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EFFECT OF SEGMENTATION, ENCODING ON LOW RESOLUTION IRIS IMAGES FOR IRIS RECOGNITION

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ABSTRACT

IRIS RECOGNITION

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Iris recognition represents one of the most convenient and reliable authentication program amongst all biometric modalities.Some advantages that make the iris recognition to be the best of biometric solutions is accuracy(low false rejection rate) ,stability (unchangable during lifetime),scalability(easily deployed in different scale programs).This paper examines an iris recognition method based on genetic algorithms (GA) which are used to provide fast and optimized implementation for future use.However, there is still space to make some improvements on accuracy and speed ,for this reason we are trying to modify some encoding parameters such as minimum wavelength and sigma in order to find some relations with accuracy.We will try to generate different functions to perform different results with different data set used each time by using encoding algorithms .We compare these results in order to find the most accurate one .Results generated by each test will be displayed by a table and the comparision will be illustrated by different graphs.All our experiments are done on CASIA(Chinese Academy of Science-Institute of Technology) database having 7 images for each person .There are 108 people in the database.Considering all these experiments we will conclude on the best performance of the algorithm .

Keywords:Iris Recognition,Accuracy,EER,Encoding

ABSTRAKT

NJOHJA E IRISIT

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Udheheqësi:Prof.Dr. Arban Uka

Njohja e Irisit paraqet një nga programet më të përshtatshme dhe më të besueshme të autentifikimit midis të gjitha modaliteteve biometrike. Disa avantazhe që e bëjnë njohjen e irisit të jetë më e mirë midis zgjidhjeve biometrike është saktësia (shkalla e ulët e refuzimit), stabiliteti (i pandryshueshëm gjatë jetës), shkallëzimi (shpërndarje në programe me shkallë të ndryshme). Ky dokument shqyrton një metodë të njohjes së irisit bazuar në algoritme gjenetike (GA) të cilat përdoren për të siguruar një implementim të shpejtë dhe të optimizuar për përdorim në të ardhmen.Sidoqoftë, ka ende hapësirë për të bërë disa përmirësime në saktësinë dhe shpejtësinë e algoritmit, për këtë arsye ne jemi duke u përpjekur për të modifikuar disa parametra enkodimi të tilla si :gjatësi vale minimale dhe Sigma ;në mënyrë që të gjejmë performancën më të saktë.Ne do të përpiqemi të gjenerojmë funksione të ndryshme për të nxjerrë rezultate të ndryshme me të dhëna të ndryshme të vendosura çdo herë në algoritmet e enkodimit. Ne i krahasojmë këto rezultate në mënyrë që të gjejmë më të saktën. Rezultatet e gjeneruara nga secili test do të shfaqen në një tabelë dhe krahasimi midis tyre do të ilustrohet me grafikë të ndryshëm. Të gjitha eksperimentet tona janë bërë në bazën e të dhënave CASIA (Akademia Kineze e Shkencave-Instituti i Teknologjisë) që ka 7 imazhe për secilin person. Në bazën e të dhënave ka 108 njerëz.

Duke marrë parasysh të gjitha këto eksperimente do të përfundojmë duke gjetur performancën më të mirë të algoritmit.

Fjalë kyçe: Njohja e Irisit, Saktësia, EER, Enkodimi

Dedicated to my FATHER and my family!

ACKNOWLEDGEMENTS

I would like to thank my supervisor Prof. Dr. Arban Uka , who supported my work and helped me to find a solution for all the obstacles I faced during all the stages of my thesis. I am grateful to him for the patience and support he had to guide me in numerous tests I run through my research. I would like to thank also my parents for their continuous encouragement and motivation throughout writing this thesis.

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LIST OF FIGURES

LIST OF ABBREVIATIONS

m	Mean (average)
sd, std	Standard deviation
DoF	Degree of freedom
Dprime	Decidability
W	wavelength

CHAPTER 1

INTRODUCTION

1.1.Authentication

Authentication determines what someone or something truly is. Its technology checks whether someone's credentials entered in a system do correctly match with the ones registered in the database. Due to this technology different organizations around the world can permit only authenticated users to access its protected resources. There are three factors that favor the authentication process*: the knowledge, the possession* and *the inheritance*. The knowledge consists on the credentials the user provides to access a specific system. The possession are the item credentials a user can carry. The inheritance is based on biometric identification. The task of authentication process is to improve the security The oldest factor is "*the knowledge*" which allows a user to enter a password, providing only this type of identification to a system is not secure because it can easily guessed or detected by someone else. "*What you have*" which is related to "*the possession*" factor can be better than the factor mentioned above but still cannot be too much secure ,because it can be lost or stolen .The factor that is the most efficient and accurate throughout the entire authentication technology is "*the inheritance*" which defines "Something you are", unique to a person. This system is provided by fingerprints, facial or iris scans and voice recognition. This type of authentication cannot be hacked, stolen or forgotten (Rathgeb, Uhl, & Wild, 2013).

1.2. Biometric

Biometrics identifies distinctive features of a person, such as fingerprints, facial or iris scans and voice recognition .Biometric authentication has its beginnings at prehistoric times .People ,who lived that time thought that their fingers where enough to identify them, so they used to sign with their fingers. Later on these technique was used for detecting the criminals. During years its purpose changed a lot. Biometric systems capture an image of your specific trait and then by using mathematical algorithms record it in a database as a biometric template. The process of transforming the taken image into a template in order to be comparable with other data saved in database is called normalization. Biometric templates cannot be accessed by someone else, because they are unique .This makes the system the most secure and the convenient one. When recording a new template, it is firstly checked if there exist a template same to it, otherwise it is entered as a new data automatically (Rathgeb, Uhl, & Wild, 2013).

A good biometric can make an immediate distinction between two different persons because each of them is characterized by a unique feature. The biometric should be stable, it should not change when years pass.

1.3. Iris recognition

Iris recognition is considered a good biometric because it fulfills all the characteristics to be considered like that such as: it does not change when a person gets older, in other words is stable and unique (G,Thapliyal & Sethi 2012).

To detect the iris of a person, it has to undergo a procedure composed of four steps:

Segmentation: the region of the iris is calculated

Normalization: The iris is captured in different positions and in different size, so a specific template is created for it in order to be comparable.

Encoding: it provides a texture information extracted from the normalized iris images

Matching: provides the accuracy of a template, the error rate(EER) ,Hamming distances between inter and intra classes.

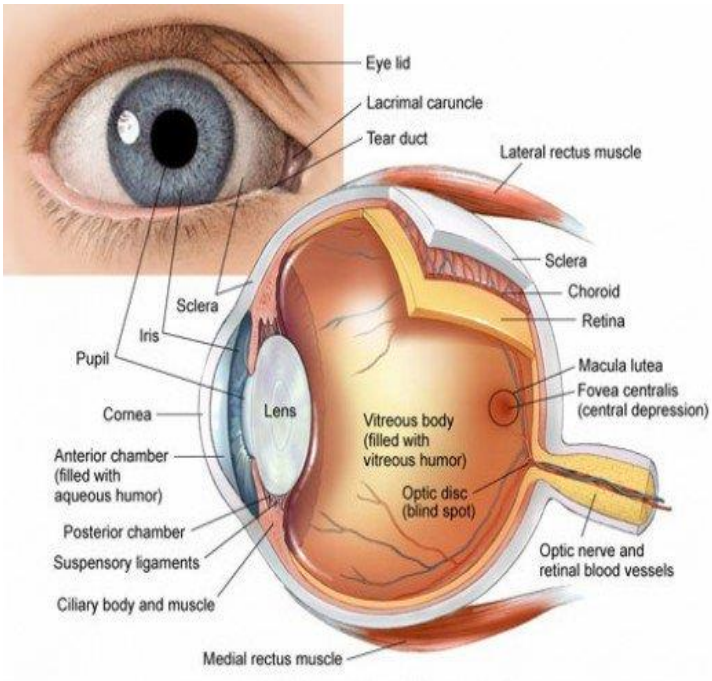


Figure1: Anatomy of a human eye

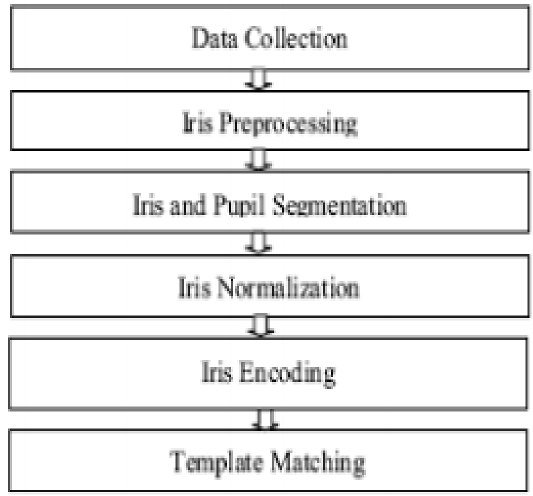


Figure2: Stages of iris recognition algorithm

1.3.1 CASIA Database

The most used database for iris recognition is The Chinese Academy of Sciences –Institute of Automation (CASIA) which is made of 108 different images of human eye. There are seven images for each captured eye in two sessions. The first four images are grouped in the first session and the last three images are in the second session .In the CASIA database ,the images are captured in the infra-red light, in which there is no reflection which makes them more convenient for studying iris recognition (Chinese Academy of Sciences ,2003).

CHAPTER 2

IRIS RECOGNITION STEPS AND USED METHODOLOGY

2.1. Segmentation

The initialization of iris recognition process starts with segmentation. This procedure displays the iris circle which is formed by bounding it from pupil (inner boundary) and from sclera (outer bound) as illustrated in figure b below. The execution of iris circle is realized by integro-differential operators such as Daugman's or Hough Transform. During segmentation stage also the noise such as: eyelids, eyelashes and light reflection are removed as shown in figure c below.

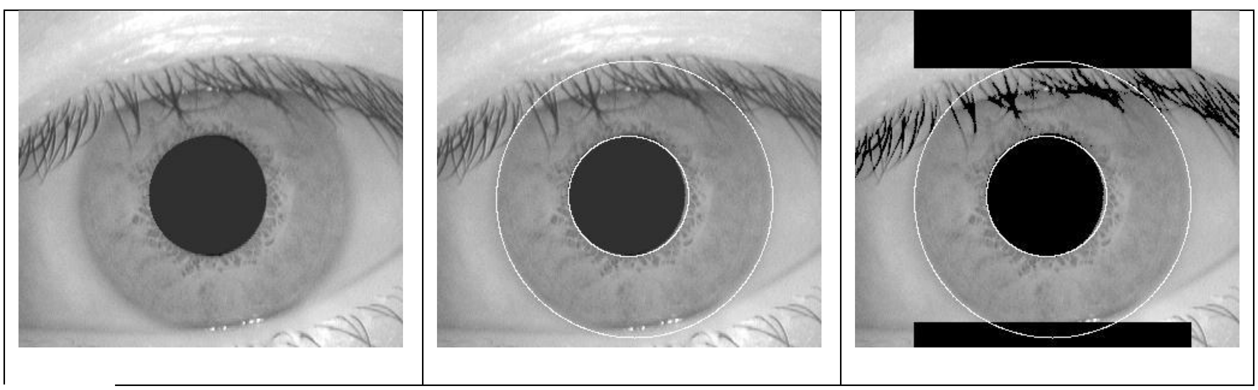


Figure 3: *Iris e025i2 from CASIA dataset during S2 segmentation*

A good segmentation depends on the quality of the captured image. According to Masek's algorithm (S1) the iris region is generated by using Hough Transform .This algorithm involves the Canny edge, which is a horizontal line to the circle with the maximum number of points.

Eyelids and eyelashes also called noise are removed by isolating lower and upper part of the eyelid with a black line using linear Hough Transform .Then a second line intersects the closest line of the iris with the pupil.

Another segmentation technique is the one proposed by Liu, Bowyer, and Flynn (S2) which is the reverse detection of iris region compared with Masek's algorithm, it firstly detects the inner boundary than the outer boundary, because to detect the boundary between iris and sclera is easier than detection of the one between iris and pupil. In this improved segmentation the eyelids are considered as two straight lines and the iris region is divided into 4 areas: left top, left bottom, and right top, right bottom. The Canny edge map should be generated at the iris boundary which is not larger the half of the pupil radius.

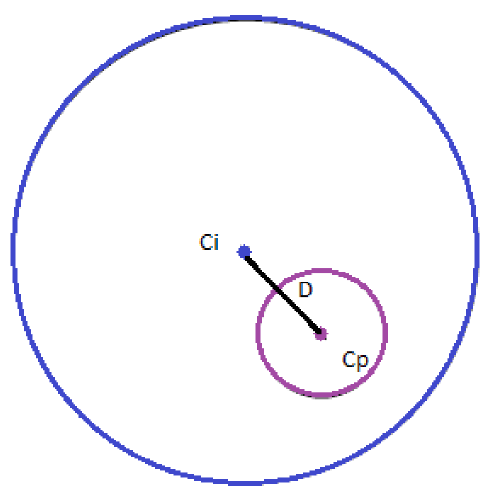


Figure 4: Illustration of d2 distance of S2

$$d_2 = \sqrt{(x_i - x_p)^2 + (y_i - y_p)^2}$$

EPK_IRIS segmentation algorithm (S3) again uses Hough Transform to detect the iris boundaries .Firstly is found the iris bound since pupil color is easily detected and later are found the outer boundaries. These outer circles will be sorted according to the condition that circles, which have a have distance $d3$ bigger than approximately 25 pixels will be excluded. Than the Canny edge map will detect the boundary of the outer region of iris from the remaining outer circles.

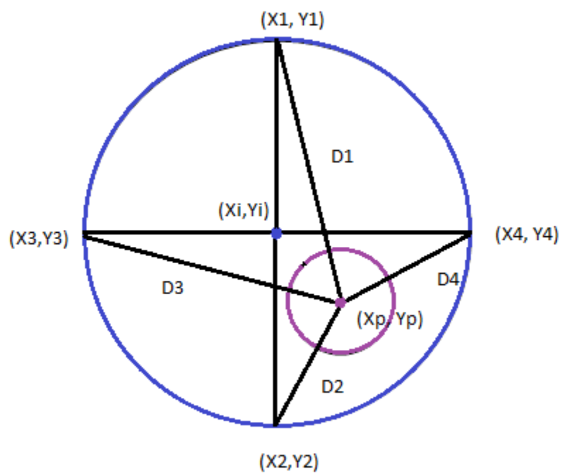


Figure 5: Illustration of d3 distance of S3

$\boldsymbol{d3}=|\boldsymbol{D1}-\boldsymbol{D2}| + |\boldsymbol{D3}-\boldsymbol{D4}|$

After the boundary is found the remaining outer circles which have small radius are eliminated.

If no circle is found ,we use S2 segmentation by finding d2 distance less than 20 pixels, if this two above mentioned segmentations are not successful than we use S1 segmentation proposed by Masek.

2.1.1. Hough Transform

The Hough Transform is a standard algorithm that calculates the parameters of circles and lines found in an image. Circular Hough Transform is used to calculate the radius and center coordinates of the iris and the pupil. Upper and inner boundary are calculated by first derivative which generates an edge map and then threshold the result. The eyelids are detected by the derivatives of the horizontal direction and the iris is detected by the derivatives in vertical direction.

$$X^2_c + Y^2_c - r^2 = 0$$

2.1.2. Noise Detection

The iris pattern is affected by eyelashes ,eyelids and also by the light reflection . The lowest intesity values conisits of eyelashes while the rest types of noise consists of highest intensity values. Eyelashes on the upper and the lower part of the iris are found by 1D Gabour filters while multiple eyelashes are detected by variance intensity.

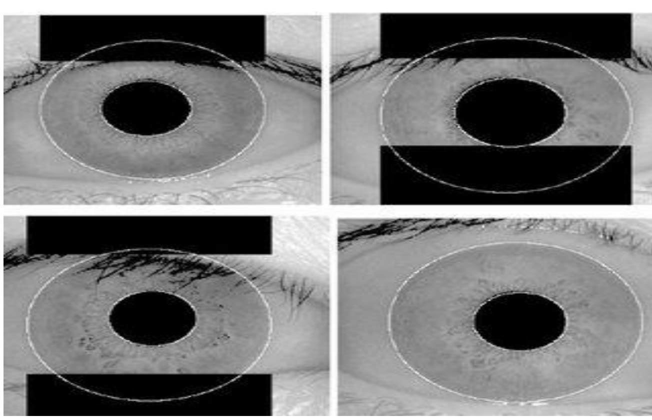


Figure 6: Segmentation stage: Localization of the iris boundary and pupil boundary, Noise detection , localization of boundaries and determines the mask .

2.2 Normalization

The second stage of recognition process is normalization. During this stage an iris template is created in order to be comparable with other irises of CASIA database. These templates are prepared by Daugman's Rubber Sheet Model. The purpose for passing through this step during recognition is fixing the size inconsistences irises because of iris stretching caused by pupil dilation, camera rotation etc. This technique transforms iris region from polar representation to Cartesian coordinates (from (r, Θ) to (x, y)). In our tests we have implemented two types of template 20x240 and 10x120.

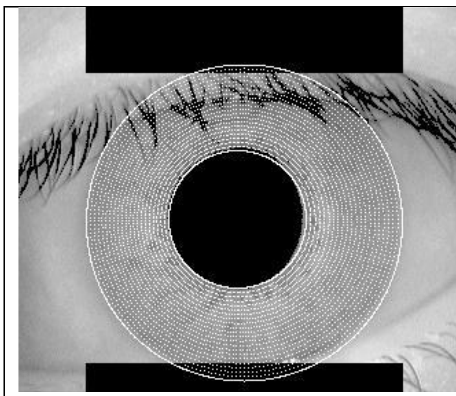


Figure 7: Illustration of normalization process

2.2.1. Rubber Sheet Model

The rubber sheet model, introduced by Daugman. It remaps each point within the iris region to a pair of polar coordinates where the radius r is on the interval (0, 1), and the angle is on the interval [0, 2π]. Then the normalized iris region is unwrapped into a rectangular region.

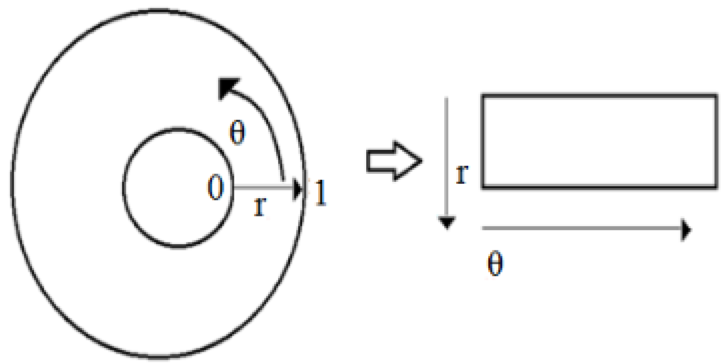


Figure 8: Rubber sheet model of the iris region normalization

2.3. Encoding

During encoding the most discriminated features are extracted from iris template created through normalization stage. There exist three encoding techniques E1, E2 and E3. The Phase space of the classical Dougman (E1) is quantized in four quadrants. Each level is assigned [11] [01] [00] [10] respectively. Each two neighboring phase spaces are encoded by 2 bits which makes them 50% different from each other.

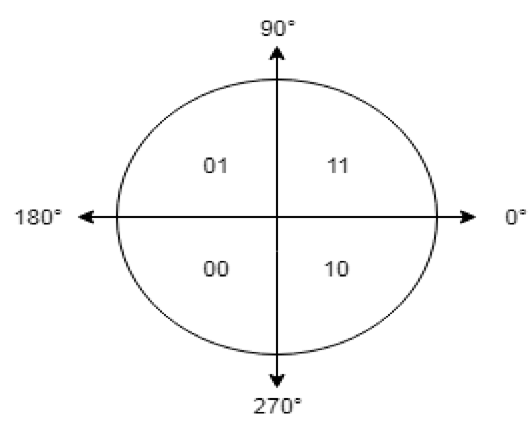


Figure 9:E1

E2 consists in eight level quantization and each two neighboring quadrants will be 33% different from each other. After applying 1D Gabor filter the normalized template will be a matrix 20x720 while at E1 scheme the resulting matrix will be 20x480. Each phase space will be encoded with 3 bits of data.

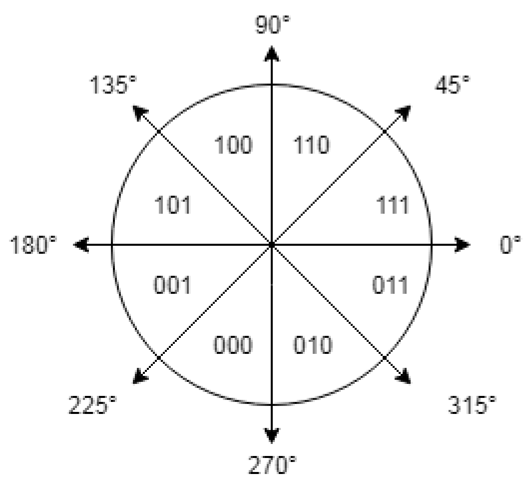


Figure 10: E2

At the last scheme (E3) we continue the same technique but the difference is that neighboring quadrants change with 25% while opposite quadrants change 100%. Each quadrant is displayed with 4 bits of data and the resulting matrix is 20x960.

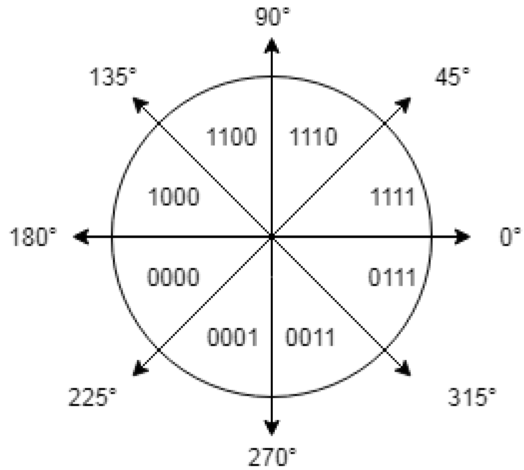


Figure 11: E3

2.3.1. 1D Gabor Wavelength

Sine/cosine wave with a Gaussian modulates Gabor filters. This type of filter provides the maximum conjoint localization in space and frequency. Sine wave is localized only in frequency but its modulation with Gaussian makes this wave to be localized in both space and frequency including some loss at the second one. Decomposition of a signal can be achieved by cosine which represents the real part and the imaginary part which is represented by the sine wave and both this waves are modulated with Gaussian. Gabor filters real and imaginary part are known as even and odd symmetric respectively. The bandwidth of filter is defined by Gaussian width while the center of frequency is defined by the frequency of the real and imaginary part

(Masek, 2003).

2.4 Matching

Hamming Distance is used to see how much an intra-class matches an inter class. The encoded templates are compared with each other in order to test how unique an iris human can be. To have a good matching result these templates will be shifted 8 bits left and right than will be calculated the hamming distance. The smallest distance will be the result.

2.5 Metrics

Metrics measures how effective a recognition process or technique is. Some important concespts that should be known at this section are: true positive" (TP), "false positive" (FP), "true negative" (TN) and "false negative" (FN) which are represented at the figure below.

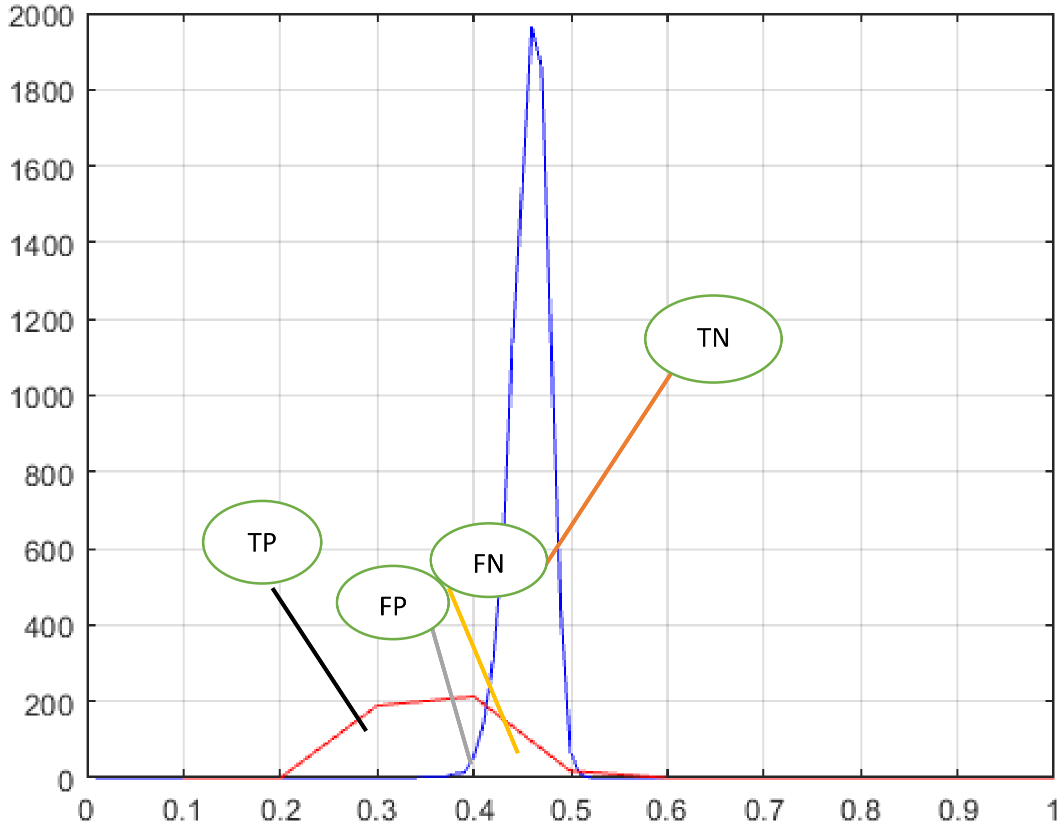


Figure 12: Illustration of TP, TN, FP, FN

The figure represents the histogram of the hamming distance between intra-class and inter-class. Inter-class is displayed with a blue color while the intra-class with a red color. In this example I have used Gaussian noise with noise 0 and template dimensions 10x120 pixels, a wavelength =13 . I have selected a random set of 20 persons with seven images for each person. The threshold value was 0.432 and TP=99, 8057.

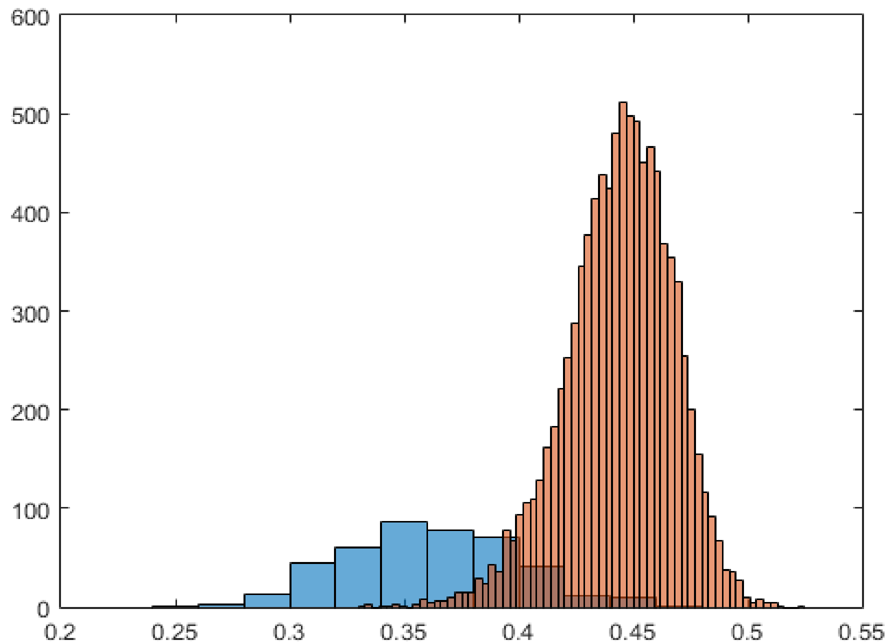


Figure13: Histogram of inter-intra values (20x240, w=18, noise=0.001)

To have an effective recognition the sum of TP and TN should be maximized and the sum of FP and FN should be minimized.

Accuracy = (TP * Intra + TN * Inter) / (Inter + Intra);

Wrongly matched templates are calculated by FAR and wrongly non-matched templates are calculated by FRR. These results should be at their minimum in order to establish a successful recognition system. When these variables have equal values and the EER value results to be zero these two conditions make the system to have a perfect result.

Decidability (dprime) is proportional to accuracy, it measures how much separated two classes are (inter and intra). It is calculated by mean value and standard deviation of inter and intra classes.

dprime = (abs(mean(a)-mean(c)))/sqrt((std(a)^2+std(c)^2)/2)

DoF (degrees of freedom) determines if an encoded normalized template is unique. It is calculated by mean and standard deviation of inter class. Also at the step when we calculate the hamming distance we need to have no shifts on both right and left side in order to have an accurate DoF result.

DoF =(mean(c)*(1-mean(c)))/(std(c)^2)

CHAPTER 3

TEST RESULTS OF OUR CONTRIBUTION

3.1 Testing S2 segmentation

This section describes the test results for S2 and S3 segmentations, which refers to second and third techniques of segmentations. The second technique (S2) is the one, proposed one by Liu, Bowyer, and the last technique called EPK-iris or S3 has implemented an improved segmentation.

There different images taken from CASIA database with a low resolution, which undergo segmentation and encoding phase .The purpose of this results is comparing which one of the segmentations or encoding techniques is better to be used in recognition . The registered data (iris images) in the database have good quality of resolution. Their resolution is lowered when a Gaussian noise is added. The set of images undergo S1 and S2 techniques with a noise which varies from 0 to 0.005 for each of the above techniques respectively.

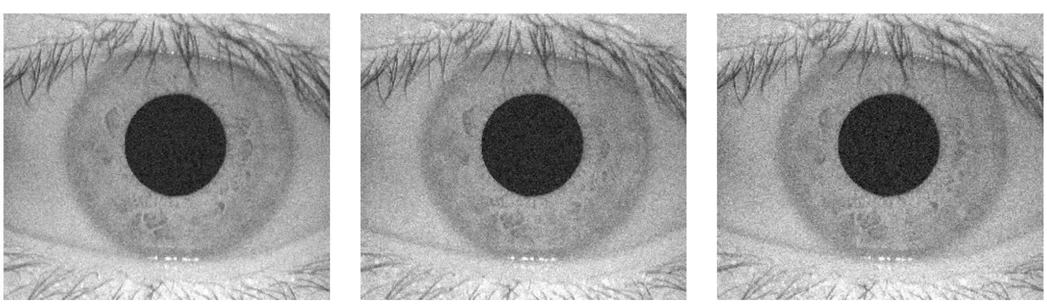


Figure 14: Image resolution when adding noise from (0 to 0.005)

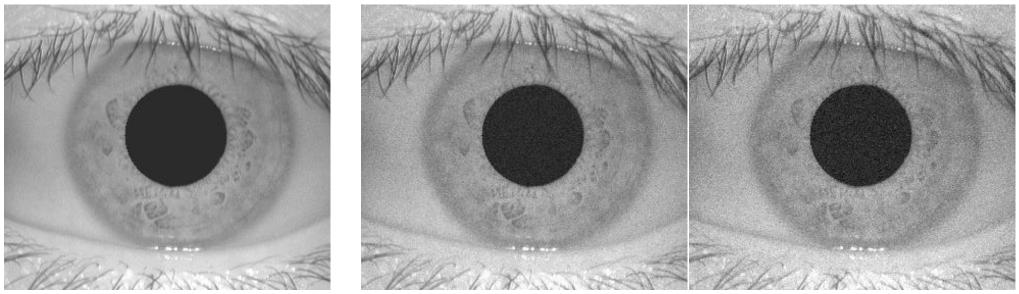


Figure 15: Original Images of the CASIA

Before creating Hough parameters a Gaussian noise was added in order to lower the resolution of the image. For each level of noise, different Hough parameters were generated (a procedure that took for about 4 hours to completely generate 108 people of the database).Then, 20 random people (out of 108) are selected from the database and this logic was used three times for each noise (this is done in order to observe if randomness can deviate the result that is expected to be when the eyes are selected directly without being random. When sets are generated, the above mentioned segmentations techniques are applied to them.

Below are given some images after passing segmentation stage. Here is seen from results that at noise 0.003 the EER starts getting larger and consequently the resolution of the image begins to weaken.

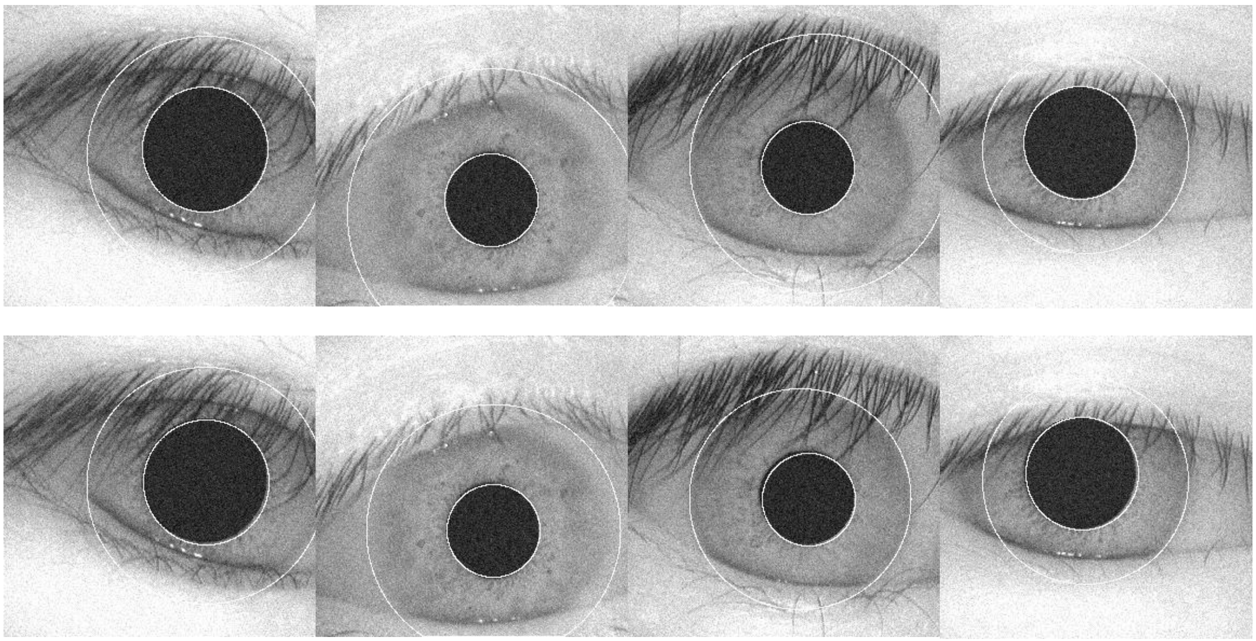
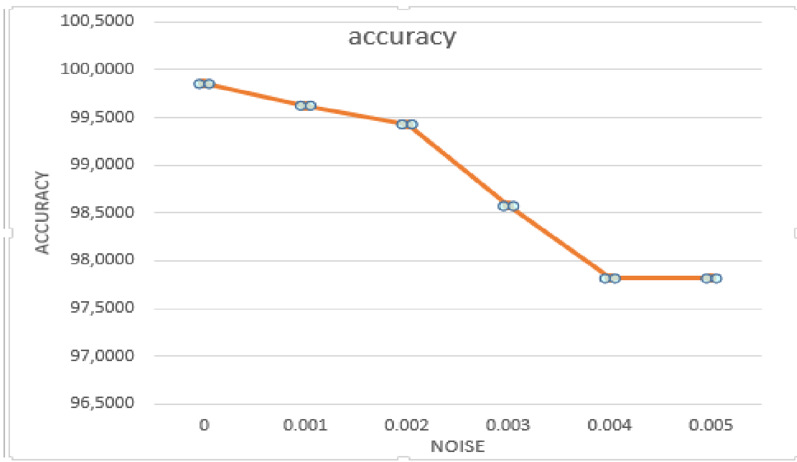


Figure 16. Iris images: e0108i2, e045i3, e086i5, e067i1from CASIA after S2 (first row), S3 (second row)

Comparing these two segmentations the S3 technique is the best improved technique of this stage.

3.1.1. Testing S2-E1 segmentation (20x240)

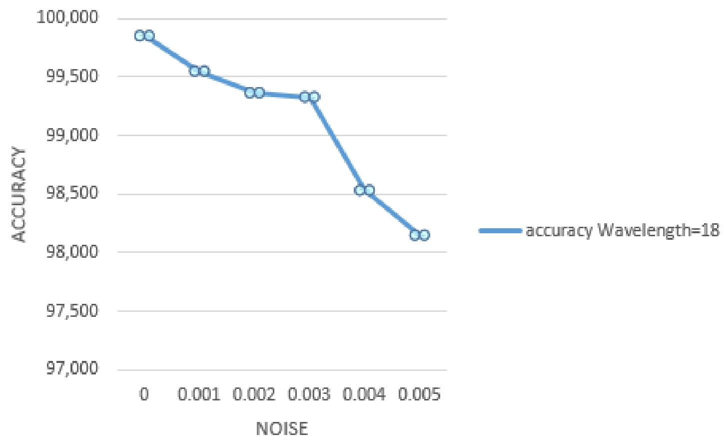
We used the 3 random sets to analyze two types of segmentation (S2 &S3). The graphs below show the average and standard deviation (in error bars) of accuracy, eer, dprime and dof of each segmentation combined with respective encoding technique for Gaussian noise from 0 to 0.005.



STD	ACCURACY	NOISE
0.03609336674	99,8527	0
0.06843091591	99,6232	0.001
0.1671475433	99,4279	0.002
0.06739402389	98,5717	0.003
0.08979337048	97,8143	0.004
0.6202646118	97,8143	0.005

Figure 17: Accuracy diagram of S2-E1 (20x240, W=13)

At the above figures is obviously seen that accuracy starts decreasing when noise level gets increasing.



Noise	Accuracy	Std
0	99,853	0.05172891014
0.001	99,551216	0.05273999424
0.002	99,36622	0.1873588066
0.003	99,32956	0.06050932684
0.004	98,53374	0.1593287558
0..05	98,15005	0.2494277718

Figure 18: Accuracy diagram of S2-E1 (20x240, W=18)

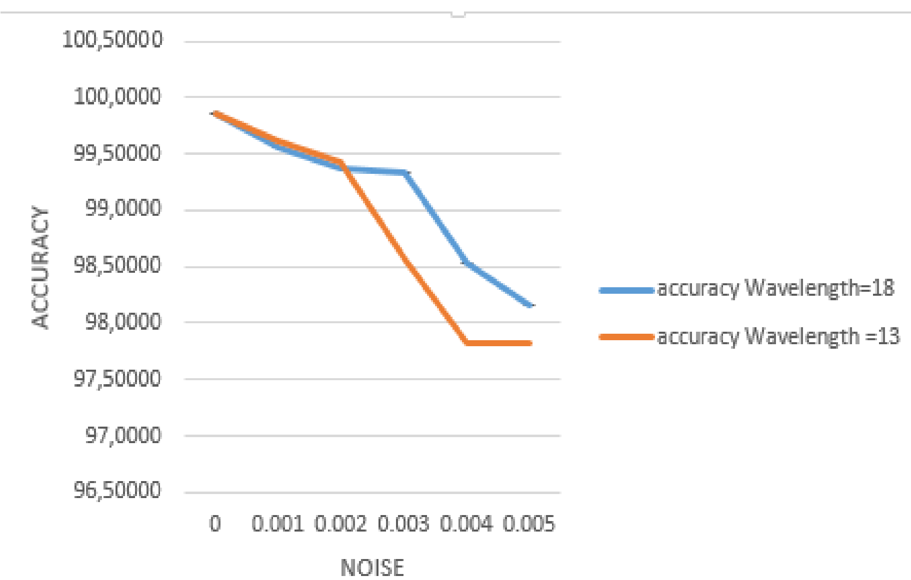
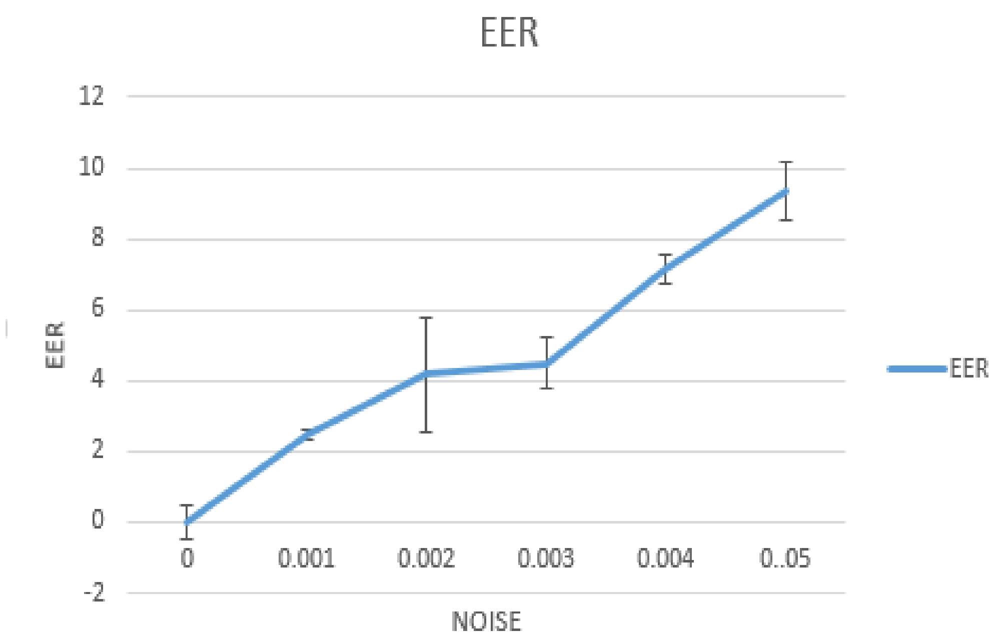


Figure 19: Accuracy of S2-E1 (w=13, w=18)

Accuracy of the iris template (20x240) after is encoded with a Gabor wavelength equal to 18 has values bigger than the accuracy of the one encoded with a Gabor wavelength equal to 13.This means that encoding with w=18 at this type of template is better than encoding with w=13.

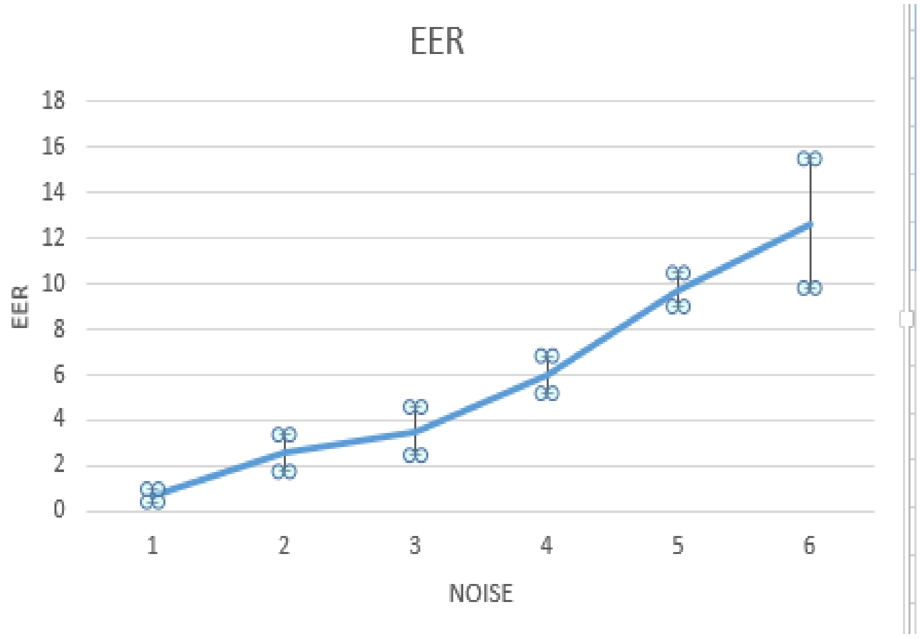
When the template dimensions are increased, the greater wavelength will be the best choice for a better recognition.



EER	Noise	STD
0.633333 3333	0	0,51316
2	0.001	0,152753
4	0.002	2
4,50	0.003	0,7
7	0.004	0,404145
9,33333	0.005	0,80829

Figure 20: EER diagram of S2-E1 (20x240, W=18)

EER starts increasing when noise gets increasing so it is seen that EER is inversely proportional with accuracy and proportional with noise.



STD2	Noise	EER
0,28	0	0,7
0,812917	0.001	3
1	0.002	4
0,822091	0.003	6
0,736569	0.004	10
3	0.005	13

Figure 21: EER diagram of S2-E1 (20x240, W=13)

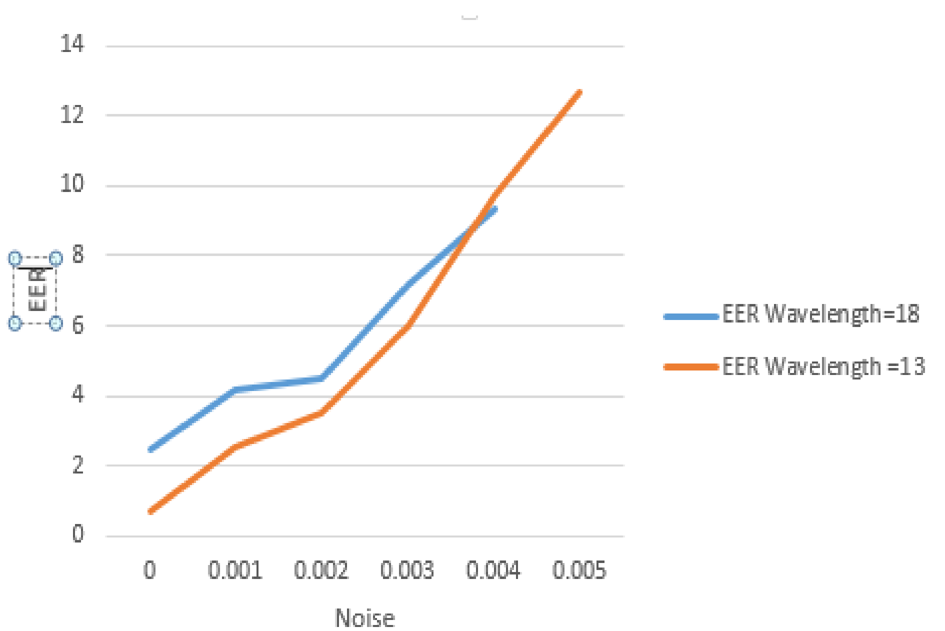
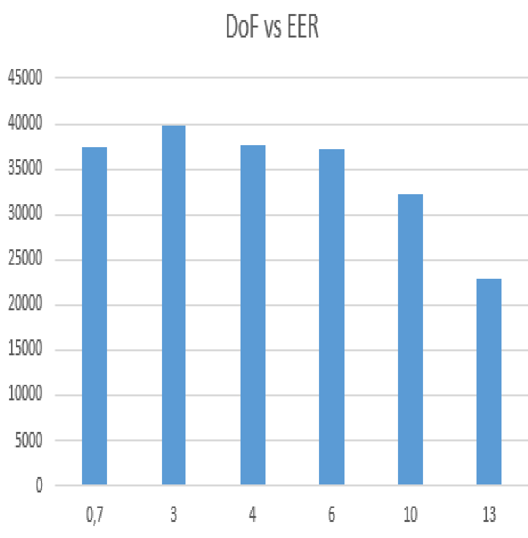
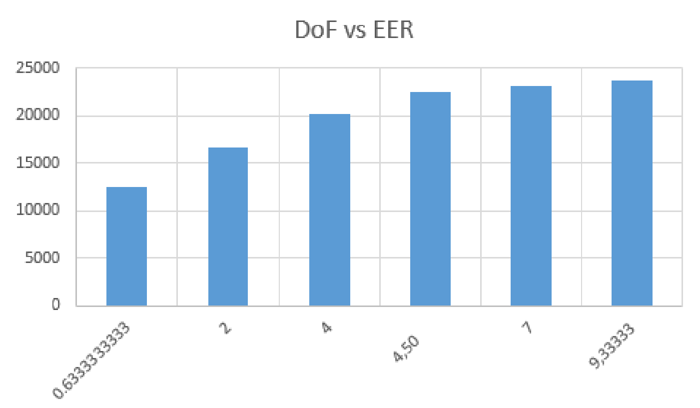


Figure22: EER diagram for S2-E1 (20x240,w=18&w=13)

Wavelength=18 produces an EER with values smaller than Wavelength=13 for the same iris template. This comparison concludes that again S2-E1 with encoded normalized template (20x240, w=18) is a better technique to be used.



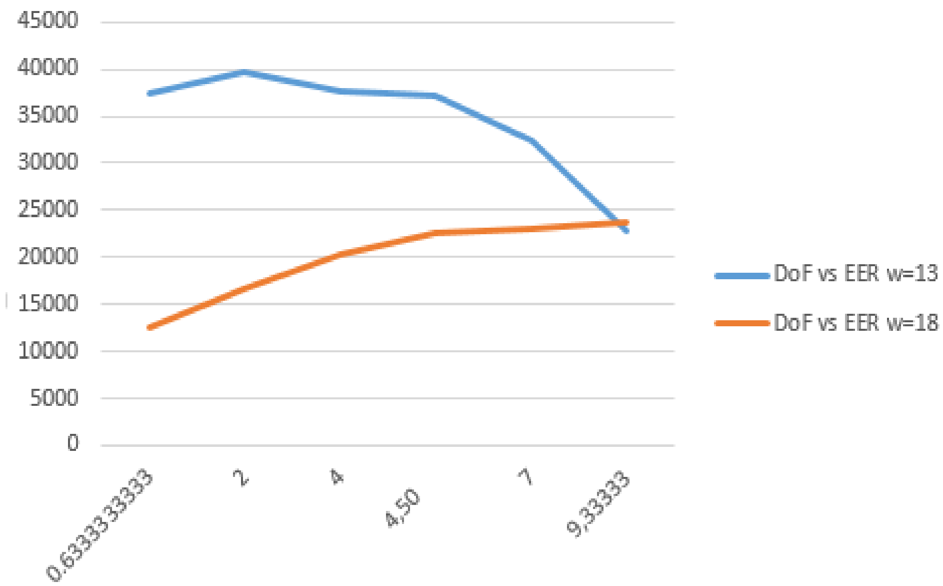
DoF	STD	NOISE
37400	155	0
39700	147	0.001
37700	471	0.002
37200	229	0.003
32300	201	0.004
22800	153	0.005



DoF	Noise	STD
12500	0	95
16700	0.001	50
20200	0.002	182
22600	0.003	428
23100	0.004	162
23700	0.005	100

Figure 23: DoF vs EER (20x240, w=13&18 respectively)

DoF must be inversely proportional to EER, but in our above illustrated tests DoF is proportional to EER when wavelength=18 and inversely proportional when w=13. This means that when wavelength gets bigger the proportionality between DoF and EER changes, so Gabor filters have a direct effect on this. The one that follows the rule is S2-E1 (w=13). The rule happens when all the parameters are perfectly matched.



DoFs of these two different wavelengths being used are inverse of each other comparing with EER. When DoF of the smallest filter is decreasing, DoF of the biggest filter starts increasing.

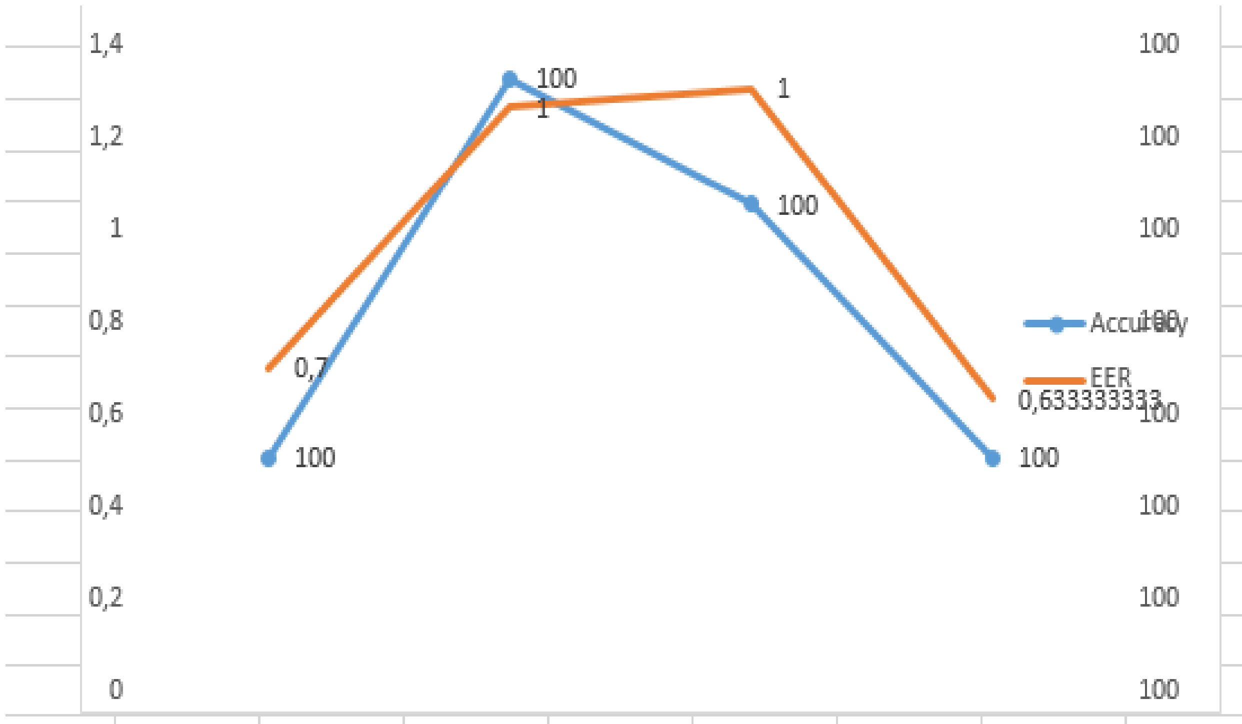


Figure 24: Accuracy vs EER (w=13, 14, 15 &18)

The relation between accuracy and EER for wavelengths 13,14,15,18. In the figure above the right vertical axis gives the rounded values of accuracy for noise 0 (but when the graph is plotted this values are distinguished from each other).So in the x-axis are taken wavelength values.

This illustration is for iris template (20x240).

3.1.2. Testing S2-E1 segmentation (10x120)

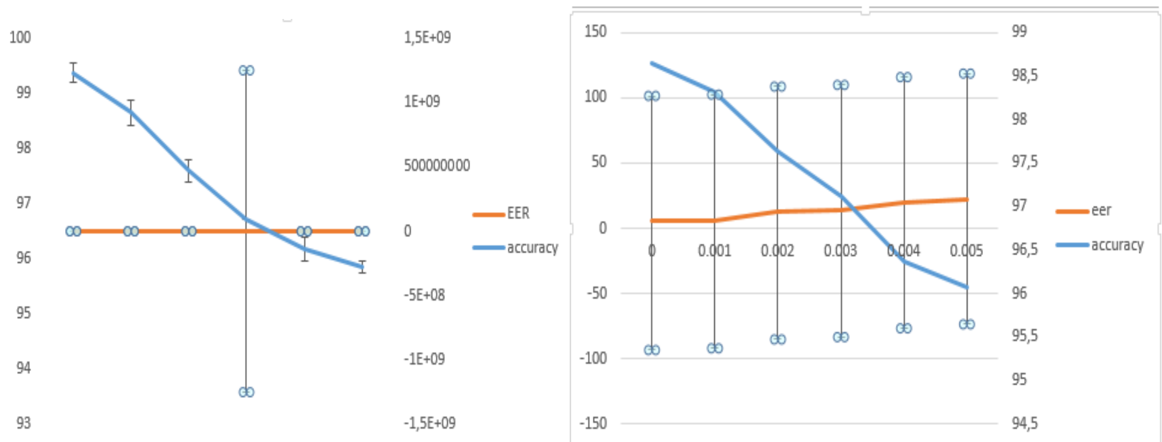
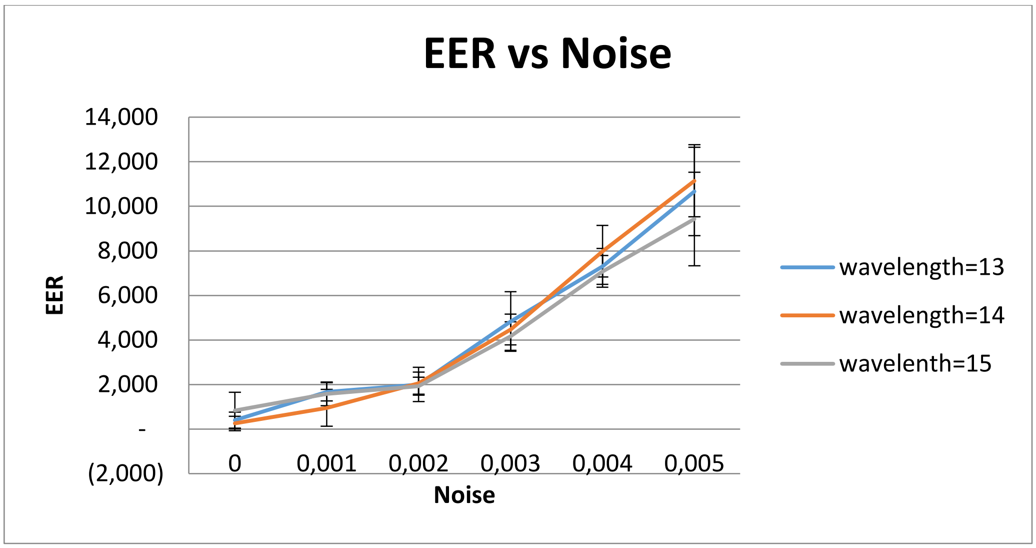


Figure 25: Accuracy vs EER (10x 120, w=13, 18 respectively)

Accuracy is inversely proportional with EER at both presented cases. At second graph standartd deviation which is displayed with error bars is greater than the std of first graph which means that the recognition at the first graph results the best one (values of EER are smaller than the second graph and the values of accuracy are bigger than the second graph).

3.1.3. Testing S3-E3 segmentation



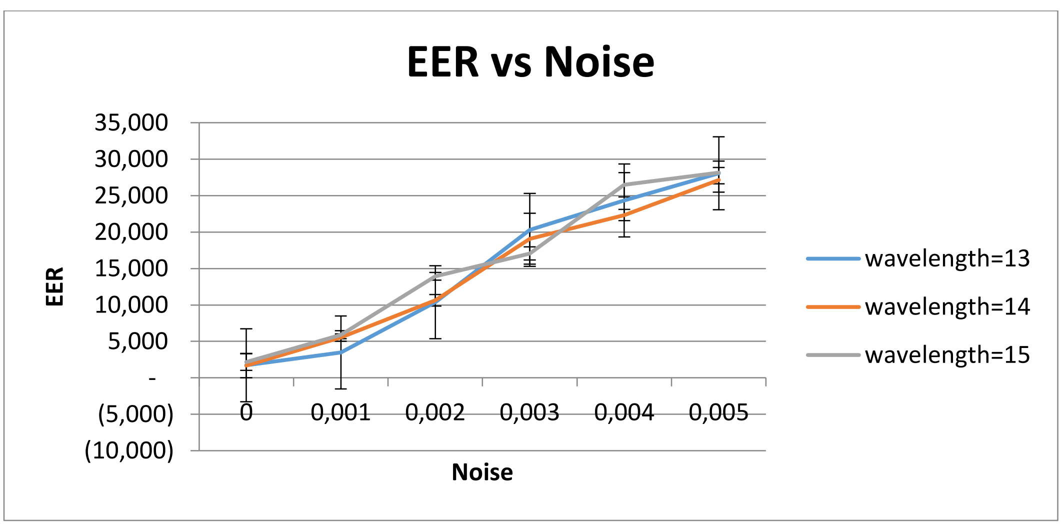


Figure 26: EER vs Noise S3-E3 (20x240, 10x 120 respectively)

At the above figures are displayed the relations of EER with noise for different dimensions of template (20x240 and 10x120) with wavelengths 13, 14, 15 and noise levels increasing from 0 to 0.005. These tests are made with 20 random persons generated three times for each noise.

EER at iris template 10x120 is bigger, so this type of segmentations with this dimensions is not advised to be used for recognition. Comparing these two changes made in S3-E3 the best segmentation is S3-E3 (20x240).

CHAPTER 4

CONCLUSIONS

We changed dimensions of iris template and also make use of different wavelengths to see how EER, accuracy, DoF, Dprime would change with respect to noise which had different values from 0-0.005.

We tried to find a combination between normalization, segmentation and encoding stage to see how much we could improve the recognition, which is resulted from high values in accuracy and low values in EER. The images we tested were taken from CASIA database where registered 108 people with seven iris images were. From this data were selected 20 random people for three runs each noise.

It is obviously seen that from the graphs displayed above for both segmentations S2 and S1 the values EER were getting bigger when noise was increasing, while accuracy ,DoF and decidability lower as the noise increases. Based on this information is said that these three parameters are inversely proportional with EER. When we add a Gaussian noise the resolution of images weakens and this makes the process of recognition to not be that efficient as the one that no noise is included. High DoF (uniqueness) and high Dprime (distance between inter and intra classes) produce low errors in recognition, in other words increasing their efficiency.

Comparing templates, the one with larger dimensions is more effective because Daugman sheet model produces a matrix with less class values when taking in consideration a low number of points throughout the iris.

In conclusion, the recognition process is better with improved implementations techniques of S3 and the encoding scheme is better than the first two ones.

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CHAPTER 5

APPENDIX

The code of histogram programmed MATLAB 2018:

```
in_1=inter ;// inter class

intra_1=intra;// intra class

 [m, n]=size(in_1);//matrix representation of inter

  in_2=reshape(in_1,m*n,1); // resize of matrix of inter into a vector representation

 [m, n]=size(intra_1);// matrix representation of intra


 intra_2=reshape(intra_1,m*n,1);// resize of matrix of intra into a vector representation


array=[]; //initialization of array

cnt=0; //counting variable initialized

array1=[];//second array initialized

cnt1=0;// second counting variable initialized


x=0.01:0.01:1; // the x-axis values for representation of inter class
```

```
for i=0.01:0.01:1
    num=find(in_2<i & in_2>(i-0.01)); //take only the values of inter which are in between this
domain
    cnt=cnt+1;// increment counter
    n=length(num); // length of num (how many inter classes are generated)
    array(cnt)=n;


end
plot(x, array,'blue') // draw this graph with a blue line
z=0.1:0.1:1;// the x-axis values for representation of intra class, here the x-axis values are taken
x10 bigger than in the inter x-axis because the values of this class are too small compared with
the values of inter class (it would be invisible).
for i=0.1:0.1:1
    num=find(intra_2<i & intra_2>(i-0.1));
    cnt1=cnt1+1;
    n=length(num);
    array1(cnt1)=n;


end

 hold on
```

grid on

plot(z,array1,'red') //plot intra with red color

- **Accuracy -** This function takes as inputs two numbers (start, data) which represent the beginning and the end of the list of people that we are going to use for the test. As an output we get the accuracy, threshold, FRR (all the values of intra class bigger than threshold), FAR (all the values of inter class smaller than threshold), inter, intra, ci (center of iris), cp (center of pupil). This function calls the testc.m, which takes as inputs again the start and data and returns inter, intra, ci, cp.
- **Createiristemplate** - This function is used to generate a biometric template of an iris of a given eye image. It takes as inputs the image filename and the eye image. As an output we get the binary iris biometric template, the binary iris noise mask, circle_iris and circle_pupil.At the beginningit defines a path for writing diagnostic images. If one of the files has not been processed before, then it performs automatic segmentation and saves the results to a file. Else, it loads the circle and noise information for that file. After that,it writes noise image and then it writes normalised pattern, and noise pattern.
- **Segmentiris** - This function performs automatic segmentation of the iris region ofa given eye image. Also, it isolates noise areas such as eyelids and eyelashes. It takes as input an eye image. As outputs we get the circle_iris (x, y, radius), the circle_pupil (x, y, radius) andan image with noise (image marked with NaN values at the location of noise).
- **Findcircle** - This function is used to find the coordinates of a circle in an image using the Hough transform and Canny edge detection to create the edge map. It takes as inputs an eye image, a lower radius to search for, an upper radius to search for, a scaling factor for speeding up the Hough transform, an amount of Gaussian smoothing to apply for creating edge map, a threshold for creating edge map, a threshold for connected edges, vertical edge contribution (0-1), horizontal edge contribution (0-1). As an output we get the x, y, radius of the circle.

- **Canny** - This function is used by findcircle and findline. It takes as inputs the eye image, standard deviation of Gaussian smoothing filter, a scaling factor to reduce input image by, weighting for vertical gradients and weighting for horizontal gradients. It performs generation of an edge map for the image taken as input. As an output we get the gradient amplitude (edge strength image) and the orientation image (in degrees 0-180, positive anti-clockwise).
- **Adjgamma** - This function is used by findcircle and findline. It takes as inputs an edge strength image and a gamma. As an output we get a new image generated by applying gamma function. Values in the range 0-1 enhance contrast of bright regions and values greater than 1 enhance contrast in dark regions.
- **Nonmaxup** - This function is used by findcircle and findline. Itis used to perform a non-maxima suppression on using a given orientation image. It takes as inputs an image in which to perform this non-maxima suppression; an image containing feature normal orientation angles in degrees (0-180), angles positive anti-clockwise; distance in pixel units to be looked at on each side of each pixel when determining whether it is a local maxima or not. As an output we get the new image.
- **Hysthresh** - This function is used by findcircle and findline.Itis used to perform hysteresis thresholding of a given image. It takes as input an image to be thresholded (assumed to be non-negative) an upper threshold value and a lower threshold value. As an output we get the thresholded image (containing values 0 or 1).
- **Houghcircle** - This function is used to perform the Hough transform for finding circles in the image. It takes as inputs the edge map image to be transformed and the minimum and maximum radius values of circles to search for. As an output we get the Hough transform.
- **Addcircle** - This function is a circle generator for adding weights into a Hough accumulator array. It takes as inputs a 2D accumulator array,(x,y) coordinates of the centre of the circle, radius of the circle and the optional weight of values to be added to the accumulator array (defaults to 1). As an output we get an updated accumulator array.

- **Findline** - This function is used to find the coordinates of a line in an image using the linear Hough transform and Canny edge detection to create the edge map. It takes as input an image. As an output we get parameters of the detected line in polar form.
- **Linecoords** - This function is used to find the (x, y) coordinates of positions along a line. It takes as inputs an array containing parameters of the line in form and the size of the image, needed so that (x, y) coordinates are within the image boundary. As an output we get the (x, y) coordinates.
- **Circlecoords** - This function is used to find the pixel coordinates of a circle defined by the radius and x, y coordinates of its center. It takes as inputs an array containing the (x, y) center coordinates of the circle, the radius of the circle, the size of the image array to plot coordinates onto and the number of sides of the polygon since the circle is actually approximated by a polygon (default is 600). As an output we get an array containing x coordinates of circle boundary points and another array containing y coordinates of circle boundary points.
- **Normaliseiris** - This function is used to perform normalisation of the iris region by unwrapping it into a rectangular block of constant dimensions. It takes as inputs an eye image to extract iris data from, the x and y coordinates of the circle defining the iris boundary, the radius of the circle defining the iris boundary, the x and y coordinates of the circle defining the pupil boundary, the radius of the circle defining the pupil boundary, the original filename of the eye image, radial resolution (defines vertical dimension of normalised representation) and angular resolution (defines horizontal dimension of normalised representation). As an output we get polar_array and polar_noise.
- **Encode** - This function is used to generate a biometric template from the normalised iris region. It also generates the corresponding noise mask. It takes as inputs the normalised iris region, the corresponding normalised noise region map, the number of filters to use in encoding, the base wavelength, the multicative factor between each filter and the bandwidth parameter. As an output we get the binary iris biometric template and the binary iris noise mask.
- **Gaborconvolve** - This function is used to convolve each row of an image with 1D log-Gabor filters. It takes as inputs the image to convolve, the number of filters to use, the

wavelength of the basis filter, multiplicative factor between each filter and the ratio of the standard deviation of the Gaussian. We get as an output a 1D cell array of complex valued convolution results and a filtersum.

- **Gethammingdistance -** This function is used for calculating the Hamming distance between two given iris templates. It incorporates noise masks, so noise bits are not used for calculating this distance. Taking into consideration that the two eye images may have been taken into different angles, it shifts templates left and right and gets the lowest Hamming distance. It takes as input template1 (first template), mask1 (corresponding noise mask), template2 (second template),mask2 (corresponding noise mask) and the number of filters used to encode the templates, needed for shifting. We get as an output the Hamming distance as a ratio.
- Shiftbits –Taking into consideration that the pictures are not always taken at the same angle, this function is used to shift the bit-wise iris patterns in order to provide the best match. It takes as inputs the template to shift, number of shifts to perform to the right (a negative value results in shifting to the left) and the number of filters used for encoding (needed to determine how many bits to move in a shift). We get as an output the shifted template.