

# Analysis of the Parameters Involved in the Iris Recognition System

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**Abstract:** *Biometric recognition is a computerized identification method which is based on unique features or characteristics possessed by human beings and Iris recognition has proved itself as one of the most reliable biometric methods available owing to the accuracy provided by its unique epigenetic patterns. The main steps in any iris recognition system are image acquisition, iris segmentation, iris normalization, feature extraction and features matching. EER (Equal Error Rate) metric is considered the best metric for evaluating an iris recognition system. In this paper, different parameters viz. the sigma for blurring with Gaussian filter while detecting edges, the scaling factor to fasten the CHT (Circle Hough Transform), the gamma correction factor for gamma correction and the radius for weak edge suppression for the edge detector during segmentation; the sigma upon central frequency and the central wavelength for convolving with Log-Gabor filter during feature extraction have been thoroughly tested and analyzed on the CASIA-IrisVI database to get an optimized parameter set. This paper provides an insight into how the parameters must be set to have an improved Iris Recognition System*

**Keywords:** Biometric recognition, Circle Hough Transform, Equal Error Rate, Log-Gabor filter, CASIA, Gamma correction

## 1. Introduction

Biometric identifiers are the measurable and distinctive features that are used to describe and represent individuals [1]. A biometric system usually functions by first capturing a sample of any biometric feature, such as capturing a digital colour or grayscale image of a face which is further to be used in facial recognition or recording a digitized sound signal which is further to be used in voice recognition. The sample may then be refined so that the most discriminating features can be extracted and noises in the sample are reduced thus facilitating the recognition. The sample is then transformed into a biometric template using some sort of mathematical function. The biometric template is a normalized and efficient representation of the sample which can be used for comparisons.

Currently, increasing numbers of applications are using biometrics for identification, authentication and recognition. For example, there are banks that deploy ATMs that authenticate users by biometric recognition. Recognition of the human eye Iris is a method of identification and verification through biometric that uses pattern-recognition techniques based on high quality images of the irises of an individual's eyes. Iris-based personal recognition is on trumps when compared with other biometric technologies such as fingerprint, face and speech recognition [2] because of its high accuracy (considered as the most accurate biometric technology available today), good stability, non-intrusiveness and high recognition speed [3–5]. A number of distinct steps are involved in the analysis of the human iris in an iris recognition system. These steps are image acquisition, iris segmentation (finding the location of the iris in an eye image), iris normalization (mapping the textural details of the iris ring into a fixed-size rectangular pattern to account for the possible differences in the size of irises), feature extraction (recording the details of the iris in a feature vector/ template) and features matching (calculating the similarity degree between any two feature vectors).

Initial prototype devices for iris recognition had been discussed earlier, but actual work for a functional model was done in the year 1990's by Professor John Daugman (University of Cambridge) [6]. The Daugman's system (1994) was the one first patented and that has been licensed to many commercial developers of the iris recognition system. A large number of studies have tested the Daugman system and all have reported a failure rate of zero. It's claimed that the Daugman system can identify an individual perfectly from a million possibilities.

Other scientists, Libor Masek [7] used near-infrared illumination in his thesis and cameras were also accepted as beneficial. Although, Masek did parametric analysis but focus deviated away from the final result of better EER (Equal Error Rate) he focused on the decidability etc. Some did analysis of Gabor filter [8], some particular angular span and length of the radius of iris [9], some analysed the frequency, scale and the orientation of Gabor filter for the iris feature extraction [10] and so on but most of them didn't do so for reducing EER (but rather on decidability index (DI) or FAR (False Acceptance Rate) or FRR (False Rejection Rate) or GAR (Genuine Acceptance Ratio)) [8][10] and some used other databases[9]. Moreover, the EER results were not satisfactory for the cases where EER was indeed considered [11].

EER metric is considered the best metric for evaluating an iris recognition system. EER is the point where the false identification and false rejection rate are combinedly minimal and optimal i.e. it is a compromise between FAR and FRR. Hence a single point describes many graphs (e.g. Detection Error Trade-off (DET)). The values of FRR and FAR are threshold dependent. By adjusting the threshold, a list of FRR and FAR values are obtained (and these are the point on a DET curve). A high FAR will increase the risk of accepting access of unauthorized personnel. On the other hand, a high FRR will cause a genuine user to have problems in accessing as the probability of rejection is

increased. As accuracy (defined in III section) is defined for all thresholds, hence accuracy and the EER are never simultaneously at their optimal value for the same threshold value.

The global market for Iris Biometrics is predicted to reach US\$ 1.8 billion by 2020, as is evident by its use in nearly every purpose related to a person's identity and the developments in the cognitive Internet of things (CIoT). In the last decade the US, UK and United Arab Emirates (UAE) have all used, and are still using, iris recognition to identify potential fraudsters and known undesirables, which clearly shows its increasing role in security applications.

## 2. Related Work

According to Wildes *et al.* [13], the first use of iris recognition for individual identification was in the late 1800's when the colour pattern of the iris of inmates in a Parisian prison was visually inspected to determine their identity. In 1936, the idea of using iris patterns as a method to recognize an individual was proposed by Frank Burch. However, it was not until the end of the Second World War (2 September 1945) that ophthalmologists started writing more seriously about the possibility of using the iris patterns of the human eye as a method of identifying individuals. Libor Masek [7] (2003) used near-infrared illumination in his thesis and cameras were accepted as beneficial and he used Canny edge detection along with Hough transforms to segment the eye images which were already proved beneficial by Wildes [13]. But he did a subjective manual evaluation of the segmentation step not the evaluation of the entire process results. Daugman's rubber sheet model [6] was used by him for translating from Cartesian to polar coordinates i.e. for normalization. A Daugman style polar unwrapping of the iris provides the separated iris image that is then encoded by convolving it using 1D Log-Gabor wavelets. Lastly, it is quantized by phase quadrature where matching between subsequent codes is 50%. For the matching stage of iris recognition, Masek created a binary template, consisting of two-bits per pixel, which is called the iris code. This iris code is then compared to the codes in the database using the Hamming distance to calculate dissimilarity scores [14]. Matching is via the Daugman Hamming distance test.

In Masek's work the impact on EER was not studied at all, although impact of parameters of Log-Gabor filter (like Centre Wavelength and Sigma/f) on decidability and on number of degrees of freedom (DOF) was studied, also separately effect on number of degrees of freedom (DOF) with different shifts while calculating Hamming distance was studied.

In work by Mayank Vatsa *et al.* [8], neither parameters that controls Textural Feature Extraction Using the 1-D Log Polar Gabor Wavelet nor parameters that controls topological feature extraction using the Euler number have been analysed. The analysis for accuracy was done only for the parameters of the ellipse in the two-stage iris segmentation using the proposed elliptical model for three databases other than the CASIA-IrisV1 [12] database used in this work.

Ajay Kumar *et al.* [11] combines phase encoding of texture information to achieve further improvement over the methods used without combining. The approaches tested were Log-Gabor, Haar wavelet, DCT and FFT. During testing the centre frequency and bandwidth of Log-Gabor filter were the only parameters analysed and that was based on GAR and DI. The experiments using CASIA-IrisV1 database provided an EER of 0.94 with single training and 0.36 with two trainings (in this proposed work it is 0.0076).

In the work done by Thiyaneswaran *et al.* [15] the Gaussian filter and the Gaussian envelop coefficients were varied to reduce the computing time on the UBIRIS Version 2.0 iris data base images. The proposed Gabor wavelet reduced the feature extraction time at average to 141 Nano seconds. So, no effort was made for reducing EER.

In the research work by Al-Waisy *et al.* [16] the focus has been on health care systems where a high-security level is required in order to protect extremely sensitive records of patients. The goal is to provide a secure access to the right records at the right time with high level of patient privacy being maintained. The pupil's parameters (i.e. the radius and center coordinates) are employed for discarding the unnecessary edge points within the iris region in order to reduce the search time of the Hough transform. But the accuracy achieved was just 99.07% for CASIA Version 1.0 database (in this proposed work it is 99.34%). First of all the role of other various parameters like sigma upon central frequency, the central wavelength of Log-Gabor filter and likewise were not studied and secondly the impact on EER was not studied. Why EER is more important than accuracy was mentioned in the previous section.

Rupesh Mude *et al.* [10] did the feature extraction by 2D-Gabor filter. The paper was based on a detailed analysis of the impact of the frequency, scale of filter defining the Gabor in the spatial domain, the frequency  $\omega$  of the 2D-Gabor filter, orientation of the filter on the decidability index. It discusses how these parameters may influence the filter performance but doesn't give any insight on final result even in terms of accuracy. No discussion on EER was made. In summary, few researchers have emphasized on improving EER along with improving on time and space and moreover they have emphasized upon the important factors like the filters used, the thresholds and so on. Here in case of this research these parameters are: the sigma for blurring with Gaussian filter while detecting edges, the scaling factor to fasten the Hough transform, the gamma correction factor for gamma correction and the radius for weak edge suppression for the edge detector during segmentation; the sigma upon central frequency and the central wavelength for convolving with Log-Gabor filter during feature extraction. Hence, there is a rare possibility of finding a research with the parameters being explicitly tested for reducing EER.

## 3. Analysis of the Parameters Used in the Various Stages of Iris Recognition

Graphs were plotted as part of the methodology for evaluation of the parameters. Further analysis was done as explained below. The results obtained when these optimum parameters are used with modification of CHT algorithm

show real improvements. Metrics FAR (False Acceptance Rate), FRR (False Rejection Rate), EER (Equal Error Rate), Accuracy, TPR (True Acceptance Rate) and TNR (True Rejection Rate) have been used to measure the efficiency of the proposed system and have been explained in this section.

FAR (False Acceptance Rate): FAR is defined as the number of false acceptance for each negative identification attempt.

$$FAR = \frac{\text{Number of false acceptance}}{\text{Actual Number of negative identification attempt}}$$

FRR (False Rejection Rate): FRR is defined as the number of false rejection for each positive identification attempt.

$$FRR = \frac{\text{Number of false rejection}}{\text{Actual Number of positive identification attempt}}$$

True Positive (Acceptance) Rate (TPR) = 1-FRR

True Negative (Rejection) Rate (TNR) = 1-FAR

TP (Total number of correct acceptances) = TPR\* Actual Number of positive identification attempt

TN (Total number of correct rejection) = TNR\* Actual Number of negative identification attempt

Accuracy: Accuracy is defined as the total number of correct rejections and acceptances over the total number of attempts made to enter the system.

$$Accuracy = \frac{TP+TN}{TP+FN+FP+TN}$$

EER: EER is the point where the false identification and false rejection rate are combinedly minimal and optimal. It is a compromise between FAR and FRR. The lower the EER, the better is the system.

#### 4. Evaluation of Sigma for Gaussian Filter of Canny Edge Detector

The size of the Gaussian filter (low pass), the smoothing filter used in the first stage of the Canny edge detection [17] algorithm, directly affects its final results. Smaller filters cause less blurring and allow detection of small, sharp lines (sharp gradient changes). The lower frequencies mean there are not a lot of changes in intensity. Low pass filters pass low frequencies

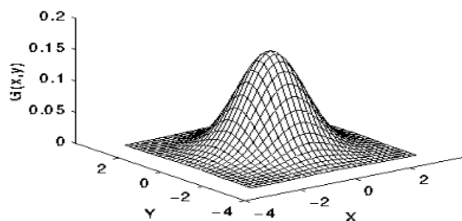


Figure 1: 2-D Gaussian distribution with mean (0, 0) and  $\sigma=1$  [17]

Edges (high frequencies) become smoother as one increases sigma because more detail is compromised and the extent of the pixels to be considered in the detail is reduced. As we decrease the sigma we get more details of the pixels. When one increases the standard deviation in the normal distribution, the distribution spreads out more and the peak becomes less spiky. With increase in the standard deviation,

the image will be more blurry for a given Gaussian filter as sigma shows variation or spread at a peak.

More spread means smoother peak (Larger standard deviation Gaussians require larger convolution kernels in order to be accurately represented as  $\sigma$  determines the width of the Gaussian kernel and the localization error to detect the edge increases).

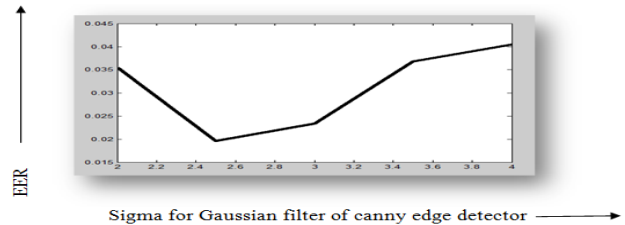


Figure 2: Sigma for Gaussian filter of canny edge detector Vs EER

The degree of smoothing should be appropriate, depending upon whether that level of blurring helps to remove useless data and get the required detail or misses out the detail required because if it increased too much, the edge to be detected can get blurred and consequently the EER increases. So firstly smoothing proves beneficial and EER is observed as decreasing but beyond a particular point (which is optimal, here 2.5) it starts increasing as is depicted in the graphical plot of Fig. 2 above.

#### 5. Evaluation of Radius for Non-Maxima Suppression

After blurring, edge extracted from the gradient value (rate of intensity change at each point in the image (figure given below)) is quite blurred and hence wide. Say, the detected edge is a 5px long edge, so now, if one wants that the location of the edge be marked by 1px wide line then the edge suppressing technique can be used which finds the "maximum" in the blurred-edge gradient and marks the middle pixel (edge thinning technique) as the actual edge. The radius parameter used in Non-maxima suppression is the distance in pixel units to be looked at on each side of each pixel when determining whether it is a local maximum or not. Thus non-maxima suppression helps to ignore all gradient values (sets them to 0) other than the local maxima as that denotes locations with the widest change (an accurate response that must be marked as edges) of the intensity value. Instead of doing an explicit differentiation perpendicular to each edge a different kind of approximation is often used.

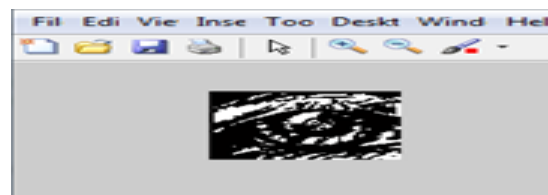
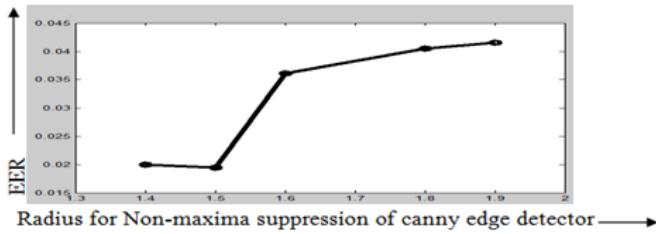


Figure 3: Image containing feature normal/gradient orientation angles in degrees (0-180), angles positive anti-clockwise for knowing gradient direction





**Figure 4:** Non-maxima suppression radius for canny edge detector Vs EER

A radius of 1.5 is deemed appropriate for the edge suppression because till that point non-maxima suppression is helpful but after which the EER starts increasing.

### 6. Evaluation of Gamma Correction Factor for Gamma Correction

Gamma correction [18], or often simply gamma, is, in the simplest cases, defined by the following power-law expression:

$$V_{out} = A (V_{in})^\gamma \quad \dots\dots\dots (1)$$

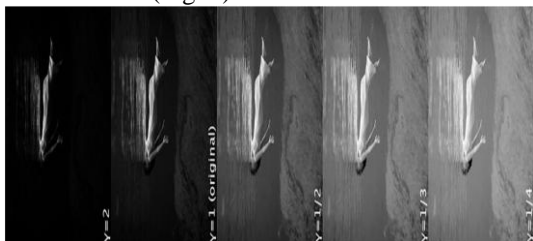
If in an electronic equipment like T.V. light intensity  $I$  is related to the source voltage  $V_s$  as:

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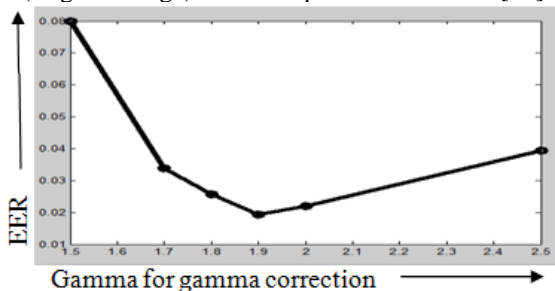
The inverse of the function above is:

$$I \propto (V_s)^{1/\gamma} \quad \dots\dots\dots (3)$$

And this relation (the inverse transfer function (gamma correction)) is used to compensate for the effect in the light intensity due to gamma function, as given in equation (2), so that the end-to-end response is linear. Gamma correction updates the contrast so that the output picture has the intended luminance and helps to segment and classify efficiently. Powers larger than 1 make the shadows darker, while powers lesser than 1 make dark regions lighter (Figure below). So, an appropriate gamma correction factor can ease the process of gamma correction to a high extent and this checking is done via a graphical plot of Gamma for Gamma correction Vs EER (Fig. 6)



**Figure 5:** The effect of gamma correction on an image (original image) when the powers are varied [18]

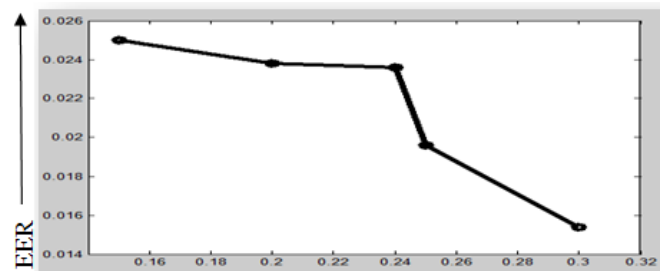


**Figure 6:** Gamma for gamma correction Vs EER

Here 1.9 is taken as the optimum gamma correction factor as there EER is least.

### 7. Evaluation of Scale for Speeding the Hough Transform

Scaling has been used in this work for speeding the Hough Transform. Scaling works by scaling down upper and lower radiuses along with their difference in the Hough Transform. It has also been used in Canny Edge Detection for scaling down the whole image before the detection is done. Scaling, if increased, will no doubt give better results (i.e. reduce EER as depicted in the figure on next slide) but will also increase the space and time consumed.



**Figure 7:** Scaling for speeding Hough transform Vs EER

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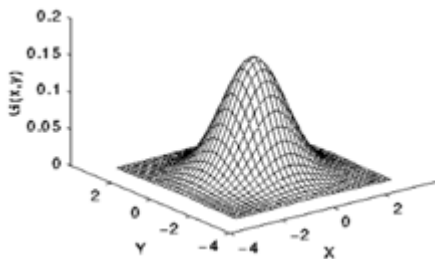
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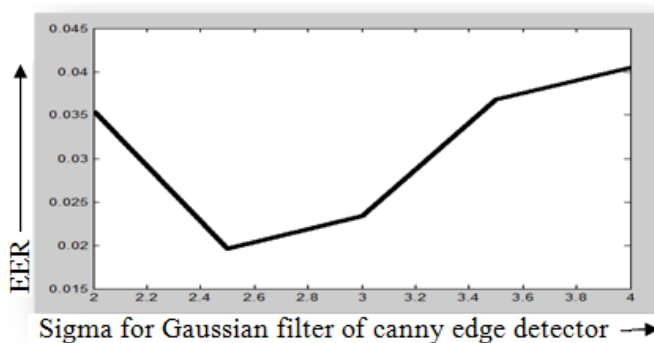
(sharp gradient changes). The lower frequencies mean there are not a lot of changes in intensity. Low pass filters pass low frequencies



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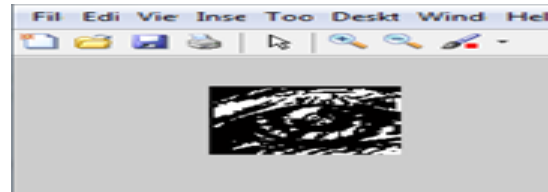
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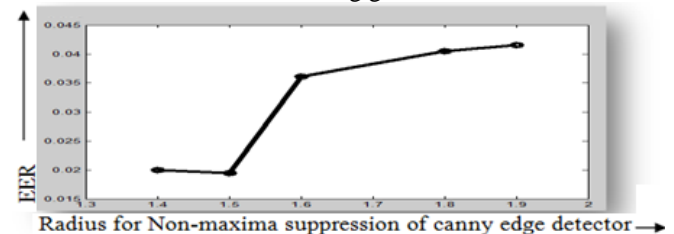
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The inverse of the function above is:

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And this relation (the inverse transfer function (gamma correction)) is used to compensate for the effect in the light intensity due to gamma function, as given in equation (2), so that the end-to-end response is linear. Gamma correction updates the contrast so that the output picture has the intended luminance and helps to segment and classify efficiently. Powers larger than 1 make the shadows darker, while powers lesser than 1 make dark regions lighter (Figure below). So, an appropriate gamma correction factor can ease the process of gamma correction to a high extent and this

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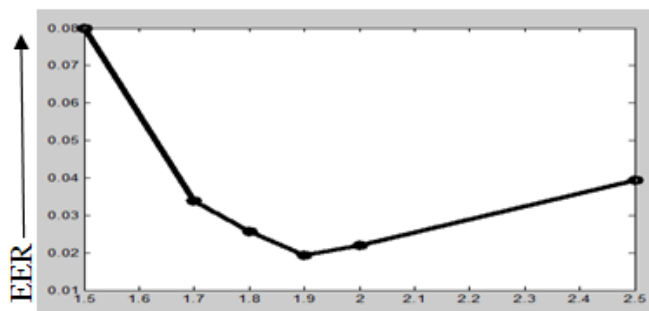


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Here 1.9 is taken as the optimum gamma correction factor as there EER is least.

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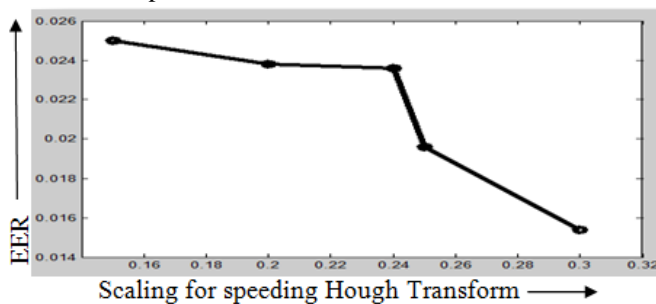


Figure 8: Scaling for speeding Hough transform Vs EER

The point 0.25 is taken as it is the middle point in the graph so that neither too much of scaling down nor lesser scaling does occur.

### 12. Evaluation of Centre Wavelength of Log-Gabor Filter

Centre wavelength of the Log-Gabor filter [19] (inverse of central frequency) is a fixed constant used in the Log-Gabor filter and defines the central frequency around which

frequency is being looked for in the texture. Increasing central wavelength decreases EER but at a reduced frequency, it is observed that accuracy suffers. Also, minute decrease in EER shouldn't deviate to a solution where only a few samples (meaning less frequency resolution) are used but this is at the cost of a higher spatial/temporal resolution (space more). So, a central wavelength of 11 (Fig. 8) is chosen as the optimal value for an efficient and properly working system with respect to all metrics (TP/TN).

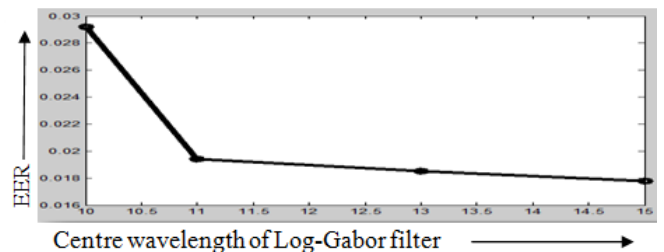


Figure 8: Centre wavelength of Log-Gabor filter Vs EER

### 13. Evaluation of Sigma upon the Filter Center Frequency for Log-Gabor Filter

Log-Gabor filter can locally represent frequency information [20]. The Gabor filter is a good method for simultaneously localizing spatial/temporal (value of the pixels of images as it is) and frequency information (rate at which the pixel values are changing in spatial domain). At some bandwidths, the Gabor filter has an effective DC component and thus it gives a feature that over-represents lower frequencies. Log-Gabor filter does not exhibit this problem.

In general, shape of the filter is determined by  $\sigma/f$  (where  $f$  is the central frequency, sometimes denoted  $f_0$ ). The Sigma appears in the Gaussian part only and has the same role (bandwidth of the filter) here as was described for the Sigma of the Gaussian filter of canny edge detector and the filter center frequency is a fixed constant which divides the sigma in the Log Gabor equation.  $f$  defines the frequency being looked for in the texture. By varying  $\sigma$ , we change the support of the basis or the size of the image region being analyzed i.e. width around the central frequency for feature extraction. The graphical plot (Fig. 9) for analysis and testing of the parameter further clarifies its effect. (EER gets reduced as the width of texture extraction increases and after a particular point when useless frequencies are extracted, it starts increasing).

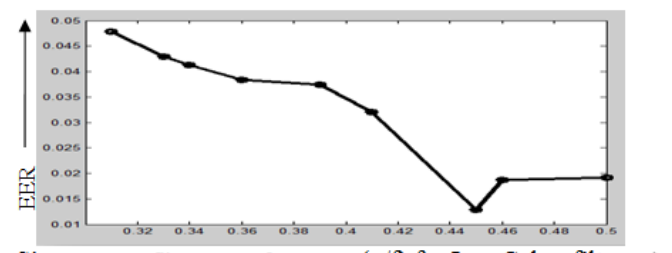


Figure 9:  $\sigma/f$  for Log-Gabor filters Vs EER.

The point 0.45 is taken as  $\sigma/f_0$  as there the EER is optimum.



## 14. Conclusion

The vital role played by the incorporation of optimized parameters used in the different stages of an iris recognition system on the EER was observed in this paper. These parameters are the sigma for blurring with Gaussian filter while detecting edges, the scaling factor to fasten the Hough transform, the gamma correction factor for gamma correction and the radius for weak edge suppression for the edge detector during segmentation; the sigma upon central frequency and the central wavelength for convolving with Log-Gabor filter during feature extraction. Further, as during the optimization of the parameters care was taken to not to adversely affect space and time hence an efficient Iris Recognition System resulted. So, the conclusion is made that a thorough analysis of various Parameters Involved in the Iris Recognition System helps to build up a system which apart from having good EER, also exhibits additional required properties and is thus optimized in its performance. Further, more work needs to be done in this type of parametric analysis so that the system acts as per the situation and is properly calibrated.

## 15. Acknowledgments

I wish to thank all the faculty members of the Department of Computer Science and Engineering DR. B R Ambedkar National Institute of Technology, Jalandhar, India for their valuable suggestions. I would also like to thank my family for their continuous support and blessings during the whole period of the work. Part of this research paper use the CASIA-IrisVI collated by the Chinese Academy of Sciences' Institute of Automation (CASIA).

## References

- [1] A. Jain, L. Hong and S. Pankanti, "Biometric Identification", Communications of the ACM, 43(2), p. 91-98. DOI 10.1145/328236.328110, 2000.
- [2] S. Sanderson and J. Erbetta, "Authentication for secure environments based on iris scanning technology", IEEE Colloquium on Visual Biometrics, 2000.
- [3] K. W. Bowyer, K. Hollingsworth and P. J. Flynn, "Image understanding for iris biometrics: A survey", Computer Vision and Image Understanding, vol. 110, pp. 281-307, May 2008.
- [4] J. Daugman, "How iris recognition works", IEEE Trans. Circuits Syst. Video Technol., vol. 14, pp. 21-30, January 2004.
- [5] R. P. Wildes, "Iris recognition: an emerging biometric technology", Proceedings of the IEEE, 1997, pp.1348-1363.
- [6] J. Daugman, "Biometric personal identification system based on iris analysis", United States Patent, Patent Number: 5,291,560, 1994.
- [7] L. Masek, "Recognition of Human Iris Patterns", 2003. [Online]. Available: <http://citeseerx.ist.psu.edu/viewdoc/download?sessionid=001A0AB43F22986C03207D0801DFFF07?doi=10.1.1.90.5112&rep=rep1&type=pdf> [Accessed June 20, 2018].
- [8] M. Vatsa, R. Singh, A. Noore, "Improving iris recognition performance using segmentation quality enhancement

- match score fusion and indexing", *IEEE Trans. Syst. Man Cybern. B Cybern.*, vol. 38, no. 4, pp. 1021-1035, 2008.
- [9] T. Marciniak, A. Dąbrowski, A. Chmielewska, A. Krzykowska, "Selection of parameters in iris recognition system", *Multimedia Tools And Applications*, vol. 68, no. 1, pp. 193-208, January 2014.
- [10] Rupesh Mude & Meenakshi R Patel "Gabor Filter for Accurate IRIS Segmentation Analysis" *International Journal of Innovations in Engineering and Technology* Volume 6 Issue 1 October 2015.
- [11] Ajay Kumar , Arun Passi, Comparison and combination of iris matchers for reliable personal authentication, *Pattern Recognition*, v.43 n.3, p.1016-1026, March, 2010 [doi 10.1016/j.patcog.2009.08.016]
- [12] T. Tan, "Note on CASIA-IrisVI", Chinese Academy of Sciences' Institute of Automation, 03 2011. [Online]. Available: <http://biometrics.idealtest.org/>. [Accessed April 30, 2018].
- [13] R. Wildes, J. Asmuth, G. Green, S. Hsu, R. Kolczynski, J. Matey and S. McBride, "A system for automated iris recognition", Proceedings of the Second IEEE Workshop on Applications of Computer Vision, Sarasota, FL, 1994.
- [14] R. Hamming, "Error detecting and error correcting codes", *The Bell System Technical Journal*, vol. 29, no. 2, pp. 147-160, 1950.
- [15] Thiyaneswaran, B. Padma, S. 2014. "Analysis of Gabor Filter Parameter for Iris Feature Extraction", *International Journal of Advanced Computer Technology (IJACT)*.3(5). pp: 45-48.
- [16] A. S. Al-Waisy, R. Qahwaji, S. Ipson and S. Al- Fahdawi, "A Fast and Accurate Iris Localization Technique for Healthcare Security System", IEEE International Conference on Computer and Information Technology; Ubiquitous Computing and Communications; Dependable, Autonomic and Secure Computing; Pervasive Intelligence and Computing; pp. 1028–1034, 2015.
- [17] Wikipedia contributors. Wikipedia Organization. "Canny\_edge\_detector". [Online]. Available: [https://en.wikipedia.org/wiki/Canny\\_edge\\_detector](https://en.wikipedia.org/wiki/Canny_edge_detector). [Accessed April 30, 2018].
- [18] Wikipedia contributors. Wikipedia Organization. "Gamma\_correction". [Online]. Available: [https://en.wikipedia.org/wiki/Gamma\\_correction](https://en.wikipedia.org/wiki/Gamma_correction). [Accessed April 30, 2018].
- [19] Wikipedia contributors. Wikipedia Organization. "Log\_Gabor\_filter". [Online]. Available: [https://en.wikipedia.org/wiki/Log\\_Gabor\\_filter](https://en.wikipedia.org/wiki/Log_Gabor_filter). [Accessed April 30, 2018]. [6]. CIGRÉ Tech. Brochure # 379, "Update of service experience of HV underground and submarine cable systems," 2009.
- [20] Wikipedia contributors. Wikipedia Organization. "Log\_Gabor\_filter". [Online]. Available: [https://en.wikipedia.org/wiki/Log\\_Gabor\\_filter](https://en.wikipedia.org/wiki/Log_Gabor_filter). [Accessed April 30, 2018].

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