 using CASIA-V4.0-Lamp database. Saravanan and

Sindhuja, [25], used optimized multi-directional Gabor filter by dividing the image into sub-images and find the optimum Gabor filter for each sub-image by measuring the edge response of different directions. They used four orientations (0°, 45°, 90°, 135°). They claimed that they achieved low EER without mentioning the details. [Rai and Yadav, [26], used the zigzag collarette area of the iris feature extraction, Gabor filter for coding and Support Vector Machin (SVM) for classification.

In addition, Vyas and others, [27] used Haar wavelet decomposition followed by Gabor filter with four orientations for feature extraction. First, the real and imaginary parts of Gabor filter outputs are binarized and combined by XOR operation to produce one coded image for each orientation, and then the four coded images are added and finally coded by bit thresholding. They achieved EER of 3.62 using IITD dataset. Sharma and Mohan, [28], used optimum Gabor filters. They used Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) to select the best of Gabor filters. They achieved an accuracy of 93.4% using GA for optimization and an accuracy of 90.36% with PSO for optimization. Firake and Mahajan, [29], compared three different methods for coding, the phase information of Gabor Wavelet, eigen irises of Principal Component Analysis and feature coefficient vector of Independent Component Analysis. They achieved accuracies of 92.85%, 87.5% and 90% for each of them respectively using CASIA-V1.0 database.

Chai and others, [30], used banks of ID Log-Gabor wavelets for iris coding. However, for matching, they used features selected randomly from the iris code. They achieved an accuracy of 95.07% using CASIA-V1.0 database. Ahmadi and Akbarizadeh, [31], used 2D Gabor filter for iris coding with Neural network with mulita-layer neural network for classification. They achieved recognition rate of 95.36% using CASIA-V3.0. Salve, [32], used 1D Gabor wavelet for iris coding with Support Vector Machin (SVM) as a classifier. Salve's system achieved accuracy of 98.5% using only 200 images of CASIA-V4.0-Lamp database. Tahir and others, [7], used Gabor filter as image coding with only one orientation for Gabor kernel at (0°). They achieved EER of (1.76, 2.45 and 3.2) for CASIA-1, CASIA-Lamp-4 and SDUMLA-HMT database.

Other approaches have also been used for iris coding. For instance, Velisavljevic, [33], used oriented wavelet transforms and achieved 94.7% using CASIA-V3.0-Lamp database. Pranith and Srikanth, [34], used the corner points as features for iris coding and achieved an overall accuracy of 95.4 % using CASIA-V1.0 database. Mattar, [35], used Principal Component Analysis (PCA) and Artificial Neural network (ANN) for developing a system, which achieved an overall accuracy of 92.85 using CASIA-V1.0 database. Ashwini and others, [36], used multiple feature extraction such as Local Binary Pattern (LBP) and Local Phase Quantization (LPQ) and achieved an accuracy of 95% with CASIA-V1.0 database.

Umer and others, [37], used Histogram of Oriented (HOG) for iris coding and SVM for classification. They achieved accuracies of 91.21%, 97.91%, 93.12%, 90.21%, 83.46% for MMU1, UPOL, CASIA-V3.0, IITD, UBIRIS-V1.0 databases respectively. Hamd and Ahmed, [38], used Fourier transform and PCA for feature extraction and Manhattan distance classifier for matching. They achieved accuracies of 96% and 94% for Fourier transform and PCA respectively using CASIA-V1.0 database. Abdulmunem and Abbas, [39], compared two classifiers, SVM and Backpropagation algorithm with PCA as feature extractor. They achieved 90% accuracy for PCA with SVM, while for PCA with BP the result was disappointing, achieved only 3.4% using only a small subset of CASIA-V4.0 database.

In most of the aforementioned works, the orientations of Gabor Kernels, most often, were chosen to cover the angular range between (0 - 180) and did not rely on strong arguments even though, in some works, optimization methods were used for the selection of best orientations. In this paper, the selection of the optimum orientations was done by visual inspection of some of the normalized iris after being enhanced.

III. GABOR FILTER

Gabor filter is a transformation that has achieved significant success in biometric coding in general and in iris coding in specific. In iris coding, the real and imaginary parts (even and odd parts) of Gabor outputs are coded either to 0 or to 1, and then resided alternatively in the rows of the normalized iris. Since the number of columns in the coded iris will be doubled, the final size of the coded iris will be twice as that of the normalized iris. However, the design of an efficient Gabor filter depends on some parameters that control shape and behavior of the filter. The general forms of the 2D Gabor filter according to [7, 40] are given below:

$$g_{\lambda,\theta,\varphi,\gamma}(x,y)even = exp\left(-\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right).cos\left(2\pi i\frac{x'}{\lambda}\right)+\varphi \quad (1)$$

$$g_{\lambda,\theta,\varphi,\gamma}(x,y)odd = exp\left(-\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right).sin\left(2\pi i\frac{x'}{\lambda}\right)+\varphi \quad (2)$$

$$\left.\begin{aligned} x' &= xcosy\theta + ysin\theta \\ y' &= -xsin\theta + ycos\theta \end{aligned}\right\} \quad (3)$$

where, $g_{\lambda,\theta,\varphi,\gamma}(x,y)even$ and$g_{\lambda,\theta,\varphi,\gamma}(x,y)odd$ are the even and odd (real and imaginary) components of Gabor filter. θ is the angle with x-axis and it represents the orientation normal to the parallel stripes of a Gabor filter and φ is the phase offset. λ is the wavelength of the sin and cosine factors of the Gabor filter kernel and β is the half-response spatial frequency bandwidth of Gabor filter. γ is the spatial aspect ratio, which specifies the shape Gabor filter, σx and σy represent the standard deviation in x and y directions, which depend on β and γ. The values of σx and σy are calculated from the following equations:

$$\sigma_x = \frac{\lambda}{\pi}\sqrt{\frac{ln2}{2}}.\frac{2^\beta+1}{2^\beta-1} \quad (4)$$

$$\sigma_y = \frac{\sigma_x}{\gamma} \quad (5)$$

IV. PROPOSED METHOD

In this paper, the system developed by [7] is modified by using three orientation angles for Gabor kernels, instead of one, for image coding. Figure 1 is the layout of the proposed system. Descriptions related to Iris localization, eyelid detection and matching can be found in [7, 20]. Here, descriptions for the stage of iris coding and the justifications for proposed Gabor kernel orientations will be given.

For the iris coding, the most effective choice of Gabor kernel orientation θ is that which makes the direction of the Gabor strips, more or less, parallel to the direction of the iris patterns. The direction of the iris pattern most likely is vertical and near vertical. This means that the change in the iris texture appears in the horizontal and near-horizontal direction. Therefore, a zero value of the orientation angle θ is logical since most of the texture features in the normalized iris will be detected and this was the reason behind the use of ($\theta = 0°$) in most of the previous works, [7]. In other previous works such as [19, 23, 25], more than one orientation within the range (0°-180°) were used, with the option of selecting the orientations that achieve better accuracy. To the authors' view, implementing Gabor filter more than four times and adding the resultant iris codes together for matching will slow the process of recognition. In addition, the directions of iris patterns may not distribute equally within the range of (0°-180°).

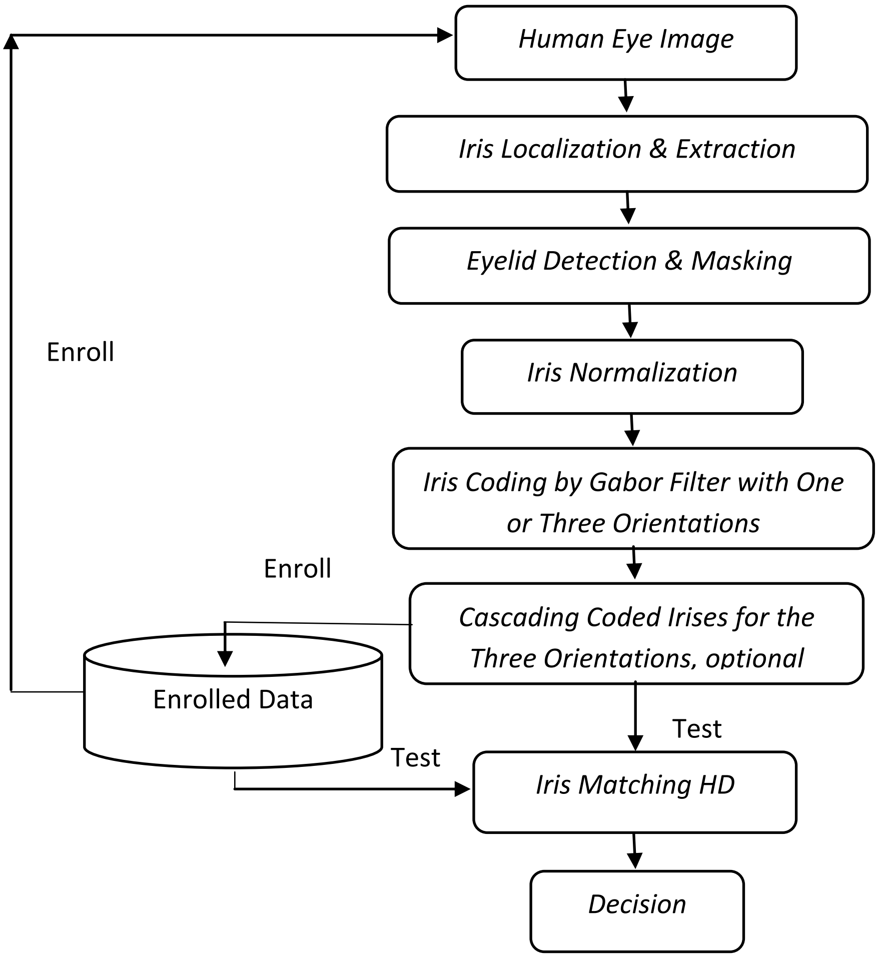

Fig.1 The layout of the proposed system

In the current work, some of the normalized iris for three databases (CASIA-1, CASIA-Lamp-4 and SDUMLA-HMT) were enhanced using histogram equalization technique and inspected visually and it was found that the directions of most patterns are near vertical, nearly within the ranges of (75° to 90 and 90 to 105°). Figure 2 shows three samples of the normalized irises from each database. It is clear from the visual inspection of Figure 2 that the directions of the iris patterns are near to vertical.

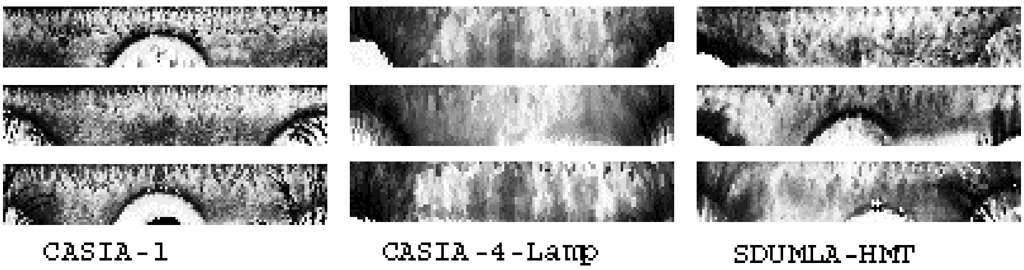

Fig. 2 Directions of iris patterns in the normalized iris for samples from CASIA-1, CASIA-4-Lamp and SDUMLA-HMT databases

This means that the orientation of Gabor kernels should be in the range of (165° to 180° and 0° to 15°) because the orientation of the Gabor kernel is normal to the direction of Gabor strips, which more or less is parallel to the directions of iris patterns. Now, if these two ranges are divided with an interval of 5°, then there will be seven orientations (165°, 170°, 175°, 0°, 5°,10°,15°) to detect most of the iris textures. In this work we took only three orientations, (165°, 0° and 15°), in order to maintain the speed of the system withing a reasonable time. The selection of other parameters such as (λ, β, φ, and γ) that control Gabor filter shape and efficiency play an important role in the detection of the texture. In this paper, the following values are selected: λ = 5, β = 1, φ = 0, γ = 1 and the value of σx and σy are calculated by equations (4 and 5). These values produce Gabor mask of size (9 X 9).

Figure 3 shows Gabor filter strips for the Gabor kernel orientation (θ) values (165, 170, 175, 0, 5, 10, 15) with the above parameters. Only three orientations of Gabor filter kernel were selected in this work, (0, 15, 165), for two reasons. The first is that, these orientations can detect most of the iris features in the near-vertical directions. The second reason is for the purpose of speeding up the process of recognition during the stage of matching.

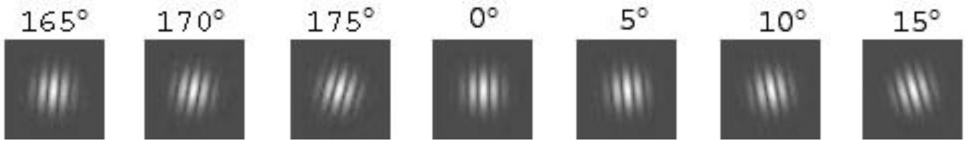

Fig. 3 Directions of Gabor strips for near vertical orientations

V. RESULTS AND DISCUSSIONS

The developed system is applied to three different databases, CASIA-1 (756 images), CASIA-Lamp-4 (1976 images) and SDUMLA-HMT (1060 images). Descriptions of these databases can be found in [41-43]. During the implementation of the system, three iris codes were generated for each database using kernel orientations (0°,15°,165°). The three iris codes were then combined together. The combination of the iris codes is done by adding an option to the system for cascading the three iris codes and for both modes, enrollment and testing, which means that the size of the final code is as big as three times the size of the individual code. Figure 4 shows the cascaded iris codes for one sample of CASIA-1 database.

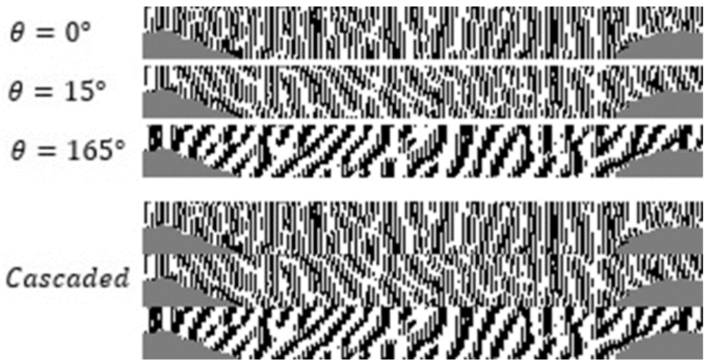

Fig. 4 Three individual iris codes and the cascaded iris codes

Here, it must be mentioned that the developed system achieves accuracy on the expense of computation time. However, as will be seen, the computation time will still be within the range of seconds, therefore it does not represent one real drawback for the developed system. All iris images were included in the enrollment mode and the strategy of leave-one-out was used is in the testing mode. That is, each iris code is matched with all other iris codes except itself. For each orientation/database, the accuracy (ACC), True Positive Rate (TPR) and the Equal Error Rate (EER) were calculated. Tables 1-4 show the performance of the system using individuals and cascaded iris codes. According to these tables, the best performance (Accu, TPR and EER) is achieved by the use of the cascaded iris code using three orientations (0°,15°,165°) for all three databases. For individual iris codes, the orientation of (15°) is the best for CASIA-1 database and(0°) is the best for CASIA-Lamp-4 and SDUMLA-HMT databases. These results ensure that the iris patterns are in the vertical and near vertical directions. Figures 5-7 show the ROC curves for the individual and cascaded iris codes for the three databases. These ROC curves were plotted by projecting the values of HD on the x-axis and the values of the False Positive Rate (FAR) and False Negative Rate (FNR) on the y-axis. The coordinates of the intersection point between the two curves represent the HD-threshold and the EER values.

TABLE. 1 Performance of the system using individual iris code with Gabor orientation $\theta = 0°$

Database	**Gabor Orientation of (0°)**			
	HD Threshold	***ACC%***	***TPR%***	***EER%***
CASIA-V1.0	0.385	96.48	98.24	1.76
CASIA-4.0-Lamp	0.375	95.1	97.55	2.45
SDUMLA-HMT	0.37	93.6	96.8	3.2

TABLE. 2 Performance of the system using individual iris code with Gabor orientation $\theta = 15°$

Database	**Gabor Orientation of (15°)**			
	HD Threshold	***ACC%***	***TPR%***	***EER%***
CASIA-V1.0	0.379	97.32	98.65	1.35
CASIA-4.0-Lamp	0.369	94.33	97.15	2.85
SDUMLA-HMT	0.369	92.80	96.35	3.65

TABLE. 3 Performance of the system using individual iris code with Gabor orientation $\theta = 165°$

Database	**Gabor Orientation of 165°)**			
	HD Threshold	***ACC%***	***TPR%***	***EER%***
CASIA-V1.0	0.3765	95.77	97.71	2.29
CASIA-4.0-Lamp	0.371	93.65	96.82	3.2
SDUMLA-HMT	0.369	92.03	96.04	4.0

TABLE. 4 Performance of the system using cascaded iris codes with Gabor orientations $\theta = 0° + 15° + 165°$

Database	**Gabor Orientation of (0° +15° +165°)**			
	HD Threshold	***ACC%***	***TPR%***	***EER%***
CASIA-V1.0	0.414	98.85	99.42	0.58
CASIA-4.0-Lamp	0.394	96.56	98.25	1.725
SDUMLA-HMT	0.3855	96.0	98.0	2.0

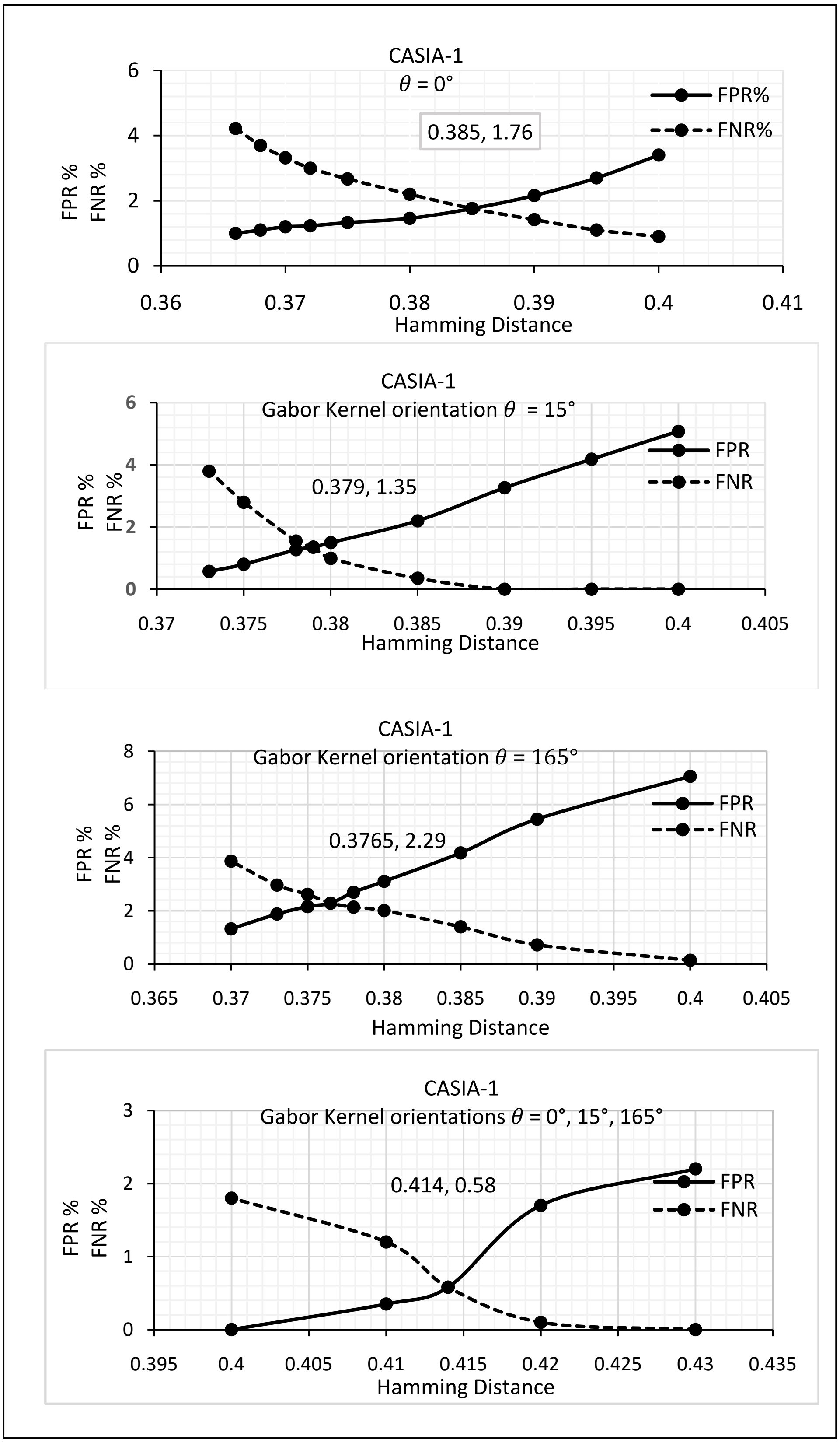

Fig. 5 ROC curves for the individuals and the cascaded cases for CASIA-1 Database

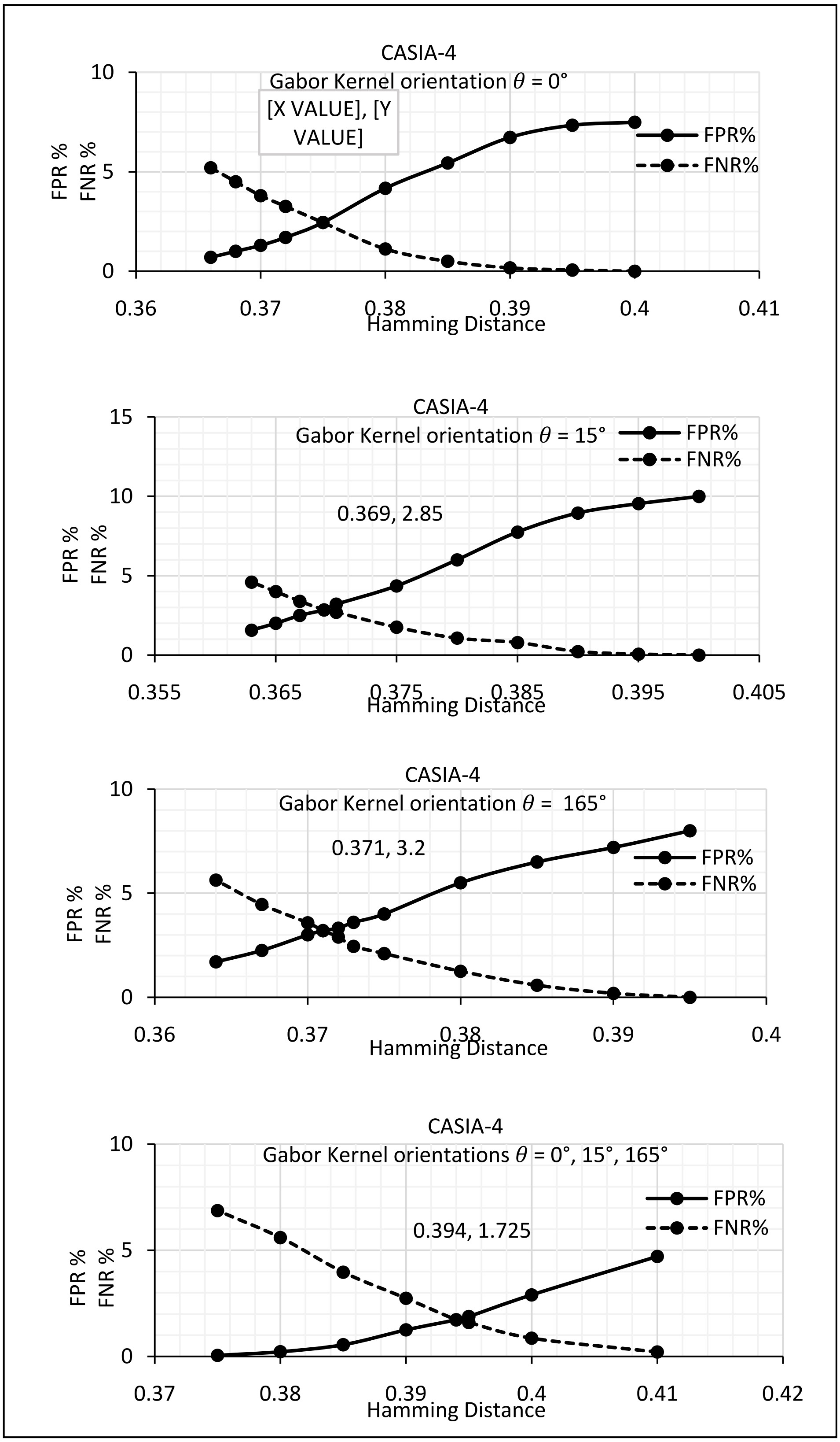

Fig. 6 ROC curves for the individuals and the cascaded cases for CASIA-4-Lamp Database

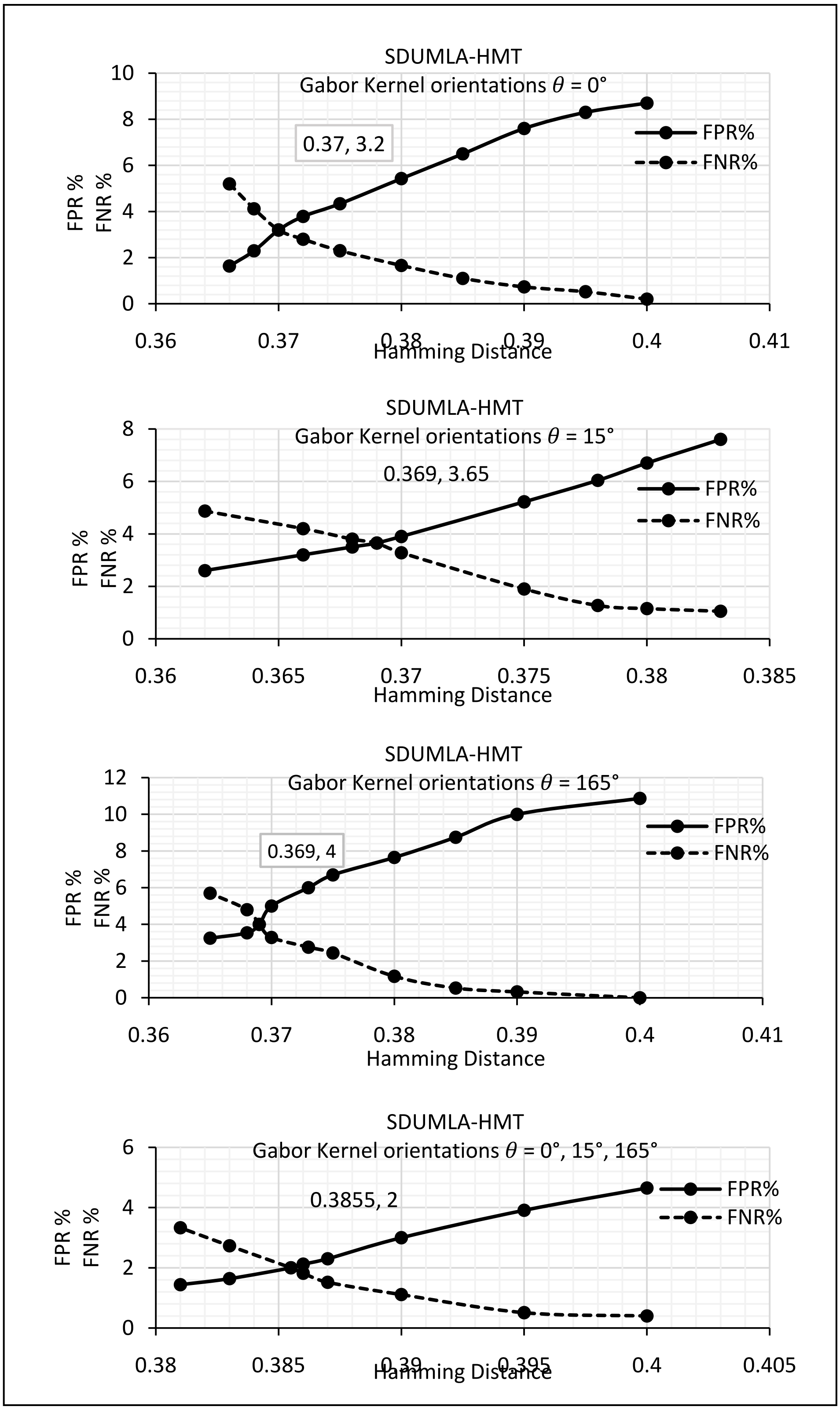

Fig. 7 ROC curves for the individuals and the cascaded cases for SDUMLA-HMT Database

In order to show the computation time for the system, table 5 is given. The time is the same for all stages whether one or three kernel orientations are used, [7]. Only the coding and matching time will be tripled in the case when three kernel orientations are used for coding and the size of the cascaded codes is three times bigger than the code of one orientation. Despite the total computation-time is increased, it is still within the range of seconds. The matching time depends on the number of enrolled codes, the more enrolled codes the more computation time. Since CASIA-4-Lamp database contains more iris codes in the enrolled data, more computation-time will be needed for its matching compared to CASIA-1 and SDUMLA-HMT database.

TABLE. 5 The average processing time for the implementation of the system for one test image

Stage	Time Sec CASIA-V1.0	Time Sec CASIA-V4.0	Time Sec SDUMLA-HMT
Pupil Boundary Detection	0.052	0.040	0.045
Limbic Boundary Detection	0.110	0.085	0.095
Eyelid Detection	0.042	0.023	0.035
Iris Coding	0.57	0.49	0.51
All Stages	0.394	0.313	0.347
Matching	29	75	40.5

VI. COMPARISON WITH PREVIOUS WORKS

In order to show the innovation of this work, the outcome results were compared to those of the previous works. The comparison was restricted on the previous works that have used the same database. Specifically, previous works that have used CASIA-1 and CASIA-4-Lamp databases were included in the comparisons, previous works for SDUMLA-HMT were not found. Table 6 shows the comparison with previous works that have used CASIA-1 and CASIA-4-Lamp databases using Gabor filter and other methods for iris coding.

TABLE. 6 Comparisons between the proposed method and the previous methods for CASIA-1 and CASIA-4-Lamp databases.

CASIA-V1.0		CASIA-V4.0 / V3.0	
Method / Reference	***ACC %***	***Method / Reference***	***ACC %***
Banks of Gabor Filters (35 filters) / [19]	98.99	Oriented WT / [33]	94.7
Corner Features / [34]	95.4	Gabor Filter / [24]	94.3
PCA + Eigen Irises / [35]	92.85	HOG / [37]	93.12
LPQ + LBP / [36]	95	Gabor filter / [31]	95.36
Gabor filter / [29]	92.85	PCA / [39]	90
ID Log-Gabor Wavelets / [(30]	95.07	DWT + PCA / [8]	95.4
Fourier Transform / [38]	96	Gabor Filter / [32]	98.5*
Gabor Filter (0°) orientation / [7]	96.48	Gabor Filter (0°) orientation / [7]	95.1
Gabor Filter with orientations (0°, 15°, 165°) [The Proposed System]	98.85	Gabor Filter with orientations (0°, 15°, 165°) [The Proposed System]	96.56

* Only 200 images out of 1976 images of CASIA-4-Lamp database were used.

Note that, CASIA-4-Lamp and CASIA-3-Lamp are the same, [43]. According to these two tables, the results of the given method of iris coding outrage those of previous works for both cases, except the works of Minhas and Javed, [19] for CASIA-1, and Salve, [32] for CASIA-4-Lamp database, which have achieved higher accuracy. However, in Minhas and Javed work, 35 filters were used with different orientations and wavelengths, while in Salve's work only 200 images out of the total 1976 images of CASIA-4-Lamp database were used.

VII. CONCLUSIONS

The results show that the horizontal and near-horizontal orientations for Gabor kernels (0°, 15°, and 165°) can efficiently convert iris texture into unique codes that improve system performance. The improvement in the accuracy of the recognition for the three databases indicates that, most of iris texture patterns in these databases take directions near-vertical after the process of iris normalization. The use of three codes into one cascaded image in the process of matching may slow down the speed of the recognition, because the time of measuring HD between two images depends on the size of the two images. Accordingly, in this work, the size of the cascaded iris code during the matching stage is three times bigger than the individual iris code, so the time of the matching one cascaded iris code during the test mode will be tripled. However, this increment in the computation time remained within the range of seconds as shown in table 5.

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REFERENCES

[1]. A. K. Jain, K. Nandakumar and A. Nagar, "Biometric Template Security," EURASIP Journals on Advances in Signal Processing, Vol. 2008, 2008, pp. 1–17.

[2]. B. Hamdan and K. Mokhtar, "Face Recognition Using Angular Radial Transform," Journal of King Saud University – Computer and Information Sciences, vol. 30, no. 2, 2018, pp. 141-151.

[3]. J. Daugman, "New Methods in Iris Recognition," IEEE Transactions on Systems, Man, And Cybernetics—Part B: Cybernetics, vol. 37, no. 5, 2007, pp. 1167-1175.

[4]. A. K. Jain, K. Nandakumar and A. Ross, "50 Years of Biometric Research: Accomplishments, Challenges, and Opportunities," Pattern Recognition Letters, vol. 70, 2016, pp. 80-105.

[5]. A. I. Desoky, H. A. Ali and N. B. Abdel-Hamid, "Enhancing Iris Recognition System Performance," International Conference on Computer Engineering & Systems", 2010, pp. 21-26.

[6]. A. A. Mustafa and A. AK. Tahir, "Improving the Performance of Finger vein Recognition System Using a New Scheme of Modified Pre-processing Methods," Academic Journal of Nawroz University, vol. 9, no. 3, 2020, pp. 397-409.

[7]. A. AK. Tahir, S. S. Dawood and S. Anghelus, "An Iris Recognition System Based On A New Method Of Iris Localization," International Journal of Open Information Technologies, vol. 9, no. 7, 2021, pp. 67-76.

[8]. H. K. Rana, S. Azam, M. R. Akhtar, J. M. Quinn and M. A. Moni, "A Fast Iris Recognition System Through Optimum Feature Extraction," Peer Journal of Computer Science, vol. 5, No. e184, 2019, pp. 1-13.

[9]. A. A. Mustafa, and A. AK. Tahir, "A New Finger-Vein Recognition System Using the Complete Local Binary Pattern and the Phase Only Correlation," International Journal on Signal and Image Sciences, vol. 7, no. 1, 2021, pp. 38-56.

[10]. N. Kanjan, K. Patil, S. Ranaware and P.A Sarokte, "A Comparative Study of Fingerprint Matching Algorithms," International Research Journal of Engineering and Technology, vol. 4, no. 11, 2017, pp. 1892-1896.

[11]. V. R. Gosavi, G.S. Sable, K. Anil, et al., "Evaluation of Feature Extraction Techniques using Neural Network as a Classifier: A Comparative Review for face Recognition," vol. 4, no. 2, 2018, pp. 1082-1091.

[12]. L. Fei, G. Lu, W. Jia, et al, "Feature Extraction Methods for Palmprint Recognition: A Survey and Evaluation," IEEE Transactions on Systems Man, and Cybernetics, vol. 49, no. 2, 2019, pp. 346-363.

[13]. X. Li, Y. Makihara, C. Xu, Y. Yagi and M. Ren, "Gait Recognition Invariant to Carried Objects Using Alpha Blending Generative Adversarial Networks," vol. 105, 2020, pp. 1-12.

[14]. P. D. Videkar and K.S. Ingle, "Finger Vein Identification Based on Minutiae Feature Extraction with Spurious Minutiae Removal," International Research Journal of Engineering and Technology, vol. 4, no. 4, 2017, pp.3403-3406.

[15]. S. Biswas and J. Sil, "An Efficient Face Recognition Method Using Contourlet and Curvelet Transform," Journal of King Saud University – Computer and Information Sciences, vol. 32, 2020, pp. 718-729.

[16]. C. S. S. Anupama and P. Rajesh, "Authentication Using Iris," International Journal of Innovations in Engineering and Technology, vol. 2, no. 4, 2013, pp. 126-138.

[17]. J. G. Daugman, "High Confidence Visual Recognition of Persons by A Test of Statistical Independence," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 15, no. 11, 1993, pp. 1148-1161.

[18]. R. P. Wildes, "Iris Recognition: An Emerging Biometric Technology," Proceedings of the IEEE, vol. 85, no. 9, 1997, pp. 1348-1363.

[19]. S. Minhas and M. Y. Javed, "Iris Feature Extraction Using Gabor Filter," International Conference on Emerging Technologies, 2009, pp. 252-255.

[20]. A. A. Tahir and S. Anghelus, "An Accurate and Fast Method for Eyelid Detection," International Journal of Biometrics, vol. 12, no. 2, 2020, pp. 163-178.

[21]. C. Sanchez-Avila and R. Sanchez-Reillo, "Two Different Approaches for Iris Recognition Using Gabor Filters and Multiscale Zero-Crossing Representation," Pattern Recognition, vol. 38, no. 2, 2005, pp. 231-240.

[22]. R. Y. F. Ng, Y. H. Tay and K. M. Mok, "Iris Recognition Algorithms Based on Texture Analysis", International Symposium on Information Technology, 2008, pp. 1-5.

[23]. A. A. Ibrahim, "Iris Recognition Encoding Using Gabor Filters," Al-Taqani, vol. 21, no. 6, 2008, pp. 1-10.

[24]. R. Shanthi and B. Dinesh, “Iris Based Authentication System”, IOSR Journal of Engineering, vol. 3, no. 4, 2013, pp. 15-20

[25]. V. Saravanan and R. Sindhuja, “Iris Authentication through Gabor Filter Using DSP Processor,” IEEE Conference on Information and Communication Technologies, 2013, pp. 568-571.

[26]. H. Rai and A. Yadav, “Iris Recognition Using Combined Support Vector Machine and Hamming Distance Approach,” Expert Systems with Applications, vol. 41, 2014, pp. 588-593.

[27]. R. Vyas, T. Kanumuri and G. Sheoran, “An Approach for Iris Segmentation in Constrained Environments,” Nature Inspired Computing Advances in Intelligent Systems and Computing, 2018, pp. 99-107.

[28]. R. Sharma and V. Mohan, “Iris Recognition Using Gabor Filters Optimized by Genetic Algorithm and Particle Swarm Optimization,” International Journal of Advanced Research in Computer and Communication Engineering, vol. 5, no. 5, 2016, pp. 726-729.

[29]. S. G. Firake and P. M. Mahajan, “Comparison of Iris Recognition Using Gabor Wavelet, Principal Component Analysis and Independent Component Analysis,” International Journal of Innovative Research in Computer and Communication Engineering, vol. 4, no. 6, 2016, pp. 12334-12342.

[30]. T. Y. Chai, B. M. Goi, Y. H. Tay and W. J. Nyee, “A Trainable Method for Iris Recognition Using Random Feature Points,” Conference on Technologies and Applications of Artificial Intelligence, 2017, pp. 142-147.

[31]. N. Ahmadi, and G. Akbarizadeh, “Hybrid Robust Iris Recognition Approach Using Iris Image Pre-Processing, Two-Dimensional Gabor Features and Multi-Layer Perceptron Neural Network/PSO,” IET Biometrics, vol. 7, no. 2, 2018, pp. 153-162.

[32]. S. Salve, “Iris Recognition Using Wavelet Transform and SVM Based Approach,” Asian Journal of Convergence in Technology, vol. V, no. I, 2019, pp. 1-9.

[33]. V. Velisavljevic, “Low-Complexity Iris Coding and Recognition Based on Directionlets,” IEEE Transactions on Information Forensics and Security, vol. 4, no. 3, 2009, pp. 410-417.

[34]. A. Pranith and C. R. Srikanth, “Iris Recognition Using Corner Detection,” 2nd International Conference on Information Science and Engineering, 2010, pp. 2151-2154.

[35]. E. Mattar, “Principal Components Analysis Based Iris Recognition and Identification System,” International Journal of Soft Computing and Engineering, vol. 3, no. 2, 2013, pp. 430-436.

[36]. M. B. Ashwini, I. Mohammad and A. Fawaz, “Evaluation of Iris Recognition System on Multiple Feature Extraction Algorithms and its Combinations,” International Journal of Computer Applications Technology and Research, vol. 4, no. 8, 2015, pp. 592 – 598.

[37]. S. Umer, B. C. Dhara, and B. Chanda, “An Iris Recognition System Based on Analysis of Textural Edgeness Descriptors,” IETE Technical Review, vol. 35, no. 2, 2017, pp. 1-12.

[38]. M. Hamd and S. K. Ahmed, “Biometric System Design for Iris Recognition Using Intelligent Algorithms,” International Journal of Modern Education and Computer Science, vol. 10, no. 3, 2018, pp. 9-16.

[39]. E. Abdulmunem and S. H. Abbas, “Iris Recognition Using SVM and BP Algorithms”, International Journal of Engineering Research and Advanced Technology, vol. 4, no. 5, 2018, pp. 30-37.

[40]. H. Wei, Y. Li and C. T. Li, “Effective Extraction of Gabor Features for Adaptive Mammogram Retrieval", IEEE International Conference on Multimedia and Expo, 2007, pp. 1503-1506.

[41]. P. J. Phillips, K. W. Bowyer and P. J. Flynn, “Comments on The CASIA Version 1.0 Iris Data Set”, IEEE on Pattern Analysis and Machine Intelligence, vol. 29, no. 10, 2007, pp. 1869-1870.
[42]. Y. Yin, L. Liu and X. Sun, “SDUMLA-HMT: A Multimodal Biometric Database”, In Sun, Z., Lai, J., Chen, X. and Tan, T. (Eds.): ‘Biometric Recognition, 2011, pp. 260–268.
[43]. Center for Biometrics and security Research, “Notes on CASIA-IrisV4”, Available: http://www.cbsr.ia.ac.cn/china/Iris%20Databases%20CH.asp.