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IRIS Recognition and Identification System

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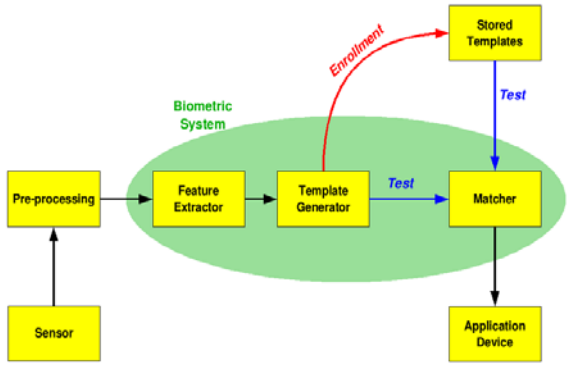
Abstract-A biometric system uniquely identies and authenticates humans based on their physical or behavioral features. Iris recognition is one of the most reliable methods of biometric authentication that recognizes a person by pattern of the iris. No two irises are alike - not between identical twins, or even between the left and right eye of the same person. The bit information or biometric template is used to compare and identify the authenticated or impostor users. Iris recognition algorithms also need to isolate and exclude the artifacts as well as locate the circular iris region from the acquired eye image. Artifacts in iris include eyelids and eyelashes partially covering it. Then, the extracted iris region needs to be normalized. The normalization process will unwrap the doughnut shaped extracted irises into a constant dimensional rectangle. The significant features of the normalized iris must be encoded so that comparisons between templates can be made. Our system makes use of a 1D Log-Gabor Filter to create a bitwise biometric template. Finally, templates are matched using Hamming distance.

INTRODUCTION

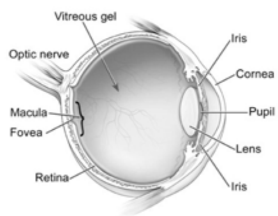
Biometric is the process of uniquely identifying humans based on their physical or behavioral traits. Biometric systems are mainly based on fingerprints, facial features, voice, hand geometry, handwriting, and the one presented in our project, the iris. Biometric characteristics can be divided in two main classes: Physiological are related to the shape of the body. Examples: fingerprint, face recognition and Iris recognition. Behavioral are related to the behavior of a person. Examples: typing rhythm, gait, and voice recognition.

Iris recognition is a method of biometric authentication that uses pattern-recognition techniques based on high-resolution images of the irides of an individual's eyes. Biometric systems first capture a sample of the feature. This extracted feature is then transformed into mathematical function or biometric template. The biometric template is a normalized, efficient and highly discriminating representation of the feature, which can then be objectively compared with other templates in order to determine identity. A good biometric template is characterized by the use of a feature i.e., highly unique, Stable and easily captured.

The iris is located behind the transparent cornea and aqueous humor of the eye, but in front of the lens. It is a membrane in the eye, responsible for controlling the diameter and size of the central darker pupil and the amount of light reaching the retina. It is a colored ring around the pupil. The color of the iris is the “Eye Color", which can be green, blue or brown. Its only physiological purpose is of course to control the amount of light that enters the eye through the pupil, by the action of its dilator and sphyncter muscles that control pupil size, but its construction from elastic connective tissue gives it a complex, fibrillose pattern. The larger the pupil, the more light can enter.



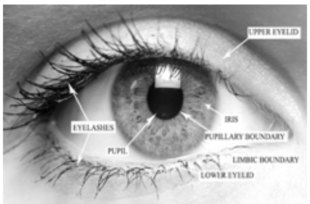
General Block Diagram of a Biometric System



Schematic Diagram of the Human Eye

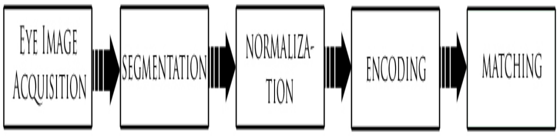
The iris has many features that can be used to distinguish one iris from another. One of the primary visible characteristics is the trabecular meshwork, a tissue which gives the appearance of dividing the iris in radial fashion that is permanently formed by the eighth month of gestation. During the development of the iris, there is no genetic influence on it, a process known as chaotic morphogenesis that occurs during the seventh month of gestation, which means that even identical twins have different irises.

The fact that the iris is protected behind the eyelid, cornea, and aqueous humor means that, unlike other biometrics such as fingerprints, the likelihood of damage or abrasion is minimal. 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 does not interfere with the recognition technology. Since the iris in this sense is highly unique, stable and easily captured, it is complex enough to be used as a biometric signature.

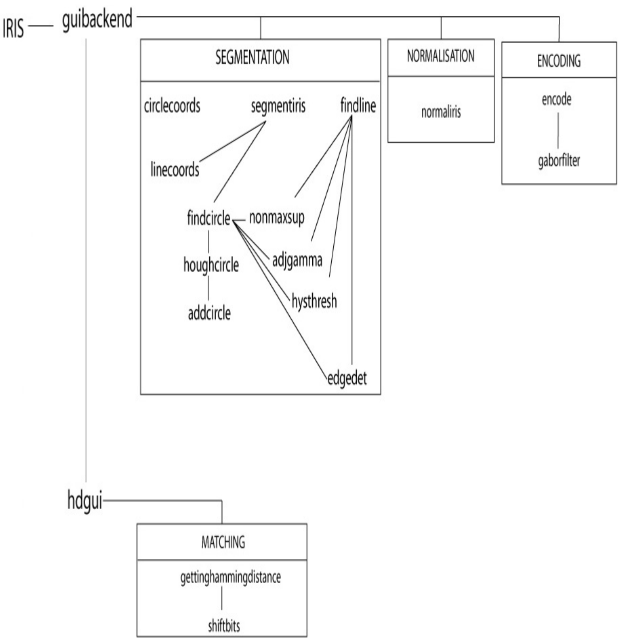


A front-on view of the human eye

Iris recognition is a method of biometric authentication that recognizes a person by pattern of the iris. Iris recognition is rarely impeded by glasses or contact lenses and can be scanned from 10cm to a few meters away. Gathering unique information of an individual from iris pattern requires extracting this pattern and encoding it into a bit-wise biometric template. Therefore, iris recognition algorithms need to isolate and exclude the artifacts as well as locate the circular iris region from the acquired eye image. Artifacts in iris include eyelids and eyelashes partially covering it. Then, the extracted iris region needs to be normalized. The normalization process will produce iris regions, which have the same constant dimensions; so that two photographs of the same iris under different conditions will have characteristic features at the same spatial location i.e. it involves unwrapping the doughnut shaped extracted irises into a constant dimensional rectangle.



Block Diagram of Iris Recognition System



System Overview

Therefore, the iris is an externally visible, yet protected organ whose unique pattern remains stable throughout the human life. These characteristics make it one of the most preferred biometric techniques for identifying individuals. Digital image processing techniques can be employed to extract the unique iris pattern from a digitized image of the eye, and encode it into a biometric template. This biometric template contains an objective mathematical representation of the unique information stored in the iris, and allows comparisons to be made between templates.

PROPOSED METHOD AND IMPLEMENTATION

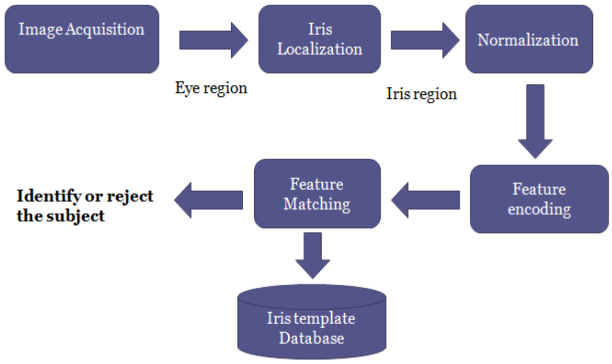
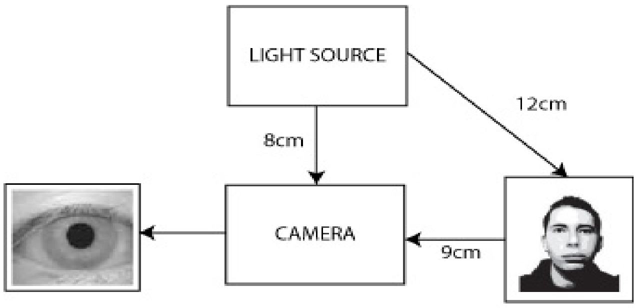


Image Acquisition



The most important step in iris recognition is to obtain a good and clear eye image. It helps in noise removal and avoids errors in calculation. Our study comprises of 5 sets of eye images, provided by CASIA. These images were taken solely for the purpose of iris recognition software research and implementation. Infra-red light was used for illuminating the eye, and hence they do not involve any specular reactions.

Since, the iris image should be rich in iris texture as the feature extraction stage depends upon the image quality; the image is acquired by 3CCD camera placed at a distance of approximately 9 cm from the user eye. The approximate distance between the user and the infrared light is about 12 cm. This removes specular reaction in eye images. Therefore, to capture a rich iris texture the system should have 1. High resolution. 2. Good sharpness and 3. Good lighting condition.

Image can be viewed as depicting a scene composed of different regions, objects, etc. Then, Image Segmentation is the process of decomposing the image into these regions and objects by associating or labeling each pixel with the object that it corresponds to. Hence, segmentation subdivides an image into its constituent regions or objects. The first stage of iris recognition is to isolate circular iris region. Iris is isolated using concentric circles, one circle is defined by the edge between sclera and iris and other is defined by the edge between pupil and iris. The process involves the extraction of circular boundaries of pupil and iris from the edge map using Circular Hough Transform. Usually, pre-segmentation process involves blurring the image using low-pass filter to remove the noise.

Gaussian Smoothing

Digital images are prone to a variety of noises. Noise is the result of errors in the image acquisition process that result in pixel values that do not reflect the true intensities of the real scene. There are several ways that noise can be introduced into an image, depending on how the image is created. One of the most preferred approaches to reduce noise is to smooth the image. The simplest such version is replace each pixel by the average of the neighboring pixel values. On the plus side, much of the spotty noise will be removed. On the downside, the sharp boundaries that make up the regions and objects will be smeared due to the averaging. Hence, smoothing filters are used for blurring and noise reduction.

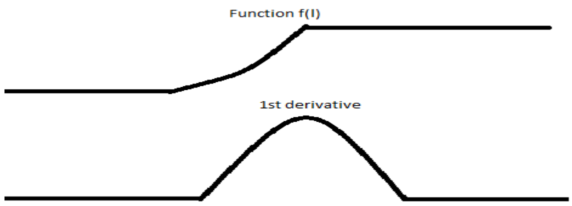
The Gaussian smoothing operator is a 2-D convolution operator that is used to `blur' images and remove noise i.e. it has an effect of reducing the image's high-frequency components. 2-D Gaussian smoothing operator is a matrix kernel that represents the shape of a Gaussian (`bell-shaped') curve i.e. central pixels have more weights. In theory, the Gaussian distribution is non-zero everywhere, which would require an infinitely large convolution kernel. In practice, when computing a discrete approximation of the Gaussian function, pixels at a distance of more than 3_ are small enough to be considered effectively zero. Thus contributions from pixels outside that range can be ignored. Typically, an image processing program need only calculate a matrix with dimensions d6_eXd6_e to ensure a result sufficiently close to that obtained by the entire Gaussian distribution. Mathematically, 2-D Gaussian function is written as:

$$g(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

The Gaussian outputs a `weighted average' of each pixel's neighborhood, with the average weight more towards the value of the central pixels. This is in contrast to the mean filter's uniformly weighted average. Because of this, a Gaussian provides gentler smoothing and preserves edges better than a similarly sized mean filter.

Edge Detection:

Edge detection is the approach for detecting meaningful discontinuities in an image. Intuitively, an edge is a set of connected pixels that lie on the boundary between two regions. To be classified as a meaningful edge point, the transition in gray level associated with that point has to be significantly stronger than the background at that point. The method of choice to determine whether a value is “significant" or not is to use a threshold. In practice, edges are usually blurred, due to the quality of image acquisition system, the sampling rate, Gaussian blur etc. As a result, edges are modeled using “ramp-like" profile. Therefore, in practice, thickness of the edge is determined by the length of the ramp.



Edge Detection methods

The derivative of the signal gives local maxima at the discontinuities and is zero at constant gray level. The first derivative is positive at the points of transition into and out of the ramp, and is zero in areas of constant gray level. Hence, the magnitude of the first derivative is used to detect the presence of an edge at a point in an image i.e. to determine if a point is on the ramp.

Gradient Operators

Gradient operators are used to detect discontinuities in an image. Image matrix is convolved with gradient kernel. First-order derivatives of a digital image are based on various approximations of the 2-D gradient. The Sobel operator performs a 2-D spatial gradient measurement on an image and so emphasizes regions of high spatial frequency that correspond to edges i.e. use a weight of two in the center co-efficient. Typically it is used to find the approximate absolute gradient magnitude at each point in an input grayscale image. Computation of the gradient of an image is based on obtaining the partial derivatives ∂f/∂x and ∂f/∂y. Here, is the 3X3 kernel of Sobel Operators.

$$G_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

$$G_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

Gradient operators are usually two pass operators, horizontal operator, Gx detects the vertical edges and vertical operator, Gy detects the horizontal edges in the image. Therefore, the gradient of an image f(x; y) at location (x; y) is given by the resultant

$$G = [G_x^2 + G_y^2]$$

Where G(x) = ∂f/∂x and G(y) = ∂f/∂y

The direction of the gradient vector is given by,

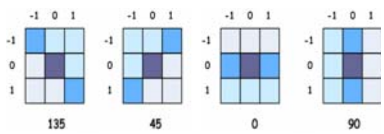
$$\alpha(x,y) = tan^{-1}(G_y/G_x)$$

Non-maximum Suppression

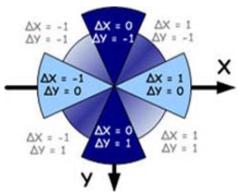
Non-maximum suppression stage finds the local maxima in the direction of the gradient, and suppresses all others, minimizing false edges. The local maximum is found by comparing the pixel with its neighbors along the direction of the gradient. This helps to maintain the single pixel thin edges before the final thresholding stage. The steps of Non-maximum suppression are as below:

1. Let a point (x, y), where x and y are integers and I(x, y) the intensity of pixel (x, y).
2. Calculate the gradient of image intensity and its magnitude in (x, y).
3. Estimate the magnitude of the gradient along the direction of the gradient in some neighborhood around (x, y).
4. If (x, y) is not a local maximum of the magnitude of the gradient along the direction of the gradient then it is not an edge point.

Usually for step 4 the neighborhood is taken to be 3 * 3 and the values of the magnitude are linearly interpolated between the closest points in the neighborhood. The above process is depicted from the above equations. The below figure depicts the directions that is possible for an edge to have. The directions as shown can be any of two diagonals (at 135 and 45 degrees), a horizontal line (at 0 degrees) or a vertical line (at 90 degrees). Thus, these are the directions that we will be testing to search for a local maximum.



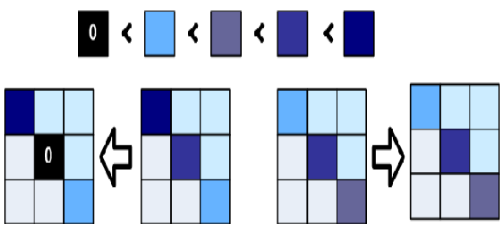
Possible directions of edge



$$\Delta x = round\left(\frac{GradientX}{Magnitude}\right)$$

$$\Delta y = round\left(\frac{GradientY}{Magnitude}\right)$$

Determine the direction D* in (0, 45, 90, 135) that is closest to the orientation D at the pixel



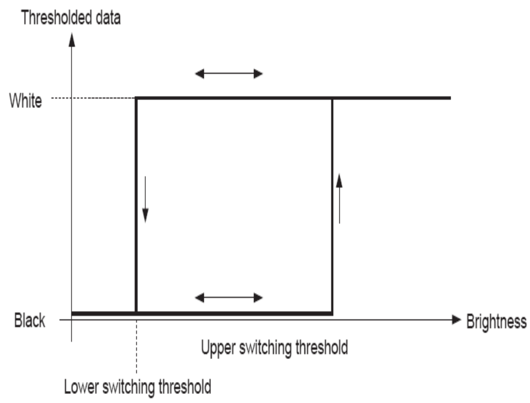
Find Local Maximum

The above figure depicts a part of the process that is used to find the local maximum in the various directions.

Hysteresis Thresholding

Hysteresis thresholding, which is a better alternative to the single static thresholding, is a dynamic thresholding method. In hysteresis thresholding we use two threshold values th as the high threshold value and tl as the lower threshold value where th > tl. Pixel values that are above the th value are immediately classified as edges. The neighboring pixel values with gradient magnitude values less than th can also be classified as edges as long as the they are above the lower threshold value tl. This process alleviates problems associated with edge discontinuities by identifying strong edges, and preserving the relevant weak edges, in addition to maintaining some level of noise suppression.

The hysteresis threshold process assumes that most edges occur in a continuous curve and also allows us to select a faint part or section of an edge (the ones that are less than th and higher than tl). The problem we have with hysteresis thresholding is that it slows down the overall process and it is difficult to select the suitable/appropriate thresholding parameters. The transfer function associated with hysteresis thresholding is shown in below figure. Points are set to white once the upper threshold is exceeded and set to black when the lower threshold is reached. The arrows reflect possible movement: there is only one way to change from black to white and vice versa.

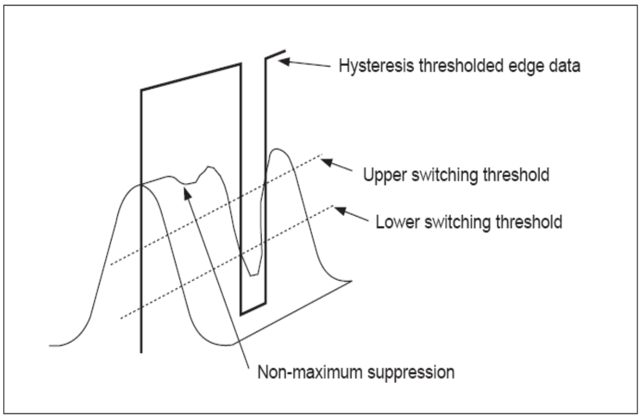


Hysteresis Thresholding Transfer Function

seed ≥ lower	seed ≥ lower	seed ≥ lower
seed ≥ lower	seed ≥ upper	seed ≥ lower
seed ≥ lower	seed ≥ lower	seed ≥ lower

Neighborhood search for hysteresis thresholding

Hysteresis thresholding needs two thresholds, an upper threshold and a lower threshold. The hysteresis thresholding process starts as soon as an edge point is found from non- maximum suppression that exceeds the upper threshold. The edge that exceeds upper threshold is marked as an edge point and is taken as the first point of a line of edge points. Then, the neighboring points of the first point are searched to determine if they do or do not exceed the lower threshold. Thus, the first edge point found becomes a seed point for a search, as shown in above figure. In turn, the neighboring points become the seed points if they exceed the lower threshold, thus extending the search along the branches from neighboring points that exceeded the lower threshold. The search terminates at the points where no neighbors exceed the lower threshold, for each branch.



Action of Non-maximum suppression and Hysteresis Thresholding

The non-maximum suppression and hysteresis thresholding stages can be collectively said as an edge thinning stage. For edge thinning, we need to use both the above stages. Use of only one of the two is not satisfactory. With the application of edge thresholding stage on the gradient image, i.e. without the application of non-maximum suppression stage, generally an edge with thickness is generated and thus some type of edge thinning post processing is required. However, under the application of edge thresholding after the non-maximum suppression stage, it generally generates thinner edge curve thus eliminating the requirement of any edge thinning post-processing.

Circular Hough Transform

The algorithm for Circular Hough Transformation can be summarized to:

1. Find edges
2. //HOUGH BEGIN
3. for each edge point: Draw a circle with center in the edge point with radius r and increment all coordinates that the perimeter of the circle passes through in the accumulator.
4. Find one or several maxima in the accumulator.
5. //HOUGH END
6. Map the found parameters (r, a, b) corresponding to the maxima back to the original image.

Template Matching

Template matching is low level method of locating shapes in an image. It can be implemented to detect the circular iris and pupil regions. Template matching is conceptually a simple process. We need to match a template to an image, where the template is a sub-image that contains the shape we are trying to find. Template matching develops an accumulator space that stores the match of the template to the image at different locations; this corresponds to an implementation of:

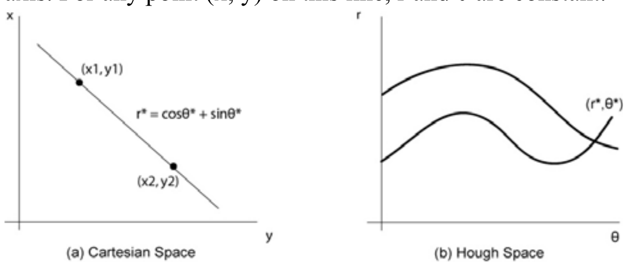
$$min\ e = \sum_{(x,y)\in W} (I_{x+i,y+j} - T_{x,y})^2$$

Where, I(x; y) image and T(x; y) template.

The advantages associated with template matching are mainly theoretical since it can be very difficult to develop a template matching technique that operates satisfactorily. Template matching is suitable for mostly for position invariance only. If invariance to rotation and scale is also required then this can cause difficulty.

Eyelid Detection : Linear Hough Transform

Hough Transform (HT) is used to detect lines in an image. The HT implementation defines a mapping from the image points into an accumulator space (Hough space) i.e. transforms from the Cartesian space to Hough space in which a straight line (or other boundary formulation) can be defined. A straight line on Cartesian space y = mx + c can be defined by r = x cosθ + y sinθ on Hough Space, where r is the length of a normal from the origin to this line and θ is the orientation of r with respect to the X-axis. For any point (x; y) on this line, r and θ are constant.



Visualization of LHT

Line on Cartesian system is denoted by a intersecting point in Hough Space. Intersection on Hough space denotes a line and each intersection is voted on accumulator. Resulting peaks in the accumulator array represent strong evidence that a corresponding straight line exists in the image.

Eye Lash and Noise Detection

Eyelash removal includes locating the eyelash pixels in the image and excludes the iris code bits generated from these pixels. Eyelashes are distinct from the background i.e. they are darker than their background in the eye images. Hence can be segmented using simple thresholding. Intensity values corresponding to the eyelashes are ignored. Thresholding can successfully detect and mask eyelashes.

Kong and Zhang Model

Kong and Zhang is an accurate method for detecting eyelash detection where eyelashes are divided into separable eyelashes, which are isolated in the image, and multiple eye lashes, which are bunched together and overlap in the eye image.

Separable eyelashes are detected using 1D Gabor filters, since the convolution of a separable eyelash with the Gaussian smoothing function results in a low output value. Thus, if a resultant point is smaller than a threshold, it is noted that this point belongs to an eyelash. Multiple eyelashes are detected using the variance of intensity. If the variance of intensity values in a small window is lower than a threshold, the centre of the window is considered as a point in an eyelash. The Kong and Zhang model also makes use of connective criterion, so that each point in an eyelash should connect to another point in an eyelash or to an eyelid. Specular reactions along the eye image are detected using thresholding, since the intensity values at these regions will be higher than at any other regions in the image.

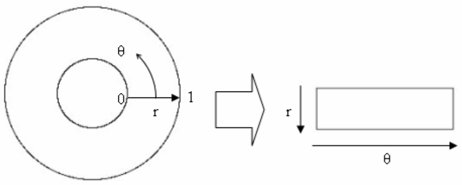
Normalization

Iris of different people may be captured in different size, for the same person also size may vary because of the variation in illumination and other factors like varying imaging distance, rotation of the camera, head tilt, and rotation of the eye within the eye socket. The purpose of iris normalization is to get the same region of iris to do matching regardless of pupil dilation caused by varying level of illumination and the different iris size caused by the different distance between the eye and video zoom factor. Moreover, the shift, accounting for the offsets of the eye in the plane parallel to the camera's sensor, should also be eliminated. Thus, the normalization process will produce iris regions, which have the same constant dimensions, so that two photographs of the same iris under different conditions will have characteristic features at the same spatial location. The pupil region and the iris region are not always concentric which is taken into account while normalizing `doughnut' shaped iris region to have constant radius.

The normalization algorithm always depends on the algorithm of feature vector extraction and match. Moreover, we should make the texture on iris become clearer and eliminate the factors that will lead to error of match in iris normalization operation.

Daugman's Rubber Sheet Model

John Daugman mapped image coordinates to polar image coordinates. The angular coordinate ranges between 0 ~2π and the radial coordinate ranges from the iris inner boundary to its outer boundary as a unit interval. This is called the homogeneous rubber sheet model. Thus, the homogenous rubber sheet model remaps each point within the iris region to a pair of polar coordinates (r, θ) where r is on the interval [0, 1] and θ is on the interval [0, 2π].



Daugman's Rubber Sheet Model

The remapping of the iris region from (x, y) Cartesian coordinates to the normalized non concentric polar representation is modeled as:

$$I(x(r;\theta), y(r;\theta)) \longrightarrow I(r,\theta)$$

With

$$x(r,\theta) = (1 - r)xp(\theta) + xi(\theta)$$

$$y(r,\theta) = (1 - r)yp(\theta) + yi(\theta)$$

Where I(x, y) is the iris region image, (x, y) are the original Cartesian coordinates, (r, θ) are the corresponding normalized polar coordinates, and xp ,yp and xi ,yi are the co-ordinates of the pupil and iris boundaries along the θ direction. The rubber sheet model takes into account pupil dilation and size inconsistencies in order to produce a normalized representation with constant dimensions. In this way the iris region is modeled as a flexible rubber sheet anchored at the iris boundary with the pupil center as the reference point. Even though the homogeneous rubber sheet model accounts for pupil dilation, imaging distance and non-concentric pupil displacement, it does not compensate for rotational in-consistencies. In the Daugman system, rotation is accounted during matching by shifting the iris templates in the direction until two iris templates are aligned.

Virtual Circles

In the Boles system, iris images are first scaled to have constant diameter so that when comparing two images, one is considered as the reference image. This works differently to the other techniques, since normalization is not performed until attempting to match two iris regions, rather than performing normalization and saving the result for later comparisons. Once the two irises have the same dimensions, features are extracted from the iris region by storing the intensity values along virtual concentric circles, with origin at the centre of the pupil. A normalization resolution is selected, so that the number of data points extracted from each iris is the same. This is essentially the same as Daugmans rubber sheet model, however scaling is at match time, and is relative to the comparing iris region, rather than scaling to some constant dimensions. Also, it is not mentioned by Boles, how rotational invariance is obtained.

Feature Encoding

Iris provides abundant texture information. Feature selection and extraction is to find out the important features to perform matching. As we know, the visible features of an iris are ciliary processes, contraction furrows, crypts, rings, cornea, and freckles and so on. How to set a model to extract the feature of different irises and match them is especially important for it determines the results of the whole system directly. A feature vector is formed which consists of the ordered sequence of features extracted from the various representation of the iris images. In order to provide accurate recognition of individuals, the most discriminating information present in an iris pattern must be extracted. Only the significant features of the iris must be encoded so that comparisons between templates can be made. Most iris recognition systems make use of a band pass decomposition of the iris image to create a biometric template.

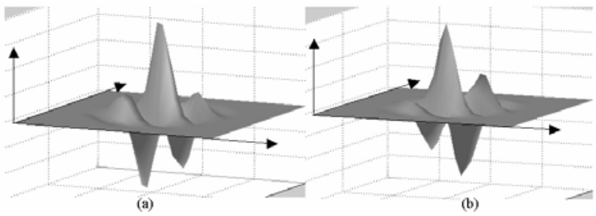
Gabor Filters

Gabor wavelets are able to provide optimum conjoint representation of a signal in space and spatial frequency.

A Gabor filter is constructed by modulating a sine/cosine wave with a Gaussian. This is able to provide the optimum conjoint localization in both space and frequency, since a sine wave is perfectly localized in frequency, but not localized in space. Modulation of the sine with a Gaussian provides localization in space, though with loss of localization in frequency. Decomposition of a signal is accomplished using aquadrature pair of Gabor filters, with a real part specified by a cosine modulated by a Gaussian, and an imaginary part specified by a sine modulated by a Gaussian. The real and imaginary filters are also known as the even symmetric and odd symmetric components respectively. The center frequency of the filter is specified by the frequency of the sine/cosine wave, and the bandwidth of the filter is specified by the width of the Gaussian.Daugman makes use of a 2-D version of Gabor filters in order to encode iris pattern data. A 2-D Gabor filter over the an image domain (x, y) is represented as:

$$G(x,y) = e^{-\pi[(x-x_0)^2/\alpha^2+(y-y_0)^2/\beta^2]}e^{-2\pi i[u_0(x-x_0)-v_0(y-y_0)]}$$

Where
(x0, y0) specify position in the image,
(α, β) specify the effective width and length,
and (u0; v0) specify modulation, which has spatial frequency ω0 = $\sqrt{u_0^2 + v_0^2}$



A quadrature pair of 2D Gabor filters

In the above figure (a) depicts the real component or even symmetric filter characterized by a cosine modulated by a Gaussian and figure (b) depicts the imaginary component or odd symmetric filter characterized by a sine modulated by a Gaussian. Daugman demodulated the output of the Gabor filters in order to compress the data. This is done by quantizing the phase information into four levels, for each possible quadrant in the complex plane. Taking only the phase will allow encoding of discriminating information in the iris, while discarding redundant information such as illumination, which is represented by the amplitude component.

These four levels are represented using two bits of data, so each pixel in the normalized iris pattern corresponds to two bits of data in the iris template. A total of 9600 bits are calculated for the template, and an equal number of masking bits are generated in order to mask out corrupted regions within the iris. This creates a compact 1200-byte template, which allows for efficient storage and comparison of irises. The Daugman system makes use of polar coordinates for normalization, therefore in polar form the filters are given as:

$$H(r,\theta) = e^{-i\omega(\theta-\theta_0)}e^{-(r-r_0)^2/\alpha^2}e^{-i(\theta-\theta_0)^2/\beta^2}$$

Where (α, β) specify the effective width and length and (r0; θ0) specify the centre frequency of the filter. The demodulation and phase Quantization process can be represented as:

$$H_{(Re,Im)} = sgn_{(Re,Im)}\int_\rho\int_\phi e^{-j\omega(\theta_0-\phi)}e^{-(r_0-\rho)^2/\alpha^2}e^{-(\theta_0-\phi)^2/\beta^2}I(\rho,\phi)\rho d\rho d\phi$$

Where H (Re, Im) can be regarded as a complex valued bit whose real and imaginary components are dependent on the sign of the 2-D integral, and I(ρ, □) is the raw iris image in a dimensionless polar coordinate system.

Setting the bits in an Iris Code:

$$H_{Re} = 1, if Re\int_\rho\int_\phi e^{-i\omega(\theta_0-\phi)}e^{-(r_0-\rho)^2/\alpha^2}e^{-(\theta_0-\phi)^2/\beta^2}I(\rho,\phi)\rho d\rho d\phi \geq 0$$

$$H_{Re} = 0, if Re\int_\rho\int_\phi e^{-i\omega(\theta_0-\phi)}e^{-(r_0-\rho)^2/\alpha^2}e^{-(\theta_0-\phi)^2/\beta^2}I(\rho,\phi)\rho d\rho d\phi < 0$$

$$H_{Im} = 1, if Im\int_\rho\int_\phi e^{-i\omega(\theta_0-\phi)}e^{-(r_0-\rho)^2/\alpha^2}e^{-(\theta_0-\phi)^2/\beta^2}I(\rho,\phi)\rho d\rho d\phi \geq 0$$

$$H_{Im} = 0, if Im\int_\rho\int_\phi e^{-i\omega(\theta_0-\phi)}e^{-(r_0-\rho)^2/\alpha^2}e^{-(\theta_0-\phi)^2/\beta^2}I(\rho,\phi)\rho d\rho d\phi < 0$$

Log Gabor Filters

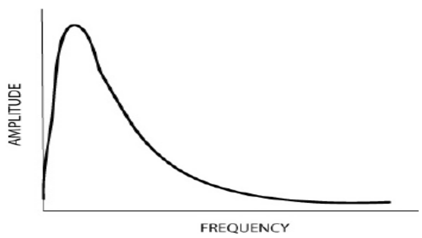
A disadvantage of the Gabor filter is that the even symmetric filter will have a DC component whenever the bandwidth is larger than one octave. However, zero DC components can be obtained for any bandwidth by using a Gabor filter which is Gaussian on a logarithmic scale; this is known as the Log-Gabor filter. Log Gabor filter is an alternative to Gabor filter/function that was proposed in 1987 by David J. Field. He suggested that natural images are better coded by filters that have Gaussian transfer functions when viewed on the logarithmic scale.

The frequency response of a Log Gabor filter is given as:

$$G(f) = exp(-(log(f/f_0))^2/2(log(\sigma/f_0))^2)$$

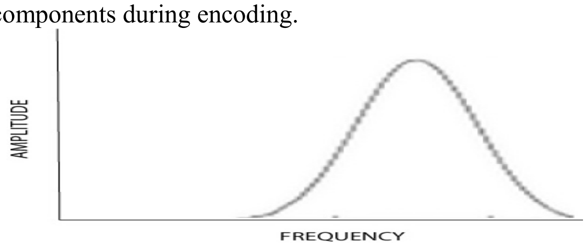
Where f0 represents the centre frequency, and σ gives the bandwidth of the filter. Details of the Log-Gabor filter are examined by Field. In order to obtain constant shape ratio filters, the term
σ /f0 should be held/kept constant for varying f0.

For example, for σ /f0 =.74, the result will be a filter bandwidth of approx. one octave, for
σ /f0 = .55, the result will be two octaves and so on.



Log Gabor transfer viewed on linear scale

The two important characteristics that are to be noted of log gabor functions are:
1. By definition, log Gabor filters never have DC Component, and 2. The transfer function has an extended tail at high frequency end. Field suggested that natural images contain amplitude spectra that fall of at approx. 1/f, according to his studies of statistics of natural images and one has to use filters that have similar spectra so as to encode those images. He suggested that log Gabor filters that have extended tails, has to be able to encode the natural images effectively and more efficiently than ordinary Gabor filters that over represents low frequency components and under represents high frequency components during encoding.



Scale Log Gabor transfer viewed on logarithmic

Matching

The template that is generated in the feature encoding process will need a corresponding matching metric system, which gives a measure of similarity between two iris templates. This metric system should give one range of values when comparing templates generated from the same eye, known as intra-class comparisons, and another range of values when comparing templates created from different irises, known as inter-class comparisons. These two cases should give distinct and separate values, so that a decision can be made with high confidence as to whether two templates are from the same iris, or from two different irises.

Hamming Distance

The Hamming Distance, HD, gives a measure of how many bits are same between two bit patterns. Using the Hamming distance of two bit patterns, a decision can be made as to whether the two patterns were generated from different irises or from the same one. In comparing the bit patterns X and Y, the HD, is defined as the sum of disagreeing bits (sum of the exclusive-OR between X and Y) over N, the total number of bits in the bit pattern.

$$HD = \frac{1}{N}\sum_{j=1}^{N} X_j (XOR) Y_j$$

X	Y	Result
0	0	0
0	1	1
1	0	1
1	1	0

Truth Table for XOR

Each iris region will produce a bit-pattern which is independent to that produced by another iris, on the other hand, to iris codes produced from the same iris will be highly correlated. If two bits patterns are completely independent, such as iris templates generated from different irises, the Hamming distance between the two patterns should be equal 0.5. This occurs because independence implies the two bit patterns will be totally random, so there is 50 percent chance of setting any bit to 1, and vice versa. Therefore, half of the bits will agree and half will disagree between the two patterns. If two patterns are derived from the same iris, the HD between them will be close to 0.0, since they are highly correlated and the bits should agree between the two iris codes. The Hamming distance is the matching metric employed by Daugman, and calculation of the Hamming distance is taken only with bits that are generated from the actual iris region. Matching process requires a threshold value of HD to decide whether the iris is of an authenticated user or an imposter. Deciding this threshold value requires comparison between inter-class and intra-class distribution.

Uniqueness of Pattern

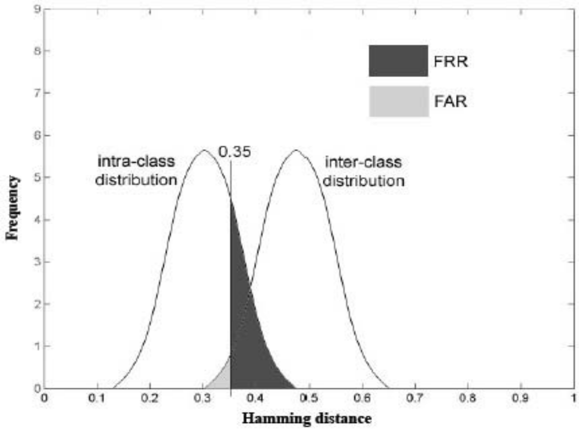
The first test was to confirm the uniqueness of iris patterns. Testing the uniqueness of iris patterns is important, since recognition relies on iris patterns from different eyes being entirely independent, with failure of a test of statistical independence resulting in a match. Uniqueness was determined by comparing templates generated from different eyes to each other, and examining the distribution of Hamming distance values produced. This distribution is known as the inter-class distribution.

Recognition of Individuals

The main objective of an iris recognition system is to be able to achieve a distinct separation of intra-class and inter-class Hamming distance distributions. A separation or threshold value of Hamming distance value can be chosen which allows a decision to be made when comparing two templates. If the Hamming distance between two templates is less than the threshold, the templates were generated from the same iris and a match is found. Otherwise if the Hamming distance is greater than the threshold the two templates are considered to have been generated from different irises. The distance between the minimum Hamming distance values for inter-class comparisons and maximum Hamming distance value for intra-class comparisons could be used as a metric to measure separation; however, this is not a very accurate measure since outliers will corrupt the value calculated, and the measure is dependent on the number of iris templates compared. A better metric is decidability, which takes into account the mean and standard deviation of the intra-class and inter-class distributions.

$$d' = \frac{|\mu_S - \mu_D|}{\sqrt{\frac{(\sigma_S^2 + \sigma_D^2)}{2}}}$$

Decidability d0 is a distance measured in standard deviations and is a function of the magnitude of difference between the mean of the intra-class distribution μs, and the mean of the inter-class distribution μD, and also the standard deviation of the intra-class and inter-class distributions, σ²S and σ²D respectively. The higher the decidability, the greater the separation of intra-class and inter-class distributions, which allows for more accurate recognition. However, the intra-class and inter-class distributions may have some overlap, which would result in a number of incorrect matches or false accepts, and a number of mismatches or false rejects.



Intra-Class and Inter-Class Hamming Distance Distributions with Overlap and threshold at 0.35

The false reject rate (FRR), also known as Type I error, and measures the probability of an enrolled individual not being identified by the system. The false accept rate (FAR), also known as Type II error, measures the probability of an individual being wrongly identified as another individual. The false accept and false reject rates can be calculated by the amount of overlap between two distributions, which is illustrated in above figure. The false accept rate is defined by the normalized area between 0 and the separation point, K, in the inter-class distribution Pdiff. The false reject rate is defined as the normalized area between the threshold, K, and 1 in the intra-class distribution Psame.

$$FAR = \frac{\int_0^K P_{diff}(x)dx}{\int_0^1 P_{diff}(x)dx}$$

$$FRR = \frac{\int_K^1 P_{same}(x)dx}{\int_0^1 P_{same}(x)dx}$$

Weighted Euclidean Distance

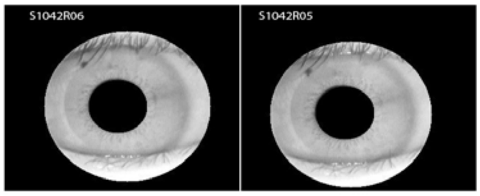
The weighted Euclidean distance (WED) can be used to compare two templates, especially if the template is composed of integer values. The weighting Euclidean distance gives a measure of how similar a collection of values are between two templates. This metric is employed by Zhu et al and is specified as

$$WED(k) = \sum_{i=1}^{N} \frac{(f_i - f_i^{(k)})^2}{(\delta_i^{(k)})^2}$$

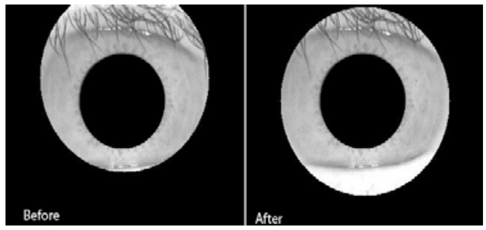
Where fi is the ith feature of the unknown iris, and $f_i^{(k)}$ is the ith feature of iris template, k, and $\delta_i^{(k)}$ is the standard deviation of the ith feature in iris template k. The unknown iris template is found to match iris template k, when WED is a minimum at k.

OBSERVATIONS AND ANALYSIS:

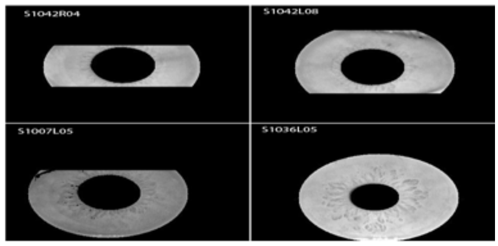
1. Segmentation



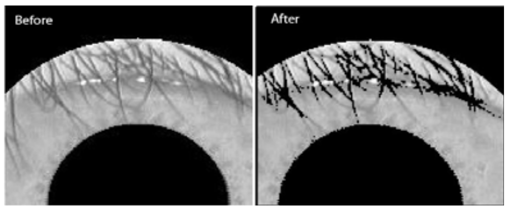
1. Error in Segmentation



2. Improvement by Center Shifting

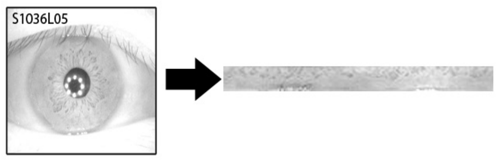


Different Eyelid Occlusions Removal



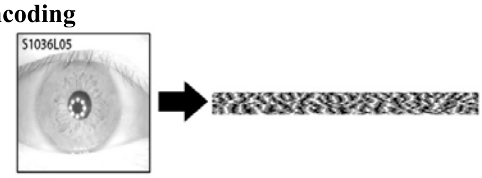
Eyelash Removal

2. Normalization



Result of Normalization

3. Encoding



Result of Encoding

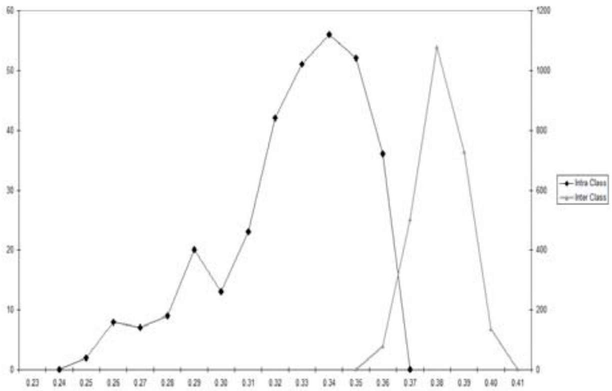
4. Matching:

N : No of Shift, SL/SR: Shift left / shift right

N	SL/SR
0.4015	0.388
0.4015	0.388
0.4015	0.388
0.4015	0.388
0.4015	0.388
0.4015	0.388
0.4015	0.388
0.4015	0.388

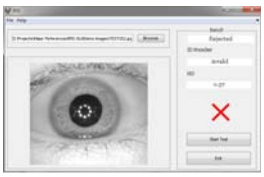
Ver- Class Hamming Distance and intra-class filter distribution.

Decidability (for σ/f=0.5)



Hamming Distance: Intra Class and Inter Class Distribution

IRIS Recognition & Identification System (Accepted)



IRIS Recognition & Identification System (Rejected)

CONCLUSION

IRIS Recognition and Identification System", presented here, gathers iris information from segmented iris and encodes the pattern into bit information. IRIS uses biometric template to compare and authenticate the users the significant features of normalized IRIS is encoded and made comparisons with ID-Log. Further, planning to proceed to study about all the characteristics relating to authentication for IRIS System.

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