CHAPTER 5

IRIS RECOGNITION AND FUZZY DATABASE

5.1 Introduction

The iris is the “colored ring of tissue around the pupil through which light enters the interior of the eye.” Two muscles, the dilator and the sphincter muscles, control the size of the iris to adjust the amount of light entering the pupil. 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.

5.2 Features of Iris

The iris is a thin circular diaphragm which lies between the cornea and the lens of the human eye. The iris is close to its centre by a circular aperture known as the pupil. The iris controls the diameter and size of the pupils and the amount of light reaching the retina. The iris is an externally visible, yet protected organ whose unique epigenetic pattern remains stable throughout adult life. These characteristics make it very attractive for use as a biometric for identifying individuals.

The iris is divided into two major regions:

1. The pupillary zone is the inner region whose edge forms the boundary of the pupil.

2. The ciliary zone is the rest of the iris that extends to its origin at the ciliary body.
From anterior (front) to posterior (back), the layers of the iris are:

- Anterior limiting layer
- Stoma of iris
- Iris sphincter muscle
- Iris dilator muscle
- Anterior pigment myoepithelium
- Posterior pigment epithelium

5.2.1 Anterior surface features

1. The Crypts of Fuchs are a series of openings located on either side of the collarette that allow the stroma and deeper iris tissues to be bathed in aqueous humor. Collagen trabeculae that surround the border of the crypts can be seen in blue irides.

2. The pupillary ruffs (crenations) are a series of small ridges at the pupillary margin formed by the continuation of the pigmented epithelium from the posterior surface.

3. The Circular contraction folds, also known as contraction furrows, are a series of circular bands or folds about midway between the collarette and the origin of the iris. These folds result from changes in the surface of the iris as it dilates.

4. Crypts at the base of the iris are additional openings that can be observed close to the outermost part of the ciliary portion of the iris.
5.2.2 Posterior surface features

1. The Radial contraction folds of Schwalbe are a series of very fine radial folds in the pupillary portion of the iris extending from the pupillary margin to the collarette. They are associated with the scalloped appearance of the pupillary ruff.

2. The Structural folds of Schwalbe are radial folds extending from the border of the ciliary and pupillary zones that are much broader and more widely-spaced, continuous with the "valleys" between the ciliary processes.

3. Some of the Circular contraction folds are a fine series of ridges that run near the pupillary margin and vary in thickness of the iris pigment epithelium; others are in ciliary portion of iris. It changes colors like a rainbow.

5.3 Iris for Recognition

As in all pattern recognition problems, the key issue is the relation between inter-class and intra-class variability: objects can be reliably classified only if the variability among different instances of a given class is less than the variability between different classes. For example, in face recognition, difficulties arise from the fact that the face is a changeable social organ displaying a variety of expressions, as well as being an active three-dimensional object whose image varies with viewing angle, pose, illumination, accoutrements, and age. It has been shown that for “mug shot” images taken at least one year apart, even the best current algorithms can have error rates of 43%–50%. Against this intra-class (same face) variability, inter-class variability is limited because different faces possess the same basic set of features, in the same canonical geometry.
For all of these reasons, iris patterns become interesting as an alternative approach to reliable visual recognition of persons and especially when there is a need to search very large databases without incurring any false matches despite a huge number of possibilities. Although small (11 mm) and sometimes problematic to image, the iris has the great mathematical advantage that its pattern variability among different persons is enormous. In addition, as an internal (yet externally visible) organ of the eye, the iris is well protected from the environment and stable over time. As a planar object its image is relatively insensitive to angle of illumination, and changes in viewing angle cause only affine transformations; even the nonaffine pattern distortion caused by pupillary dilation is readily reversible. Finally, the ease of localizing eyes in faces, and the distinctive annular shape of the iris, facilitates reliable and precise isolation of this feature and the creation of a size-invariant representation.

5.4 Operations for Iris Recognition

5.4.1 Determination of Iris Color

The iris is usually strongly pigmented with colors ranging from brown to green, blue, grey, and hazel. Occasionally its color is due to lack of pigmentation, as in the pinkish-white of oculo-cutaneous albinism or to obscuration of its pigment by blood vessels, as in the red of an abnormally vascularised iris. Despite the wide range of colors, there is only one pigment that contributes substantially to normal human iris color, the dark pigment called melanin. Structurally, this huge molecule is only slightly different from its equivalent found in skin and hair.

Iris color is a highly complex phenomenon consisting of the combined effects of texture, pigmentation, fibrous tissue and blood vessels within the iris stroma, which together make up an individual's epigenetic constitution in this context. A person's "eye color" is actually the color of one's iris, the cornea being transparent and the
white sclera entirely outside the area of interest. It is a common misconception that the iris color is entirely due to its melanin pigment, this varies only from brown to black. Iris color is determined mainly by the density of melanin pigment in its anterior layer and stroma, with blue irises resulting from an absence of pigment: long-wavelength light penetrates while shorter wavelengths are scattered by the stroma. The striated trabecular meshwork of elastic pectinate ligament creates the predominant texture under visible light, whereas in the near-infrared (NIR) wavelengths used for unobtrusive imaging at distances of up to 1 m deeper and somewhat more slowly modulated stromal features dominate the iris pattern. In NIR wavelengths, even darkly pigmented irises reveal rich and complex features.

5.4.2 Image Acquisition
To capture the rich details of iris patterns, an imaging system should resolve a minimum of 70 pixels in iris radius. In the field trials to date, a resolved iris radius of 80–130 pixels has been more typical. Monochrome cameras (480*640) have been used because NIR illumination in the 700–900-nm band was required for imaging to be unintrusive to humans. Some imaging platforms deployed a wide-angle camera for coarse localization of eyes in faces, to steer the optics of a narrow-angle pan/tilt camera that acquired higher resolution images of eyes.

Image focus assessment is performed in real time (faster than video frame rate) by measuring spectral power in middle and upper frequency bands of the 2-D Fourier spectrum of each image frame and seeking to maximize this quantity either by moving an active lens or by providing audio feedback to Subjects to adjust their range appropriately. The video rate execution speed of focus assessment (i.e., within 15 ms) is achieved by using a bandpass 2-D filter kernel requiring only summation and
differencing of pixels, and no multiplications, within the 2-D convolution necessary to estimate power in the selected 2-D spectral bands.

Images passing a minimum focus criterion are then analyzed to find the iris with precise localization of its boundaries using a coarse-to-fine strategy terminating in single-pixel precision estimates of the center coordinates and radius of both the iris and the pupil. Although the results of the iris search greatly constrain the pupil search, concentricity of these boundaries cannot be assumed. Very often the pupil center is nasal, and inferior, to the iris center. Its radius can range from 0.1 to 0.8 of the iris radius. Thus, all three parameters defining the pupillary circle must be estimated separately from those of the iris. A very effective integrodifferential operator for determining these parameters is

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

Where \( I(x,y) \) is an image such as Fig. 5.1 containing an eye. The operator searches over the image domain \((x, y)\) for the maximum in the blurred partial derivative with respect to increasing radius \(r\), of the normalized contour integral of \( I(x, y) \) along a circular arc \( ds \) of radius and center coordinates \((x_0, y_0)\). The symbol * denotes convolution and \( G*\) is a smoothing function such as a Gaussian of scale \(\sigma\). The
complete operator behaves as a circular edge detector, blurred at a scale set by \( \sigma \), searching iteratively for the maximal contour integral derivative at successively finer scales of analysis through the three parameter space of center coordinates and radius \((x_0, y_0, r)\) defining a path of contour integration. The operator in (1) serves to find both the pupillary boundary and the outer (limbus) boundary of the iris, although the initial search for the limbus also incorporates evidence of an interior pupil to improve its robustness since the limbic boundary itself usually has extremely soft contrast when long wavelength NIR illumination is used. Once the coarse-to-fine iterative searches for both these boundaries have reached single-pixel precision, then a similar approach to detecting curvilinear edges is used to localize both the upper and lower eyelid boundaries. The path of contour integration in (1) is changed from circular to arcuate, with spline parameters fitted by statistical estimation methods to model each eyelid boundary. Images with less than 50% of the iris visible between the fitted eyelid splines are deemed inadequate, e.g., in blink. The result of all these localization operations is the isolation of iris tissue from other image regions, as illustrated in Fig. 1 by the graphical overlay on the eye.

5.4.3 Segmentation
Each isolated iris pattern is then demodulated to extract its phase information using quadrature 2-D Gabor wavelets [16]. It amounts to a patch-wise phase quantization of the iris pattern, by identifying in which quadrant of the complex plane each resultant phasor lies when a given area of the iris is projected onto complex-valued 2-D Gabor wavelets:

\[
\begin{align*}
    h_{(Re, Im)} &= sgn_{(Re, Im)} \int_{\Omega} \int_{\Omega} I(p, \varnothing) e^{-i\omega(\theta_0 - \varnothing)} e^{-((r_0 - p)^2/r^2 + (\theta_0 - \varnothing)^2/\rho^2)} dp d\varnothing \\
    \end{align*}
\]  

(2)

Where \( h_{(Re, Im)} \) can be regarded as a complex-valued bit whose real and imaginary parts are either 1 or 0 (sgn) depending on the sign of the 2-D integral; \( I(p, \varnothing) \) is the raw
iris image in a dimensionless polar coordinate system that is size and translation invariant and which corrects for pupil dilation. \(\alpha\) and \(\beta\) are the multiscale 2-D wavelet size parameters, spanning an eight-fold range from 0.15 to 1.2 mm on the iris; \(\omega\) is wavelet frequency, spanning three octaves in inverse proportion to \(\beta\); and \((r_0, \Theta_0)\) represent the polar coordinates of each region of iris for which the phasor coordinates \(h_{[Re, Im]}\) are computed. Altogether, 2048 phase bits (256 bytes) are computed for each iris, now an equal number of masking bits are also computed to signify whether any iris region is obscured by eyelids, contains any eyelash occlusions, specular reflections, boundary artifacts of hard contact lenses, or poor signal-to-noise ratio (SNR) and thus should be ignored in the demodulation code as artifact.

Only phase information is used for recognizing irises because amplitude information is not very discriminating and it depends upon extraneous factors such as imaging contrast, illumination, and camera gain. The phase bit settings which code the sequence of projection quadrants capture the information of wavelet zero-crossings as is clear from the sign operator in (2). The extraction of phase has the further advantage that phase angles remain defined regardless of how poor the image contrast may be. Its phase bit stream has statistical properties such as run lengths similar to those of the code for the properly focused eye image in Fig. 5.1. The benefit which arises from the fact that phase bits are set also for a poorly focused image as shown here, even if based only on random thermal noise, is that different poorly focused irises never become confused with each other when their phase codes are compared. By contrast, images of different faces look increasingly alike when poorly resolved and can be confused with each other by appearance based face recognition algorithms.

**5.4.4 Feature Encoding**

Different approaches for analyzing the texture of the iris:
• One body of work effectively looks at using something other than a Gabor filter to produce a binary representation similar to Daugman’s iris code.

• Another body of work looks at using different types of filters to represent the iris texture with a real-valued feature vector.

• A smaller body of work looks at combinations of these two general categories of approach.

5.4.5 Alternate Means to a Binary Iris Code

Many different filters have been suggested for use in feature extraction. The gradient vector field of an iris image is convolved with a Gaussian filter, yielding a local orientation at each pixel in the unwrapped template. It quantizes the angle into six bins. (In contrast, Daugman’s method quantizes phase information into four bins corresponding to the four quadrants of the complex plane.)

Chenhong and Zhaoyang [37] and Chou [13] convolve the iris image with a Laplacian-of-Gaussian filter. Chenhong and Zhaoyang use this filter to find “blobs” in the image that are relatively darker than surrounding regions. An iris code is then constructed based on the presence or absence of detected blobs at points in the image. Chou et al. use both derivative-of-Gaussian and Laplacian-of-Gaussian filters to determine if a pixel is a “step” or “ridge” edge, respectively. One measure of the distance between two iris images is then represented by the ratio of the number of corresponding pixels at which the edge maps disagree divided by the number at which they agree. One motivation for these types of filters is that “the number of free filter parameters is only three, and hence they can be easily determined.” They suggest a genetic algorithm for designing the filter parameters. After that modified Log-Gabor filters are used because the Log-Gabor filters are “strictly bandpass filters and the [Gabor filters] are not.”
Ordinary Gabor filters would under-represent the high frequency components in natural images.

1. **Real Valued Feature Vectors**

Other researchers have also used various wavelets, but rather than using the output of the wavelet transform to create a binary feature vector, the output is kept as a real-valued feature vector and methods other than Hamming distance are used for comparison. An early example of this is the work by Boles and Boashash [52]. They consider concentric circular bands of the iris region as 1-D intensity signals. A wavelet transform is performed on a 1-D signal, and a zero-crossing representation is extracted. Two dissimilarity functions are considered, one which “makes a global measurement of the difference in energy between two zero-crossing representations” and one which “compares two representations based on the dimensions of the rectangular pulses of the zero-crossing representations.” Although the global measurement requires more computation, it is used because it does not require that the number of zero-crossings be the same in the two representations. Later on iris texture is encoded by considering a set of 1-D signals from annular regions of the iris, taking a dyadic wavelet transform of each signal, and finding zero-crossings. The Euclidean distance on the original feature values, the Hamming distance on the binarization of the feature values, and a distance measure more directly related to the zero-crossing representation are compared.

2. **Combination of Feature Types**

One group of work investigates combining information from two different types of feature vectors. If the similarity between irises is above a high
threshold, then verification is accepted. Otherwise, if similarity is below a low threshold, then verification is rejected. If the similarity is between thresholds, then the decision is passed to a second classifier that looks at “global” features areas enclosed by zero-crossing boundaries. Analyzing the iris features using local binary patterns (LBP) organized into a simple graph structure. The region of the normalized iris image nearer the pupil is divided into 32 blocks, 16 rows of 2, and a LBP histogram is computed for each block. Matching of two images is done by matching (the LBP histogram of) corresponding blocks, subject to a threshold, so that the matching score of two images is from 0 to 32.

5.5 Matching Iris Representations

The result of iris matching will be enhanced if we keep the following points in our mind.

5.5.1 Multi-Image iris Enrollment

In biometrics in general, it has been found that using multiple samples for enrollment and comparing the probe to multiple gallery samples will result in improved performance. This is also true for iris recognition. Du [53] performs experiments using one, two, and three images to enroll a given iris. The resulting rank-one recognition rates are 98.5%, 99.5%, and 99.8%, respectively. Algorithms that use multiple training samples to enroll an image must decide how to combine the scores from multiple comparisons. Ma et al. [36] suggested analyzing multiple images and keeping the best-quality image. They state that “when matching the input feature vector with the three templates of a class, the average of the three scores is taken as the final matching distance.” Some groups use multiple enrollment images not merely to improve performance, but because their ideas or chosen techniques require multiple images.
Later on multiple iris codes are acquired from the same eye and evaluate which bits are
the most consistent bits in the iris code. Masking the inconsistent bits in the iris code is
done to improve performance. Many data mining techniques require multiple images
for training a classifier.

5.5.2 Matching Sub-Regions of the Iris
Sanchez-Reillo and Sanchez-Avila [45] detect iris boundaries using an integro-
differential type operator and then divide the iris into four portions (top, bottom, left
and right) and the top and bottom portions are discarded due to possible occlusion. Ma
et al. chose a different part of the iris. They use the three-quarters of the iris region
closest to the pupil. They then look at feature representation using “a circular
symmetric filter (CSF) which is developed on the basis of Gabor filters”. After that
accuracy of iris recognition is studied when only part of the image is available. With
respect to the partial iris image analysis, conclude that these experimental results
support the conjecture that a more distinguishable and individually more unique signal
is found in the inner rings of the iris. As one traverses to the limbic boundary of the
iris, the pattern becomes less defined, and ultimately less useful in determining
identity. Later on by looking at all possible combinations of five out of ten concentric
bands of the iris region, it concludes that using the combination of bands 2, 3, 4, 5, and
7 gives the largest decidability value. The bands are numbered from the papillary
boundary out to the limbic boundary, and so the region that they find to perform well
is the part close to the pupil. This analysis is done using a simple segmentation of the
iris region as two circles that are not necessarily concentric. Therefore, it is possible
that band 1, the innermost band, was affected by inaccuracies in the pupillary
boundary, and that bands 8, 9, and 10 were affected by segmentation problems with
eyelashes and eyelids. They also look at dividing the iris into a greater number of
concentric bands and using a genetic algorithm to determine which bands to use in the iris matching.

5.5.3 Indexing in Recognition matching
Several researchers have looked at possible ways of quickly screening out some iris images from passing on to a more computationally expensive matching step. First of all divide irises into categories based on discriminative visual features named iris-textons. Then use a K-means algorithm to determine which category an iris falls into, and achieve a correct classification rate of 95% into their five categories. After that a very simple test to screen images using correlation of a Laplacian-of-Gaussian filter at four scales. It states that an “intermediate step in iris identification is determination of the ratio of limbus diameter to pupil diameter for both irises. If the two irises match, the next step is determination of the correlation...” Experimental results are shown for images from just two persons and this test will likely encounter problems whenever conditions change so as to affect pupil dilation between image acquisitions.

5.5.4 Statistical Analysis of Iris-Code Matching
A key concept of Daugman’s approach to iris biometrics is the linking of the Hamming distance to a confidence limit for a match decision. The texture computations going into the iris code are not all statistically independent of each other. But given the Hamming distance distributions for a large number of true matches and a large number of true non-matches, the distributions can be fit with a binomial curve to find the effective number of degrees of freedom. The effective number of degrees of freedom then allows the calculation of a confidence limit for a match of two iris codes.

Daugman 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.

5.6 Need of Fuzzy Database in Iris Recognition System

Iris recognition is a relatively new biometric technology. As deployed publicly today, it takes an infrared image of a Person’s eye, isolates the iris, demodulates the pattern of iris texture into a binary iris code, and compares it exhaustively against an enrolled database for a match. To deploy a large-scale biometric recognition system, the first concern is the probability of false matches, which increases with the number of records enrolled in the database. Iris patterns contain a high degree of randomness, which provides the biological basis for their uniqueness. Daugman’s algorithm is the technique used in all public deployments of iris recognition. It encodes the iris texture into a 256-byte iris code; it also produces a 256-byte mask, which excludes those iris code bits affected by eyelids, eyelashes, specular reflections, and other noise. The fast search algorithm would not apply to such scalar-based iris representations. Statistical analysis reveals that the accumulative false match rate using Daugman’s algorithm remains negligible even over large databases. To date, there have been more than a million iris codes enrolled in the UAE central database, and the UAE Ministry of Interior reports that the system has yet to make a false match. The success of the UAE deployment since 2001 has encouraged even larger deployments. A similar program exists in India. The Andhra Pradesh State government has been enrolling iris codes for 80 million local people since July 2005 under a ration-card scheme and, within the first year, about 26 million people had been enrolled. With the advent of large biometric databases, information retrieval and database management will become increasingly
challenging problems. In the iris-matching algorithm, comparing two iris codes is simple, it mainly involves counting the bits that differ between two binary vectors. Iris images may be tilted to various degrees. This problem is handled by repeating the comparisons of the iris codes over a range of relative rotations. Since the comparison requires no expensive nonlinear warping operations, searching iris-code databases can be quite fast. The exhaustive search (ES) method can compare about a million iris codes per second on a 3.2-GHz central processing unit (CPU). However, continual database expansion will slow down the search speed linearly, and the default solution is to use several search engines in parallel. Although this process needs only to be done over the time course of ID card issuance, its demands are still daunting. The 45 million U.K. enrollees generate about iris pair comparisons. At one million iris code comparisons per second per 3.2-GHz CPU, this would require two billion CPU seconds, which is 63 CPU years. There is thus a strong motivation to try to develop some kind of indexing-based approach instead, in which each iris code (despite its fuzziness due to unavoidable measurement discrepancies) could be treated almost as an address that points directly to the identity of the person from whom it was generated.

The implementation of iris database with fuzzy techniques has increased the speed of searching. The BGS Algorithm [23] for large scale database work on the same technique. This algorithm works by indexing, adopting a “multiple colliding segments principle” and early termination strategy, so that the search range is reduced dramatically. It is evaluated using 632500 real-world iris codes enrolled in the UAE border control. The experiment shows that BGS is substantially faster than the current ES, with a negligible loss of precision. It requires much less memory and it does not depend on caching data in memory, hence obliterating the need for complex memory
management. The preprocessing is simple and fast. It accommodates up to 30% bit errors in the query as well as up to seven cyclic rotations. The rapid speed of BGS allows multiple acquisitions from the same eye, thus reducing the false rejection rate due to poor capture. This makes BGS a useful technique for a wide range of fuzzy applications.