Chapter 2

State-of-the-Art

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 assuming 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 and the iris). The outer circle is the limbic boundary (between the iris and the sclera). The noise processing is often included in the segmentation stage. Possible sources of segmentation noise are eyelid occlusions, eyelash occlusions, specular highlights, and shadows. The bright spot in the bottom left of the pupil region in the image in Figure 2.1 is an example of a specular highlight.

![Iris Image Examples](image.png)

Figure 2.1 Iris image examples

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).

2.1 Classification of Biometric System

Biometric systems can be classified according to six perspectives [48], as a function of the characteristics of the recognition procedure itself:

**Overt / covert** If the user is aware about the acquisition of his biometric data, the application is defined as overt; otherwise, is defined as covert. This is clearly one of the most concerning characteristics of a biometric system, regarding the privacy issue.

**Habituated / non-habituated** When the majority of the people that interacts with the biometric system are every-day users, the recognition is performed in the habituated mode. If the average frequency of use from each user is low, the recognition is performed in the non-habituated mode. This is relevant to the degree of cooperation and training demanded from the users.

**Attended / non-attended** If the user is observed and guided by supervisors during the process, the biometric recognition is considered as attended; if not, the user is considered non-attended. Obviously, the easy-of-use of the recognition system is much more relevant in the non-attended mode.

**Standard / non-standard environment** When all the conditions can be controlled and the recognition takes place indoors within constrained conditions, it is considered that the recognition is performed within a standard environment; if not, the use is called in non-standard environment.

**Public / private** If the users are not employees of the organization that owns the recognition system, the application is public; if the users are employees, the application is called private.

**Open / closed** If the system uses completely proprietary formats, the application is
considered closed. Otherwise, when the system is able to exchange data with others, it is called open and once again, privacy and legal issues should be addressed.

2.2 Performance of Biometric Systems

Biometrics can be used in at least two different types of applications: verification scenarios and identification scenarios [91]. In a verification scenario, a person claims a particular identity and the biometric system is used to verify or reject the claim. Verification is done by matching a biometric sample acquired at the time of the claim against the sample previously enrolled for the claimed identity. If the two samples match well enough, the identity claim is verified, and if the two samples do not match well enough, the claim is rejected. Thus there are four possible outcomes. A true accept (TA) occurs when the system accepts, or verifies, an identity claim, and the claim is true. A false accept (FA) occurs when the system accepts an identity claim, but the claim is not true. A true reject (TR) occurs when the system rejects an identity claim and the claim is false. A false reject (FR) occurs when the system rejects an identity claim, but the claim is true. The two types of errors that can be made are a false accept and a false reject. The number of false accepts and the number of false rejects is dependent on the decision criteria for the system. In a biometrics system, comparisons between two samples are assigned a score related to the difference between the two samples. The system must decide on a decision threshold such that all scores below the threshold will be deemed genuine. Impostor comparisons with scores below this threshold are false accepts; genuine comparisons with scores above the threshold are false rejects [92].

Performance for the system across a range of decision thresholds can be summarized in a receiver operating characteristic (ROC) curve [100]. Each point on the ROC curve represents one possible decision threshold. The curve plots the true accept rate on the Y axis and the false accept rate on the X axis, or, alternatively, the false reject rate on the Y axis and the false accept rate on the X axis. The true accept rate is the number of true accepts divided by the total number of true claims:

\[ TAR = \frac{TA}{(TA + FR)} \]  

(2.1)
The false accept rate is the number of false accepts divided by the total number of false claims:

\[
FAR = \frac{FA}{(FA + TR)}
\]  

(2.2)

The false reject rate is

\[
FRR = 1 - TAR = \frac{FR}{(TA + FR)}
\]  

(2.3)

The equal-error rate (EER) is a single number often quoted from the ROC curve. The EER is where the false accept rate equals the false reject rate.

In an identification scenario, a biometric sample is acquired without any associated identity claim. The closed-set identification task is to identify the sample as matching one of a set of previously enrolled known samples. The open set identification task is to either identify the unknown sample or to determine that the unknown sample does not match any of the known samples. The set of enrolled samples is often called a gallery, and the unknown sample is often called a probe. The probe is matched against all of the entries in the gallery, and the closest match, assuming it is close enough, is used to identify the unknown sample. Similar to the verification scenario, there are four possible outcomes. A true positive occurs when the system says that an unknown sample matches a particular person in the gallery and the match is correct. A false positive occurs when the system says that an unknown sample matches a particular person in the gallery and the match is not correct. A true negative occurs when the system says that the sample does not match any of the entries in the gallery, and the sample in fact does not. A false negative occurs when the system says that the sample does not match any of the entries in the gallery, but the sample in fact does belong to someone in the gallery. Performance in an identification scenario is often summarized in a cumulative match characteristic (CMC) curve. The CMC curve plots the percent of probes correctly recognized on the Y axis and the cumulative rank considered as a correct match on the X axis.

### 2.3 Eye and Iris Anatomy

In this section, we start with the description of the human eye anatomy, followed by a highly detailed description of the iris, which is the most relevant part of the eye for the purposes of our work.
2.3.1 Eye Anatomy

Figure 2.2 schematizes the most relevant parts of the human eye [49]. As with the majority of the mammals, the eye is roughly globular in shape and hollow and can be divided into two main segments - anterior and posterior - which are surrounded by a leathery envelope that acts as a protection: the sclera. This is a tough and fibrous tissue consisting of highly compacted and interweaved fibers and bands. When seen from the front, sclera is commonly, and incorrectly, referred to as the white of the eye [50].

![Eye Anatomy Diagram]

Figure 2.2 Anatomy of the human eye

Regarding the anterior eye segment, it extends internally from the anterior hyaloid face forward and is externally demarcated by the limbus. It includes the structures in front of the vitreous humor: the cornea, iris, ciliary body and lens. The cornea acts as a window at the front of the eye and provides about 85% of the focusing power of the eye. It is made up of a tissue similar to that of sclera, with the relevant exception of having no blood vessels. Just beneath the cornea is a fluid-filled space called the anterior chamber, which bathes the whole of the anterior segment providing nourishment and removal products to the lens and cornea. The ciliary body is the source of the above mentioned fluid and houses the muscular fibers that enable the eye to focus. Overlying the lens, there is a structure with an opening in the whole: the iris. It is made of an elastic tissue and its function is to control the amount of light
that enters the iris whole: the pupil. Behind the iris is the lens, whose role consists in assuring that the light rays come to a sharp focus on the retina.

The posterior eye segment comprises the back two-thirds of the eye and includes the vitreous humor, retina, choroid and optic nerve. The first is the clear aqueous solution that fills the space between the lens and the retina, which is a thin layer of nervous tissue supplied with oxygen and cleaned by the choroid - that is responsible for gathering the light and perform its conversion to the electrical signals that are sent through the optic nerve to the brain. This process gives us the sense of light and the ability to see and interpret shapes, colors and dimensions.

2.3.2 Iris Anatomy
The iris is the “colored ring of tissue around the pupil through which light enters the interior of the eye” [56]. The iris’s function is to control the amount of light entering the eye. Two muscles in the iris, the dilator and the sphincter muscles, control the size of the pupil, and therefore, the amount of light passing through the pupil. Figure 2.3 shows an example image acquired by Smart ID commercial iris acquisition system at the College of Engineering Pune. The sclera, a white region of connective tissue and blood vessels, surrounds the iris. A clear covering called the cornea covers the iris and the pupil. The pupil region generally appears darker than the iris. However, the pupil may have specular highlights, and cataracts can lighten the pupil. The iris typically has a rich pattern of furrows, ridges, and pigment spots. The surface of the iris is composed of two regions, the central pupillary zone and the outer ciliary zone. The collarette is the border between these two regions.

The minute details of the iris texture are believed to be determined randomly in utero. They are also believed to be different between persons and between the left and right eye of the same person [43]. The color of the iris can change as the amount of pigment in the iris increases during childhood. Some research asserts that the texture is relatively constant [11], but other research has detected lower match scores between images taken multiple years apart [59].
2.4 Early Research in Iris Biometrics

John Daugman’s technique [11] ~ [16] and Wildes system [17] are two of the earliest and best known iris recognition systems. The systems include every stage of iris recognition as described here: image acquisition, segmentation, texture encoding, and matching. There are many other works in the field of iris recognition in recent years. Most of these focus on proposing a new method, or optimizing for a specific one or more stage in iris recognition.

Daugman’s algorithm [11] ~ [16] is the best known iris algorithm. The iris is modelled as two circles, which are not necessarily concentric. The operator for iris localisation is, as follows:

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

(2.4)

where, $G_\sigma (r) = \frac{1}{\sqrt{2\pi}} e^{-r^2/2}$ is a Gaussian filter for smoothing and $\int_{x,y,r} I(x, y) / 2\pi r ds$ is integration operator along the circle with radius $r$ in $(x, y)$ coordinates. This method tries to
find a circle in the image with maximum gray level differences with its neighbours. It is obvious that the results are inner and outer boundaries of iris.

The eyelids are modeled as parabolic arcs. An integro-differential operator as described in Equation 2.4 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. The segmented iris image is normalized and converted from Cartesian image coordinates to polar image coordinates. Then a 2D Gabor filter is used to encode the iris image to a binary code of 256 bytes in length. In the matching part, the Hamming distance is used to indicate the similarity of two iris codes. A smaller distance means a better match. A threshold is used to determine if two iris codes match well enough to be considered to come from the same person, or not. Daugman reported obtaining a false accept rate (FAR) of 1 in 4 million along with a false reject rate (FRR) of zero. The testing dataset employed in [11] ~ [16] includes several thousand eye images, but is not publicly available.

Iridian’s iris recognition system [19] is based on Daugman’s technique. The Iridian iris recognition system involves every step in iris recognition, including iris data acquisition, segmentation, encoding, matching and verification.

In 1997, Richard P. Wildes [17] [18] suggested a novel method to find both the iris inner and outer borders. Their system performs its contour fitting in two steps. First, the image intensity information is converted into a binary edge-map. Second, the edge points vote to instantiate particular contour parameter values. From the edge map, votes are cast in Hough space for the center coordinates \((x_c, y_c)\), and the radius \(r\) of circles passing through each edge point. The Hough transform for a circular boundary and a set of recovered edge points \((x_j, y_j)\), \(j = 1 \ldots, n\) is defined as:

\[
H(x_c, y_c, r) = \sum_{j=1}^{n} h(x_j, y_j, x_c, y_c, r)
\]  

Where,

\[
h(x_j, y_j, x_c, y_c, r) = \begin{cases} 
1 & \text{if } g(x_j, y_j, x_c, y_c, r) = 0 \\
0 & \text{otherwise}
\end{cases}
\]
With,

\[ g(x_i, y_i, x_c, y_c, r) = (x_j - x_c)^2 + (y_j - y_c)^2 - r^2 \]  (2.7)

In implementation, the iris boundary is detected first by calculating the gradients in vertical direction, so that the effect of eyelashes and eyelids can be avoided. For pupil boundary detection horizontal gradients are calculated inside the detected iris boundary.

The Hough transform has few deficiencies; it fails to detect some circles while performing edge detection due to the fact that it depends on a threshold value; this value might not be critically specified, thus resulting in edge points being neglected. Another point which is worth noting is the fact that the Hough transform is computationally exhaustive, leading to low speed efficiency [18].

Wildes' system models the eyelids as parabolic arcs. The upper and lower eyelids are detected by using a Hough transform based approach similar to that described above. 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 while testing on 600 iris images (60 different irises). The testing iris dataset is not publicly available.

The algorithm of Boles and Boashash [20] extracts a set of one dimensional signals from the iris image using the intensity values on a set of circular contours centered 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 transformation at different resolution levels. While 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.

In an algorithm proposed by Ma et al. [21], 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 [22]. 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. So the effectiveness of the segmentation algorithm described in this paper needs evaluation on original iris images before an accurate judgment can be made.

Iris segmentation is an essential module in iris recognition because it defines the effective image region used for subsequent processing such as feature extraction. Traditional iris segmentation methods often involve an exhaustive search of a large parameter space, which is time consuming and sensitive to noise. To address these problems, this paper presents a novel algorithm for accurate and fast iris segmentation [5]. After efficient reflection removal, an Adaboost-cascade iris detector is first built to extract a rough position of the iris center. Edge points of iris boundaries are then detected, and an elastic model named pulling and pushing is established. Under this model, the center and radius of the circular iris boundaries are iteratively refined in a way driven by the restoring forces of Hooke’s law. Furthermore, a smoothing spline-based edge fitting scheme is presented to deal with noncircular iris boundaries. After that, eyelids are localized via edge detection followed by curve fitting. The novelty here is the adoption of a rank filter for noise elimination and a histogram filter for tackling the shape irregularity of eyelids. Finally, eyelashes and shadows are detected via a learned prediction model. This model provides an adaptive threshold for eyelash and shadow detection by analyzing the intensity distributions of different iris regions. Experimental results on three challenging iris image databases demonstrate that the proposed algorithm outperforms state-of-the-art methods in both accuracy and speed.

Kong and Zhang [24] proposed an eyelash and reflection segmentation in their algorithm. The overall system is developed based on the algorithm of Boles and Boashash [20] with the
addition of an eyelash and reflection segmentation model.

Vatsa et al. [45] improved the speed of active contour segmentation by using a two-level hierarchical approach. First, they found an approximate initial pupil boundary. The boundary was modeled as an ellipse with five parameters. The parameters were varied in a search for a boundary with maximum intensity change. For each possible parameter combination, the algorithm randomly selected 40 points on the elliptical boundary and calculated total intensity change across the boundary. Once the pupil boundary was found, the algorithm searched for the iris boundary in a similar manner, this time selecting 120 points on the boundary for computing intensity change. The approximate iris boundaries were refined using an active contour approach. The active contour was initialized to the approximate pupil boundary and allowed to vary in a narrow band of ±5 pixels. In refining the limbal boundary, the contour was allowed to vary in a band of ±10 pixels.

Ryan et al. [46] presented an alternative fitting algorithm, called the Starburst method, for segmenting the iris. They preprocessed the image using a smoothing filter and a gradient detection filter. Then, they needed to find a pupil location as a starting point for the algorithm. To do so, they set the darkest 5% of the image to black, and all other pixels to white. Then they created a Chamfer image: the darkest pixel in the Chamfer image is the pixel farthest from any white pixel in the thresholded image. They used the darkest point of the Chamfer image as a starting point. Next, they computed the gradient of the image along rays pointing radially away from the start point. The two highest gradient locations were assumed to be points on the pupillary and limbal boundaries. The detected points were used to fit several ellipses using randomly selected subsets of points. An average of the best ellipses was reported as the final boundary. The eyelids were detected using active contours.

Chin et al. [25] proposed the use of an “S-iris encoding” which is generated from the inner product of the output from a 1 D Log Gabor filter and secret pseudorandom 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 × 240 using Daugman’s rubber sheet model [11]. Then the final iris code is generated from the inner product of the output from a 1 D Log Gabor filter.
and secret pseudo random numbers. In matching, Hamming distance is used to indicate the dissimilarity between a pair of iris codes.

In [23], 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 Freeman’s chain code. 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. A 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.

Jino Zuo et. al. [6] in their paper presents a segmentation methodology that aims at compensating various nonidealities contained in iris images during segmentation. The virtue of this methodology lies in its capability to reliably segment nonideal imagery that is simultaneously affected with such factors as specular reflection, blur, lighting variation, occlusion, and off-angle images. They demonstrated the robustness of their segmentation methodology by evaluating ideal and nonideal data sets, namely, the Chinese Academy of Sciences iris data version 3 interval subdirectory, the iris challenge evaluation data, the West Virginia University (WVU) data, and the WVU off-angle data. Furthermore, they compared performance to that of their implementation of Camus and Wildes algorithm and Masek’s algorithm. They demonstrated considerable improvement in segmentation performance over the formerly mentioned algorithms.
The richness and apparent stability of the iris texture make it a robust biometric trait for personal authentication [7]. The performance of an automated iris recognition system is affected by the accuracy of the segmentation process used to localize the iris structure. Most segmentation models in the literature assume that the pupillary, limbic, and eyelid boundaries are circular or elliptical in shape. Hence, they focus on determining model parameters that best fit these hypotheses. However, it is difficult to segment iris images acquired under nonideal conditions using such conic models. In this paper, they described a novel iris segmentation scheme employing geodesic active contours (GACs) to extract the iris from the surrounding structures. Since active contours can 1) assume any shape and 2) segment multiple objects simultaneously, they mitigate some of the concerns associated with traditional iris segmentation models. The proposed scheme elicits the iris texture in an iterative fashion and is guided by both local and global properties of the image. The matching accuracy of an iris recognition system is observed to improve upon application of the proposed segmentation algorithm. Experimental results on the CASIA v3.0 and WVU nonideal iris databases indicate the efficacy of the proposed technique.

Daugman and Downing [43] describe an experiment to determine the statistical variability of iris patterns. Their experiment evaluates 2.3 million comparisons between different iris pairs. The mean Hamming distance between two different irises is 0.499, with a standard deviation of 0.032. This distribution closely follows a binomial distribution with 244 degrees of freedom. The distribution of Hamming distances for the comparisons between the left and right irises of the same person is found to be not statistically significantly different from the distribution of comparisons between different persons. Daugman [44] explained his use of active contours for fitting the iris boundaries. First, he calculated the image gradient in the radial direction. He detected occlusions by eyelids and modeled those with separate splines. Then a discrete Fourier series approximation was fit to the image gradient data. In any active contour method, there is a trade-off between how closely the contour fits the data versus the desired constraints on the final shape of the contour. Daugman modeled the pupil boundary with weaker constraints than the iris boundary, because he found that the pupil boundary tended to have stronger gradient data.

Schmid [38] 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 Masek’s system [37].

Dorairaj et al. [21] 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-frontality 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 integro-differential operator [11] 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.

Schuckers et al. [47] tried two different approaches to handle “off-angle” irises. In both approaches, they sought to transform an off-angle image into an equivalent frontal image. The first method sought to determine how far an image deviated from frontal by trying multiple values of pitch and yaw. For each (pitch, yaw) pair, they used bilinear interpolation to transform the image. They found the values of pitch and yaw that resulted in the maximum circularity of the detected pupil. For encoding and matching irises, they use independent component analysis. The second method modeled the relationship between actual 3D iris points with 2D projected points. Once that relationship was obtained, the 2D off-angle image could be transformed into a frontal view image. Biorthogonal wavelets are used for encoding and matching. Schuckers et al. found that results using their two methods were “significantly improved over the iris recognition techniques which do not perform any correction for angle.” The first method showed good performance for small angle deviations from training to testing, for example, training with 15 degrees and testing with 0 or 30 degrees. However, there was relatively poor performance when training using 0 degrees and testing using 30 degree images. The probable cause of this is the use of the simple projective transform for large angle deviations. They concluded that the second method was better. However, it was unclear why they did not use the same encoding and matching step for both methods.

**Signal Transform in Iris Recognition**

Monro et al. [51] presents a novel iris coding method based on differences of discrete cosine transform (DCT) coefficients of overlapped angular patches from normalized iris images. The feature extraction capabilities of the DCT are optimized on the two largest publicly
available iris image data sets, 2,156 images of 308 eyes from the CASIA database and 2,955 images of 150 eyes from the Bath database. On this data, they achieve 100 percent Correct Recognition Rate (CRR) and perfect Receiver-Operating Characteristic (ROC) Curves with no registered false accepts or rejects. Individual feature bit and patch position parameters are optimized for matching through a product-of-sum approach to Hamming distance calculation. For verification, a variable threshold is applied to the distance metric and the False Acceptance Rate (FAR) and False Rejection Rate (FRR) are recorded.

Kazuyuki Miyazawa et. al.[3] in their paper presented an efficient algorithm for iris recognition using phase-based image matching—an image matching technique using phase components in 2 D Discrete Fourier Transforms (DFTs) of given images. Experimental evaluation using the CASIA iris image databases (versions 1.0 and 2.0) and Iris Challenge Evaluation (ICE) 2005 database clearly demonstrates that the use of phase components of iris images makes it possible to achieve highly accurate iris recognition with a simple matching algorithm. This paper also discusses the major implementation issues of their algorithm. In order to reduce the size of iris data and to prevent the visibility of iris images, they introduced the idea of 2 D Fourier Phase Code (FPC) for representing iris information. The 2 D FPC is particularly useful for implementing compact iris recognition devices using state-of-the-art Digital Signal Processing (DSP) technology.

Data quality assessment is a key issue, in order to broaden the applicability of iris biometrics to unconstrained imaging conditions [1]. Previous research efforts sought to use visible wavelength (VW) light imagery to acquire data at significantly larger distances than usual and on moving subjects, which makes this real-world data notoriously different from the acquired in the near-infrared setup. The paper proposes a method to assess the quality of VW iris samples captured in unconstrained conditions, according to the factors that are known to determine the quality of iris biometric data: focus, motion, angle, occlusions, area, pupillary dilation, and levels of iris pigmentation [1]. The key insight is to use the output of the segmentation phase in each assessment, which permits to handle severely degraded samples that are likely to result of such imaging setup. Also, their experiments point that the given method improves the effectiveness of VW iris recognition, by avoiding that poor quality samples are considered in the recognition process.
Kevin W. Bower et. al [4] survey covers the historical development and current state of the art in image understanding for iris biometrics. Most research publications can be categorized as making their primary contribution to one of the four major modules in iris biometrics: image acquisition, iris segmentation, texture analysis and matching of texture representations. Other important research includes experimental evaluations, image databases, applications and systems, and medical conditions that may affect the iris. They also suggested a short list of recommended readings for someone new to the field to quickly grasp the big picture of iris biometrics.

The iris is regarded as one of the most useful traits for biometric recognition and the dissemination of nationwide iris-based recognition systems is imminent. However, currently deployed systems rely on heavy imaging constraints to capture near infrared images with enough quality [2]. Also, all of the publicly available iris image databases contain data correspondent to such imaging constraints and therefore are exclusively suitable to evaluate methods thought to operate on these types of environments. The main purpose of this paper is to announce the availability of the UBIRIS.v2 database, a multisession iris images database which singularly contains data captured in the visible wavelength, at-a-distance (between four and eight meters) and on on-the-move. This database is freely available for researchers concerned about visible wavelength iris recognition and will be useful in accessing the feasibility and specifying the constraints of this type of biometric recognition.

2.5 Early Research in Iris Clinical Predictions

Many parts of the human body are projected in the brain. Some people believe that projection also exists in other organs-for example, the tongue, feet, ears. In 1881 von Peczely wrote a book on diagnosis using the eye, in which he gave a schematic representation of the topography of the organs in the iris. Some people now believe that many diseases manifest themselves in the iris, which is supposed to indicate not only the existence of certain diseases but also the tendency for their development ("constitution"). Iridology is practiced on a large scale especially in alternative medicine, in which it is considered to be an important diagnostic supplement to the medical history and (conventional) physical examination

Ramlee and Ranjit [8] described about using iris recognition algorithm for detection of
cholesterol. In this paper they have used existing iris recognition method as an alternative method to detect the presence of cholesterol in blood vessel. Based on the iris recognition method and iridology chart, a MATLAB program is created to detect presence of cholesterol in human body.

Wibawa and Purnomo [9] discussed early detection on the condition of pancreas organ as the cause of a diabetes mellitus by real time iris image processing. In their work the input image of iris is taken by using a video camera in real time. The presence of broken tissues in iris in a certain area represents the condition of certain organ according to the iris chart. The organ that is observed in iris research is pancreas. Pancreas’s position in iris is at 07.15-07.45 when a circle of iris is divided by 120 points. Several image processing methods are used to enhance the quality of image of iris so that the broken tissues in area of pancreas can be detected clearly. Finally, the result of this detecting method is compared with the insulin normality test.

Ma and Li [10] suggested texture feature extraction and classification for iris diagnosis. This paper proposes an iridology model that consists of iris image pre-processing, texture feature analysis and disease classification. In preprocessing a 2-step iris localisation approach is proposed, a 2 D Gabor filter based texture analysis and texture fractal dimension estimation method are proposed for pathological feature extraction; and at last support vector machines are constructed to recognise two typical disease such as the alimentary canal disease and the nerve system disease. Experimental results show that the proposed iridology diagnosis model is quite effective and promising for medical diagnosis and health surveillance for both hospital and public use.

Yu et al. [40] emphasize on extracting the autonomic nerve wreath of iris based on an improved snake approach. The autonomic nerve wreath (ANW) is a major landmark feature of iris topography in iridology. Finding the edge of the ANW is of great importance to an automated iris diagnosis system. Based on a two phase greedy optimisation approach, this paper presents an improved snake model for extracting the edge of the ANW, which solves the problem that the traditional snake initial contour should be close to the true boundary of interested object in an image.
Knipschild [41] described about looking for gall bladder disease in the patient’s iris. In his paper, alternative health care iridology is used as a diagnostic aid. The diagnosis of gall bladder disease was used to study its validity and interperformer consistency. The presence of an inflamed gall bladder containing gall stones is said to be easily recognized by certain signs in the lower lateral part of the iris of the right eye. Stereo color slides were made of the right eye of 39 patients with this disease and 39 control subjects of the same sex and age. The slides were presented in a random order to five leading iridologists without supplementary information. The prevalence of the disease was estimated at 56%. The median validity was 51% with 54% sensitivity and 52% specificity. These results were close to chance validity. None of the iridologists reached a high validity. The median interperformer consistency was 60%. This was only slightly higher than chance consistency. This study showed that iridology is not a useful diagnostic aid.

2.6 Summary of State-of-the-Art

In recent years, a lot of work has been done in the field of iris recognition. However, the lack of large-scale experimental evaluation on a public iris dataset is still a restriction in iris recognition. CASIA is the public iris dataset used most frequently in iris recognition publications. It was once the biggest public iris dataset available to researchers. However as indicated earlier, the iris images in the CASIA version 1 dataset are not original images. It is not proper to use the CASIA dataset to evaluate iris segmentation algorithms. The Iris Challenge Evaluation (ICE) dataset, UBIRIS dataset, MMU dataset, ND Iris 04 05 are bigger. The images in mentioned above datasets are original iris images obtained from the data acquisition conducted at University of Notre Dame, University of Beira Interior, Multimedia University, and Chinese Academy Sciences Institute of Automation. Since their release, they have already been distributed to more than 60 research groups and 24 groups presented results publicly on these datasets.

Iris recognition involves various modules such as Image capture, Quality Assessment, Normalisation, Feature extraction and classification. The overall performance of iris recognition depends on each and every module involved in recognition regime and has challenging issues.
Iris segmentation is the most important module in iris recognition system. The performance of the iris recognition system depends on the accuracy of segmentation module. The accuracy and robustness of iris segmentation are challenging issues in iris recognition system. The boundaries of iris region can be approximated using two circles, one for the iris/sclera boundary and another for the iris/pupil boundary. The aim of iris segmentation is to estimate the center as well as radius of two circles with removal of reflection, eyelids and eyelashes. The segmentation of iris is an important step in the iris recognition process; if it is incorrectly segmented, the resultant noise (e.g., eyelashes, reflections, pupil, eyelashes, sclera, and eyelids) in the image may cause a degradation of the resulting iris code and matching performance.

The usage of iris for clinical prediction; though appealing, has limited work reported in the literature. Nonetheless, this work attempts to explore iris analysis for clinical prediction with emphasis on diabetic subjects (Type II).

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