Novel techniques in iris recognition

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NOVEL TECHNIQUES IN IRIS RECOGNITION

by

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Bachelor of Arts, Computer Science
University of Nevada, Las Vegas
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ABSTRACT

Novel Techniques in Iris Recognition

by

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Using Daugman’s algorithm and comparable alternatives, we find that we are able to identify an iris with as little as less than half of the iris information available, and an equal error rate comparable with that of popular biometrics like the fingerprint and face recognition biometrics. Different experiments were done based on percentage of iris shown, the resolution of the iris, and the position of the iris covered to determine if partial iris recognition is a viable biometric. It was found after over 500,000 different iris comparisons amongst five different experiments that regardless of the model used and the resolution, the equal error rates of partial iris recognition were competitive with its more popular counterparts. There is a slight decrease in the equal error rate in partial iris recognition, but not nearly as drastic as expected.
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CHAPTER 1

INTRODUCTION

Many of us have secrets, ideas and possessions that we wish to keep from other people. Security helps facilitate keeping our secrets away from people that we don’t want to know. In this increasingly secure world, for many that hold confidential information or possessions, passwords and keycards are no longer enough. Iris recognition is one of the many forms of biometrics used in helping increase the security of our daily lives. Iris recognition is a unique biometric in that it combines a high level of security with a tolerant level of convenience.

Iris recognition is used in approximately 11 percent of all biometric security systems. While this number is growing, it is still far less common than that of fingerprint or face recognition biometrics. It is still far more common than retina and signature biometrics [1].

The iris is one of the most stable biometrics in the human body. The iris is formed at birth and its iris patterns become permanent after two years [1]. It is said that no two iris patterns are alike, even amongst identical twins. Because of the many different iris patterns available and the abundance of degrees of freedom, the iris is considered to be one of the most efficient biometric systems available today.

An iris scanner scans an iris in near-infrared light (NIR) approximately three to five feet away from the machine. Current technology can scan an iris as far as 31 feet (10
meters) [2]. Usually for image resolution, the higher resolution an image, the better the patterns can be taken. However, experiments have been done showing that given a blurred or low-resolution iris, similar results of identifying an iris have given results that are almost as good.

Iris scanners in the past used a single image of an iris to determine if irises match. This posed a security problem because a person could place a high quality image of an iris that is in the database to the camera and the scanner would accept it. This can be considered a “static” scan. Most scanners now take multiple images of an iris in a single second and can determine if the iris is a living iris in one of two ways. It can check the pupil to determine if it is dilating, or responding, to the infrared light. It can also check the rest of the eye for a reaction time. This is a “dynamic” scan, and is the standard for most iris scanners today.

Error rates for irises are extremely low, the second lowest of any known biometric next to a retina scan, and many magnitudes better than the more popular fingerprint or face recognition scans. The error rates can be increased when occlusions such as eyelashes, eyelids, and irregular pupils get in the way. Recent algorithms, however, have been able to find a way around these occlusions when determining two irises, but the error rates do increase. Figure 1 shows an example of an iris and its represented iriscode to the right, graphically represented with the white colors representing ‘1’ and the black colors representing ‘0’. In partial iris recognition, gray colors would also be shown representing ‘X’, meaning don’t care or the information is not available.
A person that is having his iris scanned is considered a “subject” in the database. In almost all cases of iris recognition, the subject is willing to give a sample of his or her iris which results in having almost the entire iris available to be analyzed by the scanner. This security is good for confidentiality of one’s possessions or information. However, iris recognition can also be used for unwilling subjects and covert operations.

In these cases, the subject may either have refused to have their iris scanned and the iris is being scanned anyway, or they may not know that there is an iris scanner in sight. The iris scanner would find it very difficult to get a complete iris from an unwilling subject. This is where partial iris recognition comes into play. Partial iris recognition is new in that it has yet to be tested in scanners, but different algorithms for it have been looked at. Partial iris recognition requires at least a piece of the iris and a portion of the pupil. It then extrapolates what the iris and pupil would look like and take the data given to find a match for the iris. Examples of iris and pupil extrapolation and representation of the iris are shown in the next chapter.

Figure 1 An example of the image of an iris and its iriscode graphically represented.
This thesis focuses on partial iris recognition and how much of the iris is needed to have a confident conclusion whether or not two irises are the same or different ones. Questions that will be looked at are follows: How much the resolution of the camera is needed for partial iris recognition? How much of an increased error rate is there for partial iris recognition and is it viable? How much of the iris (and pupil) is needed for the scanner to make a decision on the iris, and ultimately, is partial iris recognition viable for iris scanners to use? Before we can continue the thesis, however, a few basic terms in biometrics have to be introduced to bring familiarity to the remainder of the thesis.

1.1 Biometric Terms and Keywords

There are three different forms of security. The first two are possession and knowledge. Possession security requires something that the user would have to gain access to a confidential area. Examples of this may be a passcard, ATM card, or the simplest of them, a key. The second is knowledge security. Knowledge security requires an answer to a question that only a user or one that would have access to a confidential area would know. Examples of this include a password or a personal question. The third form of security is biometric. Biometric security requires information from a part of a person’s body in order to gain access to a confidential area [3].

Biometrics provides a higher form of security and convenience than that of knowledge and possession security because of two advantages. The first is that the biometric that is researched does not go away or disappear easily. It stays with the user and does not require the user keep something in memory. This also adds on to the convenience factor. There are two different types of biometrics: physiological and behavioral.
physiological biometric involves a person’s physical characteristic while a behavioral biometric involves a person’s behavioral characteristic. The most powerful biometrics researched are in the physiological category such as the fingerprint, face recognition, retina recognition, and as in this thesis, iris recognition.

In an iris scanner, the person who’s iris is being scanned is known as the subject. Almost all the algorithms that are done in an iris scan can be divided into three steps. The first step is called isolation where the iris is isolated from the rest of the eye. The second step is called representation where the isolated iris is represented into a small iriscode. The iriscode is a series of ‘0’ and ‘1’ bits unless information is missing from the iris, like that of partial iris recognition. In this case ‘X’ bits are added, and are considered insignificant and are not considered in further testing and comparison of the irises. An example of this is shown in Figure 2.

![Figure 2 An example of an incomplete iris code.](image)

The third step goes one of two ways. If the iriscode is to be added to the database, the iris is enrolled, or added, into the database. Otherwise, the iriscode is being compared against other iriscodes in the database. The comparison can be one similar to identification, where we identify one iris against the entire database to see if the iris is in the database or which iris best matches the iris being compared with. The comparison can also be similar to verification where only one iris is selected from the database and
compared against the other iris. To do this, additional security might be required, like a password or an ATM card [3].

During the comparison test, when two iriscodes are matched, a *score* is given. This is known as the *subject score*. The subject score is then compared against a *threshold score* which is the minimum score to confirm that the iris is the iris. If the subject score is equal to or exceeds the threshold score, the iris is confirmed and accepted. If the subject score is less than the threshold score, the iris is rejected. In an identification test, either zero or one irises are able to exceed the threshold score given each iris in a database came from a different eye, but not necessarily a different subject.

There are times when the distinctness of either confirmation or rejection can be incorrect. These are known as errors. An error where the subject is not the correct iris but the scanner confirms their iris as so is called a *false accept* (FA). An error where the subject is the correct iris but the scanner rejects the iris is called a *false reject* (FR). The rate at which these errors are done, either in theory or in practice, are called *false accept rates* and *false reject rates* (FAR and FRR) respectively. The rate at which the false accept rate is equal to the false reject rate is known as the *crossover comparison rate* (CCR). Some also call this the *equal error rate* or *crossover error rate* (EER or CER). The crossover comparison rates of biometric systems can range from the fingerprint, face recognition, and signature biometrics (1:50 to 1:500) to the iris and retina biometric systems (1:186,000 and 1:10,000,000 respectively) [1]. Crossover comparison rates also depend on the algorithm and are not an accurate representation of the biometric. For example, in most cases, security comes before convenience and there are times where the false accept rate is increased a bit in order to significantly decrease the false reject rate.
Chapter 2 focuses on past literature work and experiments on both complete and partial iris recognition. Chapter 3 looks at the methodology used to determine the matching of two irises for partial iris recognition. Chapter 4 looks at the data of the experiments regarding partial iris recognition. Chapter 5 is the conclusion.
CHAPTER 2

RELATED WORK

While partial iris recognition is relatively new, iris recognition has been around for a long time. The algorithm is made so that theoretically, every iris pattern is unique. The number of distinct patterns with the algorithms that have been created exceed that of the number of possible subjects by several orders of magnitude. This chapter focuses on related work to iris recognition, both complete and partial.

2.1 John Daugman, Father of Iris Recognition

The “father of iris recognition” is Professor John Daugman, Ph.D, from Cambridge University [4]. He created the most efficient algorithm, in both space and uniqueness, for the iris. Like all algorithms following it, Daugman’s algorithm followed a three-stage process. The first stage is isolation, where the iris had to be isolated from the rest of the eye. The second stage is representation, where patterns within the iris are used to translate the iris into an iriscode. The iriscode is 2048 bits (256 bytes) in length. The final stage goes one of two ways. If the iris is being added to the database, the third stage is enrollment, where the iriscode is added to the database. The second option is comparison, where the iriscode is compared against other iriscodes, one at a time, in the database. If a certain percentage of the bits are equal, the irises being compared are considered the same iris by the scanner. Otherwise, they are seen as different [4].
In the isolation stage, Daugman created an integrodifferential operator for the positions and radii of the pupil and iris as shown in Figure 3 to create parameters for that define the pupil. The operator is:

$$\max_{r, x_0, y_0} \left| G_\sigma(r) \ast \frac{\partial}{\partial r} \int_{r, x_0, y_0} \frac{I(x, y)}{2\pi r} ds \right|$$

Figure 3 Integrodifferential operator for the pupil parameters.

where $I(x, y)$ is a monochromatic image containing the eye. The operator searches over an $(x, y)$ domain for the maximum in the blurred partial derivative with respect to radius $r$ along a circular arc $ds$ and center coordinates $(x_0, y_0)$. It is then convoluted with a Gaussian function [4]. The result of the operator is the iris isolated from the pupil and the remainder of the eye.

Next, we have the representation stage where the iris is segmented into small pieces and its features are extracted. The iris is segmented into small pieces of arbitrary parameters and each piece is placed as an iris pattern waiting to be demodulated. Each of the isolated iris patterns are then demodulated using complex two-dimensional Gabor wavelets shown in equation 1 [4]. The rectangular format is shown in equation 2 [7], and is used more due to convenience.

$$h_{Re, Im} = \text{sgn}_{Re, Im} \iint_{p, \phi} I(p, \phi) e^{-i\omega(\theta - \phi)} e^{-\frac{(\delta - \rho)^2}{\alpha^2}} e^{\frac{-i\omega}{\rho^2}} p d\rho d\phi$$

Equation 1 - Equation for two-bit representation of a 2-D block of the iris image (in polar form)
\[ h_{[\text{Re,Im}]} = \text{sgn}_{[\text{Re,Im}]} \int \int I(x, y) \frac{1}{2\pi \sigma_x \sigma_y} e^{-\frac{1}{2} \left( \frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2} \right)} \{ \cos, \sin \}(2\pi F_x) \, dx \, dy \]

**Equation 2 - Equation for two-bit representation of a 2-D block of the iris image (in rectangular form)**

The result is a 256-byte binary iriscode, with each iris pattern being represented by two bits, a real bit and an imaginary bit represented in this equation by \( h_{[\text{Re,Im}]} \). \( I(p, \phi) \) is the image under polar coordinates and \((r_0, \theta_0)\) is the polar coordinates computed in the system. \( \alpha \) and \( \beta \) are wavelet parameters, spanning in eight different ranges in the iris [4], and \( \omega \) is the wavelet frequency that spans in three octaves in inverse proportion to the parameter \( \beta \). In the rectangular format, the wavelet parameters are replaced with deviations of the Gaussian envelope along the \( x \) and \( y \) axes, named \( \sigma_x \) and \( \sigma_y \) respectively.

A more popular approach to this method that many have used is unwrapping the iris into a wide rectangular format [4, 9, 12]. The outer iris is used as the horizontal image while the inner iris is stretched out to compensate for the size of the image based on the inner iris’ radius. The iris is then divided into pieces, or blocks, of \( m \) by \( n \) pieces. Each block is encoded using the rectangular format of the Gabor wavelet translated from equation 1. Each block would then represent two bits, an imaginary and a real bit creating an iriscode of \( 2mn \) bits. The number of blocks that can be used is variable, but to receive the 256-byte (2048-bit) iriscode from Daugman’s format, the standard is to make \( m \) equal to 64 and \( n \) equal to 16. The variables \( m \) and \( n \) can be decreased for lower-
resolution images and increased for higher-resolution images and may vary commercially.

The iriscode is then either enrolled to the database or, if doing a comparison, is placed against a given iris for comparison. We will call the iris being compared iris A and the iris in the database iris B. The Hamming distance between the two iriscodes is taken to determine a score. A mask for both irises is also added to eliminate bits that contain occlusions like eyelids. The resulting formula is shown in equation 4:

\[
\text{HD} = \frac{\|(\text{code}_A \oplus \text{code}_B) \cap \text{mask}_A \cap \text{mask}_B\|}{\|\text{mask}_A \cap \text{mask}_B\|}
\]

Equation 3 - Matching the code of two irises together

where \(\text{code}_A\) and \(\text{code}_B\) represent the bits of the identified iris and comparing irises respectively. They are XOR’ed, then masked with two AND masks, \(\text{mask}_A\) and \(\text{mask}_B\) to not count the noise in the iris. The denominator tallies up the total number of bits to compute the Hamming Distance [4-5]. The lower the number, the more likely that the two irises match. It is also known that of the 2048 bits in the iris, the number of independent bits was 173 and thus the probability of finding two irises, given the parameter \(N = 173\) where \(N\) is an independent bit is \(1 \text{ in } 2^{173}\) [4].

In testing his algorithm, Daugman found that ideally, two different irises averaged a score of about 0.5 and two of the same irises averaged a score of 0. Figure 3 shows the results of the tests of 2.3 million different iris comparisons with irises of non-ideal conditions. The results of the same iris test were significantly different than that of the
different iris tests. Under these conditions, Daugman determined a threshold score of about 0.33 as an ideal score to determine if an iris should be accepted or rejected. The average score amongst different iris comparisons was 0.45 and the average score amongst same iris comparisons was 0.11. The result was approximately 0.04 under ideal conditions [4]. He would later do a larger test using a database of over 200,000 irises in the United Arab Emirates government iris database resulting to over 200 billion iris comparisons. It was found that no false accepts or false rejects when the images were created under ideal conditions and a threshold score of 0.26. Theoretically, had the score been pushed back even as little as 0.25, there wouldn’t be a false match for $2 \times 10^{12}$ comparisons [6].

This algorithm is used in some variation by almost every iris scanner that is used today commercially. The number of patterns that are put into the filter create a large distinct number of irises that can be identified, and theoretically, no two irises would hold the same pattern, or even hold as many as 80 percent of the same amount of bits. The effect also holds sturdy, as similar tests show that under low-resolution, poor-compression, and blurry irises, the result indicates only a slight drop in the crossover comparison rate [7, 8]. The results of Daugman’s test regarding non-ideal imaging can be seen in Figure 4. Even in non-ideal conditions, the results hold fairly steady and no irises cross his supposed threshold of 0.32 to create a false reject. At the same time, no different iris test resulted in a score of less than 0.32 to create a false accept.
2.2 Isolation using the Hough Transform

The Hough Transform would be used to improve upon Daugman’s algorithm for isolating the iris. The Hough transform models both the iris and the pupil as circles, and thus the circular transform can localize the iris. First, an edge map is created from a gray scale iris image by taking the first derivative of intensity values and thresholding the results. A voting procedure is then done by allowing each edge point in the circle of the iris/pupil to “vote” in the Hough space given a center \((x_0, y_0)\) and radius \(r\). The parameters with the most votes are considered to be the center and radius of the iris and pupil. This is a computationally intensive but more accurate way to isolate the iris from the rest of the eye [9]. This provides a simpler and more accurate method that does not rely on the more complex integrodifferential operator for the transform shown in Figure 3.

![Decision Environment for Iris Recognition: Non-Ideal Imaging](image-url)

**Figure 4** The results of John Daugman’s algorithm under non-ideal conditions.
2.3 Representation using Log-Gabor Wavelet Filters

The concept of Log-Gabor wavelet filters was introduced by the University of Scientist & Technology at China and the Nanyang Technological University at Singapore. Minor modifications were made to the representation stage of the iris. The advantage of this being that the log-gabor wavelet filter is a strictly bandpass filter, which means no DC components would pass the filters, which would eliminate the need to worry about background brightness [10]. Many iris scanning algorithms use this modified version when extracting features because of the better distribution of 0’s and 1’s that come out from the feature extraction process. An example of this can be shown below in figure 5 [10].

Their own tests had shown that using log-gabor wavelet filters in place of the 2D complex Gabor filters in Daugman’s algorithm resulted in a slightly lower crossover comparison rate. In practice, the crossover comparison rate of Daugman’s algorithm was 0.36% while the log-gabor wavelets had a crossover comparison rate of 0.28% [10].

2.4 Techniques in Non-Perfect Iris Recognition

Several works have been issued to techniques in non-ideal iris recognition. This may include partial iris recognition, but would also include bad data compression, occlusion of patterns in the iris by eyelashes, and a difference in the viewing of angles. Image compression and bad images were the most researched regarding Daugman’s algorithm as discussed in [7]. The research found that even with a JPEG compression of 20:1, the average score on Daugman’s algorithm was around 0.2 compared to an average of 0.05
when the image is uncompressed. This is still far lower than the threshold score of 0.32 that is used to determine whether the iris matches or not [4, 8].

Figure 5 Examples of Iriscodes

Additional work was done based on the angle of the iris. In some cases, an iris sample could be rotated as far as 30 degrees on either the $x$ or $z$ axes in a three-dimensional plane. Compensation has to be made for the change in angles as some of the patterns cannot be seen. The journal article in [13] creates an algorithm that, given a rough estimate of the angle needed to compensate, will compensate for that angle.

2.5 Partial Iris Recognition - One-Dimensional Approach

The one-dimensional approach was used by the U.S. Naval Academy as a primitive way to look into partial irises. Figure 5 shows the architecture of the one-dimensional approach that was used in their experiments. The processes are all divided into different
modules that share a function that isolates, extracts features, and compares the resulting output code. In this one-dimensional approach, all the boundaries are found so that the iris can first be isolated from the rest of the eye using the Preprocessing and Mask Generation Modules [11]. Each row is treated as a separate identification in an array. The iris patterns are then calculated by using overlapped windows to find variances in each pattern. The Iris Signature Generation Module was added to check each row to determine if a row should be counted or not in the system.

![Figure 6 The architecture of the 1-D approach.](image)

If 65% of the pixels were non-iris, the row was set to 0 and would not be counted in comparison tests. After the iris is represented, the iris is then either put through the Enrollment Module and added to the database or put through the Iris Identification Module, with the output being the ten closest matches for the iris.

Three different partial models were used in the experiments. The Left-to-Right model involved showing only the leftmost parts of the eye. The Inside-to-Outside model involved showing more of the inner iris before the outer iris, and the Outside-to-Inside model was the exact opposite [11]. The results showed the Outside-to-Inside model
being the most efficient of the models, having an accuracy rate of 80% when 60% of the iris was shown, compared to 70% for the Inside-to-Outside model and 50% for the Left-to-Right model [11].

2.6 Partial Iris Recognition – Novel Algorithms

In [12], a novel algorithm was used for partial iris recognition that is similar to Daugman’s algorithm except that it uses a different normalization technique to make up for the difference in pupil size and for high noise in small occlusions like eyelashes. In the representation phase, feature encoding the unwrapped rectangular iris would involve a matrix of four bits, one for each phase orientation $\theta$ at $0, \frac{\pi}{4}, \frac{\pi}{2}, \frac{3\pi}{4}$. Only one of the parts, real or imaginary, was encoded into the matrix of four bits [12]. Using their technique, they found the FRR to be 0.6% and the FAR to be 1.0% when the threshold was at 0.35. In comparison, they found the traditional algorithm’s FRR to be 4.5% and the FRR to be 6.0%.

Recently, there have been studies done [14] regarding creating a technique of a “hallucinating image” that created an algorithm that would reiterate a pattern to create an extrapolation of what the remainder of the unwrapped iris would look like. They compared their “hallucinating image” against either the noise left alone or the noise being replaced by a constant value, similar to other partial iris recognition experiments. Examples of the new iris are shown in figure 5. Overall, there was only a slight difference in a hallucinating image from which a constant value is given.
Figure 7 The original (top) and hallucinating (bottom) iris images.
CHAPTER 3

METHODOLOGY AND EXPERIMENTATION

This chapter will focus on methodology behind partial iris recognition in regards to covert operations. The difference in covert operations against the occlusions of an eyelid in a public database as shown in experiments done in [7, 9, 12] is made clear. I will also go over the different experiments that were used to determine if partial iris recognition was a viable biometric, including the different parameters used in each experiment.

Partial iris recognition can mean different things, but it involves around compensating for the loss of data due to occlusions. These occlusions include eyelashes, eyelids, or even foreign objects such as hats or visors. In a perfect iris recognition, the subject is most likely willing to give a sample of their iris and is fully aware of the scanner taking their data. Any research done in partial iris recognition up to this point involves the occlusion of the upper eyelid, where the willing subject does not open their eye enough to gather all the data in the upper part of the iris.

In covert operations, the subject may not be entirely aware of an iris scanner, nor will they be willing to give a sample of their iris. In many cases in the commercial industry, a sample of something must be given to keep away trespassers or those ‘blacklisted’ from the premises. In these cases, getting a subject’s complete iris is nearly impossible. However, gathering information from a piece of that subjects’ iris is not impossible if the person, or computer, operating the scanner is patient enough.
3.1 Gathering the Information

Gathering information from a covert subject is tricky, and requires an operator in charge of a scanner to find the best angle to retrieve iris information, or automated by a computer constantly checking for iris bits in the person’s face. The latter would also require a face recognition technique just to determine if the face exists in the camera.

The first technique to gather information is a ‘manual’ technique, which requires the operator to be under constant supervision of the subject for any signs of their iris. The advantage to this is that an iris scanner could be placed just about anywhere a camera would be placed, although the recommended elevation for the scanner would be around eye-level. The operator would be working from a remote location and the iris scanner would in this way double as a security camera.

The second technique is the ‘automated’ technique, where the scanner is connected to a computer that checks a subject’s iris constantly. A scanner would scan for any signs of a person’s eye. This includes using the Hough transform to determine where the circles of the pupils and patterns of the irises would be located. Face recognition would also be needed in order to determine if the circular object is really an eye or something circular on the table like a small coin, button or a poker chip. After the given face recognition algorithm is complete, the Hough transform confirms that the circular pattern is in the vicinity of the face.

Once confirmed, the iris is isolated from the rest of the current frame and its features are extracted. The partial iriscode is used as information against the rest of the database. In Daugman’s algorithm particularly, the way that filtering and extraction is divided into blocks show an organization of the code patterns. Starting from an orientation of 0
degrees (east), the iris is unwrapped by going counter-clockwise, eventually ending back
at 0 degrees. The inner iris is stretched to the measure of the outer iris by a ratio of \(x_o/x_i\).
The variable \(x_o\) represents the circumference of the outer iris while \(x_i\) represents the
circumference of the inner iris.

The feature extraction for the iris is divided into two parts. The first is where the iris is
divided into blocks. As stated in the previous chapter, enough blocks should be made to
create \(2mn\) bits of data. The number of bits for each real and imaginary would be \(mn\).
Blocks that would contain completely the constant value would be ignored. Blocks that
contain the iris would have its data added. Blocks that contain only part of the data
would also be ignored because the Gabor wavelet filter would reveal incorrect data given
the changing intensities.

In the second part, each of the remaining blocks would go through filtering and its
features would be extracted. Blocks that are ignored would be given a data of ‘X’ (‘0’ or
‘1’ according to the scanners’ choice and would not count toward the final matching
score when two irises go through the matching phase. This organizes the bits by phase
orientation. The first quarter of the bits column-wise would be for the orientation of 0 to
90 degrees. The second quarter would be from 91 to 180 degrees and so on. This can be
easily done by using the mask layer that is already provided in Daugman’s algorithm, and
counting the missing data as “noise”. The result would be a similar matching algorithm
to the complete iris, except only half of the iris (or whatever part is available) is
measured, rather than the iris itself. The matching phase of such a scanner would follow
Daugman’s algorithm and at this point, use the Hamming Distance.
3.2 Property of Searchability

It is inevitable that the equal error rate of the iris (EER) would increase as less information is given for testing. With less information, we have less information available for testing as well as added noise. There are some cases where the difference in score $S$ between a partial iris test and a different iris test is significant, but still does not meet the threshold score $T$ provided. However, with the close score, the user of the scanner can still declare the iris with the lowest score in the database the best possible choice given a level of confidence. Of course, it has to be distinguished between an iris that has yet to be enrolled in the database and a partial iris sample that has its subject already enrolled in the database. This is where the property of searchability for a partial iris sample would come in.

Assume a threshold score of $T$ where the iris is accepted if its matching score with another iris $S < T$ and is rejected if $S > T$. Assume the average of all matches of different irises is $\mu$ and its standard deviation is $\sigma$. The probability of confidence variable $C$ that part of an iris is the iris that it is matching to is given by the following equation:

$$C = \frac{1 - e^{\frac{|\mu - S|}{\sigma}}}{2}$$

Equation 4 - Probability of Confidence to determine Searchability

This is the same formula used for a one-handed confidence interval. We will make $C$ equal 1.0 when $S < T$ because confidences do not reach beyond 100%. The probability of confidence would also need a threshold, where the scanner is mostly confident that they
have the iris needed. From the tests given below, we find that a confidence interval of approximately two standard deviations, approximately 95%, or $C > 0.95$, is suitable to consider the iris searchable.

The property of searchability can be described as follows: Information of a partial iris sample is considered searchable if the probability of confidence $C$ is approximately 0.95. That is, the partial iris is approximately two standard deviations from the average of the different iris test $\mu$. This property states that the iris is similar enough (compared to the rest of the database) that we can be confident that the irises match given the partial iris sample. With a low theoretical equal error rate (EER) of 1 in 186,000 given by Dr. John Daugman for this algorithm, there is much flexibility regarding the significant loss of data.

3.3 Testing

There were four different kinds of testing that was done to determine whether or not partial iris recognition was a viable biometric. It is assumed that at the camera would be able to receive at least a portion of the subject’s pupil before taking a picture, and thus, approximately half of the eye would at least be seen before still pictures of the iris would be taken. In each of the tests done, there were three different tests done. The first was the same iris test, where two iris samples taken by the same subject are tested against each other. The second was a different iris test, where two iris samples taken by different subjects are tested. The final is a partial iris test, where only part of the iris is tested against another iris sample from the same subject. Whatever needs to be covered up is
covered up with a constant value. An example of this is an iris sample for the bottom-
half partial iris test in Figure 8.

Figure 8 An example of a partial iris sample. The top part of the iris is covered.

In all there were four different partial iris tests. Each of the tests were of the most
realistic scenarios that would occur in covert operations or in biometric security. The
first test involved covering the top half of the iris. The top half, or more, of the iris can
be easily covered with a foreign object like a hat or a visor. The second experiment
involved covering the left half of an iris. The third experiment, similar to the second,
involved covering the right half of an iris. Both tests involve getting the side view of a
subject’s iris when a front or back view is not available. We assume that the angle of the
iris can be compensated by rotating the camera slightly to get a slightly better side view
[13]. We can compensate for the angle of the side view when it reaches approximately
30 degrees. More of the information on the subjects’ iris can also be taken by rotating the
camera to make for angle compensation [13].

The final experiment looks at the % of the eye that would be covered in comparison
with the threshold score. There are many times when security will be unable to take a
picture of anything regarding the iris, and should deal with whatever information is given
to them in a covert operation. This is especially true if the subject would be wearing an object that covers their face, also fuzzing any face recognition algorithms that would be working with the iris scanner. Approximate landmark percentages of the iris are shown on table 1 over when pupil information starts, the pupil’s center is known, and so on. Regarding information of the pupil, the larger the pupil is, the less percentage of an iris needs to be seen in order to get any known information of the pupil.

<table>
<thead>
<tr>
<th>Landmark</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Complete Iris</td>
<td>100%</td>
</tr>
<tr>
<td>Typical percentile of iris w/ eyelid covered</td>
<td>80-90%</td>
</tr>
<tr>
<td>Known information of pupil center</td>
<td>50%</td>
</tr>
<tr>
<td>Any known information of pupil</td>
<td>25-35% (depending on size of the pupil)</td>
</tr>
<tr>
<td>Any known information of iris</td>
<td>0%</td>
</tr>
</tbody>
</table>

Following these tests, it can be found that the resolution of an iris image plays a role in partial iris recognition. For an additional test, higher resolution (720x568) images were compressed into JPG in the relatively same ratio as the images on the CASIA Iris Image Database. The irises for this experiment were provided by Michal Dobes’ database [15-17]. The images were originally of a PNG compression format with 24-bit color and was converted to a 4:1 JPEG format with grayscale color, which is the similar format used in the CASIA Iris Image Database. This test is used to determine if with higher resolutions, partial irises would have a better chance of being identified to their corresponding iris against partial irises and databases of lower resolutions.
All five experiments used the CASIA Public Iris Image Database Version 3.0 and the software used to test all the irises was the Iris Recognition System Software Version 1.0 by Libor Masek. This software used Daugman’s algorithm by first taking the Hough Transform to localize the iris and find two circles, the iris and the pupil. It then uses a Log-Gabor transform to extract features from the iris and create a result that depends on the size of the iris. For the resolution that was used in the main experiments, which were 640x480 JPEG images, the output was a matrix of 2048 bits. Different irises were used throughout all tests so as to give better confirmation of the results. The approximate runtime for the iris images to be added into the database are shown in table 2. With a higher resolution, there is a slower runtime to add irises to the database, therefore only one image of each iris subject was added to the database to save time.

Table 2 List of resolutions of images used in the test and how long it took to add to the database.

<table>
<thead>
<tr>
<th>Iris Resolution</th>
<th>Time (per iris added to database)</th>
</tr>
</thead>
<tbody>
<tr>
<td>320x280</td>
<td>22 sec.</td>
</tr>
<tr>
<td>640x480</td>
<td>64 sec.</td>
</tr>
<tr>
<td>720x568</td>
<td>95 sec.</td>
</tr>
</tbody>
</table>
CHAPTER 4

ANALYSIS AND OBSERVATIONS

This chapter looks at the results of all four experiments and draws observations to determine whether or not partial iris recognition is a viable biometric. From what is known already, it is difficult to receive a complete iris, especially when the upper eyelid covers the subject’s iris [14]. It is far more difficult to receive any information on an iris during a covert operation or when the subject is unwilling. In these experiments, we look at the average scores for each of the irises, their false accept and false reject rates, and compare them with the tests for a subject’s complete iris. For all tests, assume the threshold $T$ to be equal to 0.32. The images are colored in grayscale used in the database have a resolution of 640x480 and compressed using JPEG2000 on an approximately 2:1 ratio.

Before the experiments began, testing was done using a smaller sample using 320x280 grayscale images and compressed using JPEG2000 on an approximately 2.5:1 ratio. 238 subjects’ left and right irises were taken from the image database and three different irises were taken from each subject. The first iris would be used to be added to the database. The second iris would be compared for the same and different iris tests. The third iris would be compared for the partial iris test. If there were only two irises available, the second iris would be used for all three tests. A subject would be taken out if there was less than two irises for an iris.
The results are shown in figure 9. The histogram is given in sets of 3. The leftmost set is the result of the same iris test. The middle set is the result of the partial iris test for the bottom half of the iris. The rightmost set is the result of the different iris test. The mean of the same iris test is 0.2516, the partial iris test is 0.3998, and the different iris test is 0.4413. The standard deviation of the different iris test was 0.0203. Most of the partial irises in this test fell within two and a half standard deviations, stating an approximate 98-99% confidence that the given iris information matches the iris it tested. In this case, the partial iris samples are not accepted by an ordinary scanner, but would be hold the searchability property in a partial iris scanner.

Figure 9 Results of the Pre-Test Experiment
4.1 Experiment Results

In the first experiment, the top half of a subject's iris was covered and replaced with a constant value of 127. This was the first experiment that used the 640x480 images that would be used throughout all four experiments. The results of that test are shown in figure 10.

![Figure 10 Results of the Bottom-Half Iris Test (640x480 Resolution)](image)

The average of the same iris test was 0.2448. The partial iris test mean was 0.2932, and the different iris test was 0.4105. The standard deviation of the different iris test was 0.0214. 90 percent of the irises met the threshold score of 0.32 or less. No partial iris sample had a score above 0.375, indicating that even at the worst under a 640x480 resolution image, there is at least a searchability confidence of greater than two standard deviations, making all the partial irises at least searchable.
In the second experiment, the left-half of an iris was covered and replaced with a constant value of 127. The results can be shown on figure 11. The same iris test mean was 0.2212. The partial iris test mean was 0.2895 and the different iris test mean was 0.4198. The standard deviation of the different iris test was 0.0195. 92 percent of the irises met the threshold score of 0.32 or less.

![Figure 11 Results of the Left-Half Iris Test (640x480 Resolution)](image)

The third test was the right-half of the iris. The results for the third test are shown in Figure 12. The same iris test mean was 0.1892. The partial iris test mean was 0.2773. The different iris test mean was 0.4250. The standard deviation of the different iris test was 0.0212. 93 percent of the partial irises in this test met the threshold score of 0.32 or less. The scores are similar to the left-half of the iris and are together making up the side view of the iris.
The improvement of the left-half and right-half tests to the bottom-half tests could be contributed to the lack of occlusions on most of the images on the left-half and right-half sides. This is especially true when there was more noise in the bottom-half test that went undetected. Referring back to Figure 7 in the previous chapter, occlusions mostly occur in the 90-180 and 270-360 degree orientations of the iris. The different colored circles are the occlusions of the resulting unwrapped iris.

In the final experiment, the percentage of the eye was looked at for a threshold score rather than just half of the eye. We want to determine at what percentile of the image does it become no longer relevant to use the information that is given. The bottom-half partial iris test was used to determine the data for this test. The percentage of the eye that is covered up is the percent of the image that would be covered up in a covert operation or a realistic situation.

To determine how many pixels needed to be covered to get a percent of the eye, some variables must be defined. We can define $y_t$ and $y_b$ as the top-most and bottom-most pixels of the iris, respectively. To find these variables, we use the following equation, given a radius $r$ and a center point of the pupil $y_0$.

$$
y_t = y_0 - r$$
$$
y_b = y_0 + r$$

Equation 5 - Finding the top-most and bottom-most positions of the iris
Finally, we define the number of rows to cover with our given constant value in the experiment (defined as $y_x$) using the following equation and using the percentile $p$:

$$y_x = y_t + \left(\frac{y_b - y_t}{100}\right)p$$

Equation 6 - Formula for Percentile of Iris Covered Based on Pixels

The equations from variables $y_t$ and $y_b$ from Equation 5 can be substituted into Equation 6. The like terms are then further simplified. Therefore, equation 6 can also be defined as:

$$y_x = y_t + \left(\frac{y_0 + r - (y_0 - r)}{100}\right)p = y_t + \frac{2rp}{100}$$
From there, a number of tests was done similar to that of the partial iris tests done previously. The same iris test was treated as a 100 percent partial iris test and information from the 50 percent partial iris test was also used here. Tests were done in increments of 10 percent. The averages of each test is then placed into a graph. The final results can be shown on Figure 13. Landmark points include the 70 percent and 30 percent experiments. Any points less than 70 percent involved most irises losing data of the pupils and most irises no longer have any data of the pupils at all after only 30 percent of the iris can be seen.

The rationale for more positive results for the experiments over the pre-test could be due to the resolution and the quality of the images. While it was stated that image compression is not a factor in determining images, the combination of image compression with partial iris recognition combined with such a low resolution of the iris could contribute to a higher combined equal error rate.

Next, a third test on resolution was added using the 720x568 JPEG-compressed pictures. A sample of 20 different subjects with 200 total irises was taken. Only the bottom-half partial iris test was used in this one. The results of that test is shown in Figure 14, and the comparisons amongst the three picture resolutions in the bottom-half partial iris test is shown in Figure 15.
Figure 13 Iris score against Percentile of Iris Rows Revealed

The average of the same iris test for this resolution in the bottom-half test was 0.1760. The average of the partial iris test for this resolution was 0.2112. Only one of the tests resulted in the partial iris score being lower than the complete iris score. The results of both of these tests are much improved from both the 320x280 and 640x480 resolution JPEG tests. The average of the different iris test for this resolution was 0.4226 and the standard deviation for the test was 0.0425.

Figure 14 Results of the Bottom-Half Iris Tests using 720x568 resolution
4.2 Observations

There was some notice that a few of the data from the partial iris test scored better than on its corresponding same iris test. Overall, while the partial iris test averages scored worse, there wasn’t a huge change in score, and the average was closer to the same iris test than the different iris test. Also, in about one percent of the first three experiments, the score from the partial iris test was actually lower than the corresponding same iris test.

![Same/Partial Iris Tests by Resolution](image)

**Figure 15 Results of the Same/Partial Iris Tests by Resolution**

This should be considered significant because not only was there less information to process, but there was also less information to match together during the matching phase. Anything that was covered by the constant gray value was taken out toward the final Hamming Distance. Overall, with less information comes more noise, and the equal error rate is still slightly higher than that of the same iris test. The graphs for the equal error rate and the threshold against the false accept rate (FAR) are shown in figure 16. It is
observed that there is a slightly higher equal error rate, but overall it is still comparable to many popular biometrics used today like fingerprint and face recognition biometrics.

![Graph showing Equal Error Rate curves for same and partial iris tests.](image)

**Figure 16** The Equal Error Rate curves of the same and partial iris tests.

This makes partial iris recognition a viable biometric scheme. The equal error rate is still extremely low, and thus with most cameras erring on the side of security, the false accept rate will still be extremely low. The false reject rate would be slightly higher, but that would be expected.
Another characteristic that we can notice from these tests is that the pupil of the iris is paramount to getting the information needed to make a secure decision on the iris database. The strongest evidence for this statement is in figure 10 on the previous page. The pupil information started with 30% of the iris information and the scores between 20 and 30 percent of the iris was significantly greater than any other percentile. This makes sense considering that Daugman’s algorithm requires two circles, the iris and the pupil. The pupil’s center needs to be given in order to get an accurate data of the iris. However, when no pupil data is shown, the algorithm is programmed to make up a circle. This circle could be anywhere and contain any size radius. This would lead to big problems when comparing 30 percent or less of an iris (row-wise) against complete irises in a database. At 50 percent of the iris, we would have the pupil center known without having to extrapolate the iris. At this point, the score of the iris is not very different from having the complete iris. This makes sense since the noise of the iris is not counted during the matching process. At less than 50 percent of the iris, the pupil center has to be extrapolated by the algorithm.

Finally, Figure 16 shows us a comparison amongst the three different resolutions in a bottom-half partial iris test. The hypothesis of a higher resolution bringing about a lower overall score was true for both the partial and complete iris tests. However, the results that came from Daugman’s experiments [7-8] still stand regarding compression in affecting the determination of whether or not an iris passes a matching test or not. Compression and low resolution iris images only increase the overall score of the iris, but with a threshold of 0.32, a standard iris identification will result in an accepted iris.
Therefore, low resolution cameras could enjoy the benefits of Daugman’s algorithm and the iris biometric system up close.

However, for matters of distances longer than a few feet, a higher resolution would be needed. There are not enough pixels in many low-resolution cameras to capture the pattern of an iris from any further than that of the standard willing subject. High-resolution cameras, preferrably with a combined face recognition biometric system, would work in receiving the iris image that we need. Alternatively, a good zoom-in on a targeted subject in covert operations could provide some relief from the necessity of a super-high resolution.
CHAPTER 5

CONCLUSION AND RECOMMENDED FURTHER WORK

From the results given, we can come to a few conclusions regarding partial iris recognition. This chapter looks at the conclusions from the results. Primarily, partial iris recognition is a viable biometric because the Equal Error Rates are comparable with popular biometrics. Second, partial iris recognition only works with at least some information from the pupil available. The results that were given in the previous chapter have equal error rates comparable with the other tests that involve partial iris recognition and only have a slight decrease from a complete iris recognition test.

5.1 Applications for Partial Iris Recognition

With the points stated above, partial iris recognition would be a good specification to add to many forms of security, especially in the enterprise and entertainment industries. The technology today allows us with a high enough resolution that we should be able to receive a subject’s iris from a distance as far as approximately ten feet. This would be only a little closer than most distances from security cameras to the closest gaming tables or store counters, where unwanted subjects are likely to be. With the continuing advancement of technology, partial iris recognition could only get more enhanced as a viable biometric security source as a complement or even replacement to more popular biometrics such as the fingerprint and face recognition biometric due to its better security.
and its harder to spoof pattern-recognition technology. Resolutions will continue to get higher and with the development of 720p (1280x720) and 1080p (1920x1080) digital cameras, irises can be seen more accurately from a further distance.

The main question comes down to if partial iris recognition is a viable biometric or not. In order to answer this question with a direct “yes” or “no”, we must see partial iris recognition as a separate biometric rather than a variation of the iris biometric. We do know that its error rates compare with that of the more popular biometric systems like that of fingerprint and face recognition as mentioned throughout the thesis and shown in the experiments. The less information required than that of the predecessor, the iris biometric, makes it more flexible especially for covert operations or unwilling subjects. While low resolutions create a problem in partial iris recognition the likes that are not seen in a complete iris test, technology has allowed the increase of processor speed needed to receive information from high resolutions in a short amount of time. The higher the resolution, the more pixels there are to play with an unwilling subject at a distance. So this answers the question that a combination of today’s technology, the flexibility of this biometric, and its equal error rates make partial iris recognition a viable biometric that deserves its own line of applications.

5.2 Further Work

The work that is stated in this thesis is only an elementary look into the comparisons between a complete iris test and a partial iris test. Further work is to be needed in partial iris recognition in order to determine its characteristics with other biometric systems. With the work done so far, it was found that there was not as large a decrease in partial
iris recognition as first expected. In a few cases, the partial iris test turned out to score better than the complete iris test. While having less information of an iris should logically result in a lower false acceptance rate, the amount of information that is being counted in most cases also decreases because scanning algorithms manage to correctly identify the covered parts as “noise”. A pattern found in the partial iris tests was that the more noise that was removed from the iris by Libor Masek’s masking system, the closer the score came to that of the complete iris test. Additional further work would look into if partial iris recognition could have its equal error rate decreased by tweaking with the algorithm to take out more of the “noise” that the original algorithm would not take out.
APPENDIX A

ADDITIONAL CODE TO SOFTWARE

The following code are additions to the Libor Masek software that was used to ease experimentation.

**ack.m** – acknowledgment of creation of the iris templates as well as adding them to the database.

```matlab
function thereturn=ack()
    half = xlsread('half.xls');
    for N=1:x
        createiristemplate(['partial2/',num2str(N),'.jpg']);
        N
    End
```

**irismatch.m** – Creates an iris into the database and matches it against other irises in the database.

```matlab
%irismatch function
%By David Walker
%February 14, 2009
%
%Function: Using Libor Masek's Source Code, find the
%hamming distance
%between two irises.

function fire = irismatch(file1, file2)
    % requires all files already in workshop including file1
    % and file2
    fire=1;
    [a,amask]=createiristemplate(file1);
    [b,bmask]=createiristemplate(file2);
    for i=0:20
        currenthd = gethammingdistance(a,amask,b,bmask,i);
        if (fire > currenthd)
            fire = currenthd;
        end
    end
```
mass.m – Using the previous irismatch function, does a mass match of different irises and saves them into an Excel worksheet file.

```matlab
function matrix=mass()
    for i=1:370
        matrix(i,1)=i;
        if((i ~= 127) && (i ~= 205) && (i~=291) &&
        (i~=367))
            b=irismatch(['database' num2str(i),'.jpg'],['iris',num2str(i),'.jpg']);
            matrix(i,2)=b;
            b=irismatch(['database' num2str(i),'.jpg'],['partial',num2str(i),'.jpg']);
            matrix(i,3)=b;
            b=irismatch(['database' num2str(i),'.jpg'],['partial2',num2str(i),'.jpg']);
            matrix(i,4)=b;
            b=irismatch(['iris' num2str(i),'.jpg'],['partial2',num2str(i),'.jpg']);
            matrix(i,5)=b;
        else
            b=irismatch(['database' num2str(i),'.jpg'],['database',num2str(i+1),'.jpg']);
            matrix(i,6)=b;
            b=irismatch(['iris' num2str(i),'.jpg'],['iris',num2str(i+1),'.jpg']);
            matrix(i,7)=b;
        end
        if(i<370)
            b=irismatch(['database' num2str(i),'.jpg'],['database',num2str(i+1),'.jpg']);
            matrix(i,6)=b;
            b=irismatch(['iris' num2str(i),'.jpg'],['iris',num2str(i+1),'.jpg']);
            matrix(i,7)=b;
        else
            matrix(i,2)=0.6;
        end
    end
end
```
matrix(i,3)=0.6;
matrix(i,4)=0.6;
matrix(i,5)=0.6;
matrix(i,6)=0.6;
matrix(i,7)=0.6;
end
i
end
xlswrite('test2.xls',matrix)
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