Chapter 1

INTRODUCTION
1 INTRODUCTION

People easily recognize one another by looking at each other’s faces. Recognizing person is such a fundamental task that even toddler does it. However, such a trivial task is not simple for computer to perform. A biometric system is essentially a pattern recognition system that recognizes a person based on a feature vector derived from a physiological or behavioral characteristic of the person. Biometrics represents the most secure way of identifying individuals because verification of identity is established using a physical & behavioral characteristics. To make a personal recognition, biometrics relies on who you are and what you do— as opposed to what you know (such as password) or what you have (such as ID card). Biometrics has several advantages compared with traditional recognition. In some application, it can either replace or supplement existing technologies, in others it is only viable approach to personal recognition. Several biometric characteristics such as fingerprint, face, hand geometry, iris and voice are in use for various applications. Each biometric has its strengths and weakness, and the choice typically depends on the applications.

Identity verification becomes a challenging task when it has to be automated with high accuracy and with low probability of break-ins and low rates of false match. Moreover, person verification is not a new problem and society had created three traditional modes of design:

1. **Possessions**: Physical possessions such as keys, passports & smart cards.

2. **Knowledge**: Pieces of information those are secret and known only to the right person such as Person Identification Number(PIN), passwords, user names etc.

3. **Biometrics**: Physiological & behavioral characteristics of individuals that distinguish one person from the others. These characteristics are different in each person.
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**Table 1.1 – Common Biometrics**

The Table 1.1 shows the most common used biometrics distinguished into behavioral and physiological biometrics.

A good biometric is characterized by use of a feature that is:

1. highly *unique* so that the chance of any two people having the same characteristic will be minimal,
2. *stable* so that the feature does not change over time, and
3. be easily *captured* in order to provide convenience to the user, and prevent misrepresentation of the feature.

Currently, there are various biometric technologies, such as fingerprint recognition, face recognition, iris recognition and voice recognition. Some of these technologies are intrusive, like fingerprint recognition, which requires skin contact between the subject and the imaging facility. Some other technologies have relatively low recognition rates, like face recognition and speaker recognition. Traditional features include iris, retina, fingerprint, voice, & face images. Over the last ten years, algorithms used to digitize and process biometric signals have been enhanced to increase both accuracy over repeated uses and precision in matching users to their respective database entries. Of the five biometric features cited, iris images and fingerprint patterns are currently the most reliable and trusted forms of biometric identification. For the above reasons, iris recognition shows the advantages of non-intrusiveness and higher accuracy. It is non-intrusive, since it only requires the subject to look into the camera for iris image
acquisition. It also has a very high identification rate, because of the unique texture patterns and abundant information contained in iris images. Compared with other biometric features such as face and fingerprint, iris patterns are more stable and reliable. Since ophthalmologists Flom and Safir first noted the uniqueness of the iris patterns in 1987, various algorithms have been proposed for iris recognition.

The iris is a thin circular diaphragm, which lies between the cornea & the lens of the human eye. The iris is perforated close to its center by a circular aperture known as the pupil. The function of the iris is to control the amount of light entering through the pupil, and this is done by the sphincter and the dilator muscles, which adjust the size of the pupil. The iris begins to form in the third month of gestation and the structures creating its pattern are largely complete by the eighth month, although pigment accretion can continue into the first postnatal years. Its complex pattern can contain many distinctive features such as arching ligaments, furrows, ridges, crypts, rings, corona, freckles, & a zigzag collarats. Even identical twins will have two different irises. In fact, a person’s right & left irises do not share the exact same physical characteristics. The iris is also not subject to the effects of aging which means it remains in a stable form from about the age of one until death. The use of glasses or contact lenses (colored or clear) has little effect on the representation of the iris and hence doesn’t interfere with the recognition technology. The probability that two irises could produce exactly the same iris code is approximately $1 \times 10^{78}$.

1.1 Objective of Iris Recognition

The complexity of designing any biometric system can be seen as a function of three variables such as Scale (size of the database), Usability (ease of use, security and privacy), and Accuracy (False Accept Rate (FAR) & Genuine Accept Rate (GAR)). Most of the applications require that the biometric system operates on the extreme of
one of the three axes. The great challenge consists in the planning and implementation
of a system that could operate on the extreme of all the three axes simultaneously
which contribute for the wide spread adoption of biometrics. The main motivating
factor of our research work and of this thesis.

1. To increase population coverage by reducing the failure to enroll rate.

2. To extend the range of environmental conditions under which authentication can
be performed.

3. To enhance performance, in recognition

4. To improve resilience to spoofing.

1.2 Literature Survey

A complete iris recognition system can be split into four stages: data acquisition,
segmentation, encoding and matching. The data acquisition step captures
the iris images. Infra-red illumination is used in most iris image acquisition. The iris
segmentation step localizes the iris region in the image. For most algorithms, and as-
suming near-frontal presentation of the pupil, the iris boundaries are modeled as two
circles, which are not necessarily concentric. The inner circle is the pupillary boundary
(between the pupil & the iris). The outer circle is the limbic boundary (between the iris
& the sclera). The noise processing is often included in the segmentation stage. Possible
sources of segmentation noise are eyelid occlusions, eyelash occlusions, specular high-
lights, and shadows.

Most segmentation algorithms are gradient based; that is, they involve finding
the edges between the pupil and iris, and the iris and sclera. The encoding stage
encodes the iris image texture into a bit vector code. In most algorithms, filters are
utilized to obtain information about the iris texture. Then the outputs of the filters
are encoded into a bit vector code. The corresponding matching stage calculates the
distance between iris codes, and decides whether it is a match (in the verification
context), or recognizes the submitted probe iris from the subjects in the gallery set (in
the identification context). A survey of recent literature shows that, many recognition
techniques have been proposed and demonstrated significant promise.

**Daugman’s method**

Daugman’s algorithm [1-6] is the best known iris algorithm. The iris is mode-
led as two circles, which are not necessarily concentric. Each circle is defined by three
parameters \((x_0, y_0, r)\), where \((x_0, y_0)\) locates the center of a circle with radius \(r\). It
utilizes an integrodifferential operator to estimate the three parameter values for each
circular boundary. It searches the whole image with respect to an increasing radius \(r\) to maximize.

\[
\left\| G(r) \frac{d}{dr} \int_{(x_0, y_0, r)} \frac{I(x, y)}{2\pi r} ds \right\| 
\]

(1.1)

where \(I(x, y)\) is the intensity value in the image at location \((x, y)\), \(ds\) means the circular
arc, \(2\pi r\) is used to normalize the integral, \(G(r)\) is a Gaussian filter used as a smoothing
function, and \(*\) means the convolution operation. The eyelids are modeled as parabolic
arcs. An integrodifferential operator as described Equation 1, is also used to locate the
upper and lower eyelids. In that case the integral is computed over a parabolic arc
instead of a circular arc. The regions detected for the eyelids are excluded from the iris
image.

**Wilde’s method**

Wilde’s system [7] is also a patented iris recognition system. It uses the gradient-
based Hough transform to decide the two circular boundaries of an iris. It includes
two steps. First a binary edge map is generated by using a Gaussian filter. Then, votes
in a circular Hough space are analyzed to estimate the three parameters of one circle 
\((x_0, y_0, r)\). A Hough space is defined as

\[
H(x_0, y_0, r) = \sum_i h(x_i, y_i, x_0, y_0, r) \tag{1.2}
\]

where \((x_i, y_i)\) is an edge pixel and

\[
h(x_i, y_i, x_0, y_0, r) = \begin{cases} 
1 & \text{if } (x_i, y_i) \text{ is on the circle } (x_0, y_0, r) \\
0 & \text{otherwise}
\end{cases}
\]

The location \((x_0, y_0, r)\) with the maximum value of \(H(x_0, y_0, r)\) is chosen as

the parameter vector for the strongest circular boundary. Wildes system models the

eyelids as parabolic arcs. The upper and lower eyelids are detected by using a Hough

transform based approach. The only difference is that it votes for parabolic arcs instead

of circles. Wildes system utilizes a Laplacian pyramid decomposition to encode the iris

texture patterns. It uses normalized correlation to determine the similarity of two iris

codes. The final decision is obtained from a Fisher linear discriminant based on the

strength of match of each frequency band. A 100 % verification accuracy was claimed

when testing on 600 iris images (60 different irises). The testing iris dataset is not

publicly available.

**Boles and Boashash method**

The algorithm of Boles and Boashash [8] extracts a set of one dimensional

signals from the iris image using the intensity values on a set of circular contours cen-

tered at the pupil center, which is located using edge detection techniques. Then the

set of one dimensional signals is further encoded by using a zero crossing transforma-

tion at different resolution levels. When calculating the overall dissimilarity between
two iris codes, it uses the average of the dissimilarity at each resolution level. A 100 %
verification and identification accuracy was reported with the experiments conducted
on 11 iris images. The source of the testing iris images was not indicated.

Li, Ma method

In an algorithm proposed by Ma et al. [9], the iris images are projected to the
vertical and horizontal directions to estimate the center of the pupil. This saves time
in searching for the iris boundaries. After normalizing the located iris patterns, the
image contrast is enhanced by subtracting estimated background illumination. When
extracting the iris patterns, a filter modulated by a circularly symmetric sinusoidal
function is employed. Instead of using the whole iris image, their region of interest
is constrained to the area close to the pupil because in this area the pupil texture is
claimed to be more abundant. By doing this, they avoid the eyelid and eyelash noise.
Their representation of the iris is a feature vector of length 1,536 bits. A Fisher linear
discriminant is used to reduce the dimension of the feature vector. The minimum
distance classifier is utilized in classification. The algorithm was tested on the CASIA
version 1 dataset . The reported identification rate is 99.43 %, and the FAR is 0.001
% while the FRR is 1.29 % . The iris images in the CASIA dataset are not raw
images obtained directly from the data acquisition. In each image, the pupil region
was modified manually so that it contains a circular region of constant intensity level.

Ya-Ping et al. method

Ya-Ping et al. Approach [10] is close to Daugman approach in the sense that
it depends on the same integro-differential operator. However, it made use of the
canny operator to find the approximate boundaries first. Rescaling the image to reduce
computational complexity and using Canny operator to extract the image edges, and
form a binary image. Choose the maximum circle \((xs, ys, zs)\) based on histogram as the outer (sclera) boundary. Search the inner (pupillary) boundary \((xp, yp, zp)\) where \((xp, yp)\) lies on the rectangle noting that this boundary lies within the outer boundary.

C. Chin method

Chin et al. [11] proposed the use of an “S-iris encoding” which is generated from the inner product of the output from a 1D Log Gabor filter and secret pseudo random numbers. In the segmentation stage, first an edge map is generated using a canny edge detector. A circular Hough transform is used to obtain the iris boundaries. Linear Hough transform is used in excluding the eyelid and eye lash noises. Then the isolated iris part is unwrapped into a rectangle with a resolution of 20 x 240 using Daugmans rubber sheet model. Then the final iris code is generated from the inner product of the output from a 1D Log Gabor filter and secret pseudo random numbers. In matching, Hamming distance is used to indicate the dissimilarity between a pair of iris codes. A 100 % verification accuracy was reported by testing on the CASIA iris image database version 1.0. As noted earlier, the CASIA images are manually processed, meaning no claim about automatic processing is appropriate.

N.A. Schmid method

Schmid [12] proposed an algorithm to predict the iris biometrics system performance on a larger dataset based on the Gaussian model constructed from a smaller dataset. It analyzes the performance of Maseks system. In the matching stage, it uses a sequence of K iris codes to represent an iris subject. So the distance between a pair of iris subjects is defined as a K-dimensional Hamming distance, modeled as Gaussian distribution. The Gaussian models were constructed on the CASIA version 1.0 and West Virginia University (WVU) dataset separately. When using Shapiro-Wilk test
to evaluate the fitness of the model, it fits better on the CASIA dataset than on the WVU dataset.

**Dorairaj method**

Dorairaj et al. [13] proposed an iris recognition system dealing with off-angle iris images. It is assumed that the approximate value of the off-angle is known. The exact angle of non-frontal is computed by maximizing the Hamming distance between the off-angle iris image and a frontal view iris image from the same subject if available, or by minimizing Daugman’s integrodifferential operator when no frontal view iris image from the same subject is available. Then the off-angle is adjusted to a frontal view using a projective transform.

**Masek’s method**

Masek [14] proposes a method that begins with the binary edge image map construction, using the Kovesi edge detector, a variation of the well known Canny edge detector. The next step consists of applying the circular Hough transform to determine the iris/sclera border and then the one corresponding to iris/pupil. In fact, several other authors proposed minor variants to wildes method, essentially to adjust the process to different image intensities and contrasts.

**Liam and Chekima’s method**

This approach [15] is based on the fact that the pupil is typically darker than the iris and the iris darker than the sclera. Based on this assumption, these authors propose the use of a threshold technique that converts the initial captured grayscale image to binary. The threshold must be exactly calculated in order to join the pupil and the iris together in a dark region. Assuming that both iris and pupil, have a circular
form, the next step consists of creating a ring mask that will run through the whole image searching for the iris/sclera border. This step is followed by the elimination of all image information outside the iris ring, and upgrading the threshold value in order to capture intensity dissimilarities between the iris and the pupil. Pupil/Iris border determination is made using same method as described for the iris/sclera border. this method’s accuracy is strongly dependent on threshold values that have to be chosen by the user according to captured image characteristics.

**Tisse method**

This is a modification of the Daugman’s algorithm, with two major differences. The two innovations are in the iris location and feature extraction stages. The use of dimensionless polar coordinates and Hamming distance remain the same. In order to locate the iris, the Tisse[16] algorithm applies a gradient decomposed Hough Transform to find the approximate center of the pupil, and then applies the integro-differential operator, as in Daugman’s algorithm, to find the precise location of the iris boundaries. This combined approach has the advantage of avoiding errors due to specular reflection in the images. In the feature extraction and encoding step, Hilbert Transform is used to create an analytic image, whose output is then encoded as an emergent frequency vector and an instantaneous phase.

**NOH method**

An algorithm developed by Noh [17], performs a comparison of different feature extraction techniques including Gabor wavelets, Haar wavelets, DAUB4 wavelets, Independent Component Analysis (ICA), and Multi-resolution ICA (M-ICA). ICA is an unsupervised learning algorithm using high order statistics, and M-ICA is a new method of feature extraction, introduced by these authors. The Fisher Discrimination Ratio is used as a comparison tool. the Haar wavelets had the best performance in
their tests, followed closely by 2-D Gabor filters. The new M-ICA method performed well and further study is warranted.

**P. E. Merloti method**

In [18], a feed forward and back propagation neural network (NN) is used in the classification step. In the segmentation stage, the pupil region is first detected with a linear threshold method followed by using Freemans chain code [19]. Then a contrast filter is applied to the image to enhance the intensity difference in the iris image. The limbic boundary is decided by checking the intensity values along a horizontal line passing through the detected pupil center. The segmentation stage of this approach was not very successful, 78.6% segmentation accuracy was claimed by testing on CASIA iris database which, as noted above, contains manually edited pupils. As indicated earlier, the effectiveness of the segmentation algorithm needs evaluation on original iris images. There are three layers in the NN: one input layer, one hidden layer, and one output layer. The input layer is corresponding to the iris feature vector. The number of input units equals to the length of the iris feature vector. The number of output units equals to the number of subjects involved in the experiments. The number of the hidden nodes is equal to half the number of input nodes. To reduce the computation complexity, they utilized a Singular Value Decomposition (SVD) and Independent Component Analysis (ICA) to reduce the length of the iris pattern vectors, and thus reduce the number of input units of the NN. The experimental results demonstrate that using ICA works much better than using SVD. The identification rate on the CASIA data set is 92.1% when using ICA to decrease the input vector to a length of 50.
W. Kong and D. Zhang method

Kong and Zhang [20] proposed an eyelash and reflection segmentation in their algorithm. The overall system is developed based on the algorithm of Boles and Boashash [8] with the addition of an eyelash and reflection segmentation model. The iris segmentation is implemented by using curve fitting approaches. The eyelashes are subclassified as separable eyelashes and multiple eyelashes. The separable eyelashes are segmented using a Gabor filter. The multiple eyelashes are segmented by checking if the variance of intensity of a given area is less than a threshold. Reflections can be distinguished as strong reflection and weak reflection. The strong reflections are detected by setting a threshold for the intensity value, and the weak reflections are detected by using a statistical model on the intensity distribution. They tried four types of 1-D wavelets (Mexican hat, Haar wavelet, Shannon, and Gabor) to extract the iris features. They claimed an equal error rate (EER) of 11%, which was reduced 3% by using their eyelash and reflection segmentation model. The testing dataset was composed of 238 iris images (48 irises). The source of the dataset was not indicated.

B. J. Kang method

Kang et al. [21] discussed how to overcome the problem of defocussing. They first estimate the focus score by measuring the high frequency components after a convolution with a kernel of a size of 5 x 5 pixels. If the estimated focus score is lower than a threshold of 80, the defocused iris image will be restored to a focused image before further experiments. The relation of between the defocused image $d(x, y)$ and the focused image $f(x, y)$ is defined in Equation

\[
d(x, y) = b(x, y)f(x, y) + n(x, y) \tag{1.3}
\]
where b(x, y) is the blurring function and n(x, y) is the noise function. In the frequency domain, the clear image (focused) F(u, v) can be obtained from the defocused image D(u, v) by using Equation

\[
F(u, v) = \frac{D(u, v)}{H(u, v)}
\]  

(1.4)

where H(u, v) is the degradation function which can be estimated by a set of training data. When H(u, v) is zero, a constant will be added to it to avoid the divide by zero errors. The proposed algorithm was tested on the CASIA I dataset.

**Fancourt method**

Fancourt et al. [22] discussed the problem of iris recognition using images acquired at up to 10 meters away. The pictures were captured with the aid of a telescope. The pictures have a resolution of 640 x 480. The automatic segmentation algorithm was based on [8]. They also used manual iris segmentation as a bootstrap to the automatic segmentation. The similarity between the gallery image and probe image is measured by the average correlation coefficient over sub-blocks with a size of 12 x 12 pixels. They tested the algorithm on two iris databases with no subjects in common. There are 50 subjects (50 irises) in the database I, and 200 subjects (247 irises) in the database II. Neither of these two databases is available to the public.

**Proenca and Luis A. Alexandre method**

Proenca and Luis A. Alexandre [23] had focused on non-cooperative iris recognition proposed a method for iris classification which divides the segmented and normalized iris images into six regions, makes an independent feature extraction and comparison for each region, and combines each of the dissimilarity values through a classification rule.
Ya-Ping Huang Chen method

Ya-Ping Huang Chen [24] iris recognition algorithm is proposed which adopts Independent Component Analysis (ICA) to extract iris texture feature and competitive learning mechanism to recognize iris pattern. The algorithm is efficient and adaptive to environment.

GU Hong-ying, Zhuang method

GU Hong-ying, Zhuang Yue-ting, PAN Yun-he [25] had proposed iris feature extraction approach using both spatial and frequency domain is presented. Steerable pyramid is adopted to get the orientation information on iris images. The feature sequence is extracted on each sub-image and used to train Support Vector Machine (SVM) as iris classifiers. SVM has drawn great interest recently as one of the best classifiers in machine learning, although there is a problem in the use of traditional SVM for iris recognition. It cannot treat False Accept and False Reject differently with different security requirements. Therefore, a new kind of SVM called Non-symmetrical SVM is presented to classify the iris features.

A. Poursaberi and B. N. Araabi method

A. Poursaberi and B. N. Araabi[26] had proposed two different Algorithms are for iris segmentation. The first Algorithm, a circle is located around the pupil with an appropriate diameter the Iris area is encircled by the circular boundary is used for recognition purposes. The second algorithm again circle is located around the pupil with larger diameter. Hamming and harmonic mean distance classifiers are exploited as a mixed classifier in their algorithm. It is observed that relying on a smaller but more reliable part of the iris, though reducing the net amount of information, improves the overall performance. The sensitivity of the proposed method is analyzed
versus contrast, illumination, and noise as well, where lower sensitivity to all factors is observed when the lower half of the iris is used for recognition.

**Hui Zheng, Fei Su method**

He proposed Symmetry Gabor wavelet\[27\]. In iris image preprocessing, an effective segmentation using Integro differential operator and circular edge detector. Eyelids occlusion detection approach by using intensity projection are introduced. During recognition, only the imaginary part of complex 2-D Gabor filter is used in coding for shorter code length but without affecting the recognition performance. A simple effective filter parameters selection scheme is proposed at the same time.

**Junying Zeng, Yikui Zhai, Gunying Gan method**

In this paper \[28\] presents a new method for effective iris recognition using Biometrics Pattern Recognition (BPR), which is a new theory proposed by academician Shoujue Wang. A model for iris recognition that is based on BPR was introduced and thoroughly discussed. Experimental results on the Chinese Academy of Sciences, Institute of Automation (CASIA) iris image database clearly demonstrates that the use of Biometric Pattern Recognition makes it possible to achieve highly accurate and efficient recognition results with the proposed iris recognition model.

**Yikui Zhai, Junying Zeng, Junying Gan, and Ying Xu method**

Biometrics pattern recognition (BPR) has been proposed for several years, but it has never been applied to iris recognition yet. In this paper \[29\], a new iris recognition method high dimensional space covering method combined with BPR was proposed. Experiments on the CASIA iris image database show that the iris recognition method based on BPR is reliable and efficient.
This paper proposes [30] a non-orthogonal view iris recognition system comprising a new iris imaging module, an iris segmentation module, an iris feature extraction module and a classification module. A dual-charge-coupled device camera was developed to capture four-spectral (red, green, blue, and near infrared) iris images which contain useful information for simplifying the iris segmentation task. An intelligent random sample consensus iris segmentation method is proposed to robustly detect iris boundaries in a four-spectral iris image. In order to match iris images acquired at different off-axis angles, propose a circle rectification method to reduce the off-axis iris distortion. The rectification parameters are estimated using the detected elliptical pupillary boundary. Furthermore, propose a novel iris descriptor which characterizes an iris pattern with multi scale step/ridge edge-type maps. The edge-type maps are extracted with the derivative of Gaussian and the Laplacian of Gaussian filters. The iris pattern classification is accomplished by edge-type matching which can be understood intuitively with the concept of classifier ensembles.

1.3 Limitations of The Existing Iris Recognition Algorithms

1. Hough transform is a very CPU and memory hungry method which requires enormous time to compute even with modern microprocessors.

2. Hough transform can only detect line/circles but not their thickness, thus increasing the chances of false detections.

3. Redundant analysis is more in this method making computation requirement higher and thus making it impossible to implement in small image processing processors.

4. Efficiency of the Hough transform is dependent on the quality of the input data,
so denoising stage must be used before. Consequently Radon transform is preferred, since it has the nice effect of attenuating the noise.

5. Daugman method assumes perfect illusion conditions like-non reflectance of specular light reflected in the pupil.

6. Wavelets are used for Feature extraction is based on conventional Haar which has zero vanishing moment. They are also separable wavelets, not sensitive to direction in all angles which is crucial for iris feature extraction.

7. Efficiency of the Daugman algorithm with CASIA standard database is only 98.843 %.

1.4 Problem Specification

Broadly the goal of the research is to investigate the performance of the popular iris recognition techniques in a real time scenario and to develop an efficient iris recognition system. In such an efficient system as the subjects enter the scene the system should:

–Capture images from the camera on-line,

–Detect the existence of an iris in each frame,

–Efficiently segment the iris,

–Normalize the iris & finally,

–Recognize and display the ID of the person.

The Principal objective of the research is to arrive at the most appropriate segmentation method keeping in view the recognition and classification efficiency, and to study the existing feature extraction methods and to come up with a near optimal solution to the present problem.
1.5 Specific Contributions

The principal contributions of our research work and of the thesis are represented and the publications that resulted from each stage of our work identified. They include:

- The discussion and comparison between the most common biometric traits.
- The construction of a new iris image database (CASIA-IrisV3 are CASIA-Iris-Interval, CASIA-Iris-Lamp, CASIA-Iris-Twins and CASIA-IrisV4), freely available through the web for research purposes. This database has characteristics that clearly distinguish it from the remaining public and free ones and was remarkably well accepted within the academic and research environments.
- The proposal of a more robust iris segmentation and feature extraction method, able to deal with highly heterogeneous and noisy iris images.
- The study of the influence that small iris segmentation errors have in the final recognition accuracy and the proposal of a method able to identify these inaccuracies.
- The proposal of a method for the identification of noise regions in normalized iris images. This method produces a binary map that can be used in further stages, namely in the feature extraction, comparison and selection.
- The proposal of an iris classification method based on the iris partition, in the independent feature extraction on each partition and in the further iris classification through a cropping rule. This strategy avoids that localized noise regions in the iris images corrupt the whole biometric signature and degrade the recognition accuracy.
- The proposal of a feature quality measure, used in the feature comparison stage, which avoids that features extracted from predominantly noisy iris
regions can be taken into account in the feature comparison.

1.6 Thesis Outline

The remainder of this thesis is organized as follows: chapter 2 introduces the main concepts associated with biometrics, the most common biometric traits, their classification and measures of effectiveness. Further, a review of the iris recognition state-of-the-art is given and some discussion about the biometric recognition is presented. A detailed description of the existent public and freely available iris image databases is given, with particular emphasis on the CASIA version II, III, MMU and IITA Czech Republic iris database. Chapter 3 summarizes the most common iris segmentation methods and reports their small robustness when dealing with noisy images. An overview of the most common strategies for Image enhancement is given in chapter 4, and a detailed description of our proposal is further presented. Chapter 5 describes the problems associated with feature extraction, comparison and selection in the classification of noisy iris images. In order to overcome these problems, the method that contributes for the recognition robustness and accuracy within noisy environments are presented. Finally, chapter 6 presents the conclusions summarizes our achievements and points possible directions for further work.