Chapter 2

Segmentation
and
Normalization Methods
Chapter 2

Segmentation and Normalization Methods

2.1. Segmentation

The first step of Iris recognition starts with finding an iris in an image, determining its inner and outer boundaries at the pupil and sclera, detecting the upper and lower eyelid boundaries if they occlude, and detecting and excluding any overlaid eyelashes or reflections from the cornea or eye glasses, these processes may collectively be called segmentation [1].

In order to get accuracy for detecting inner and outer iris boundaries, even if they are partly invisible, is important because the mapping of the iris in a dimensionless (i.e., size invariant and pupil dilation invariant) coordinate system is critically dependent on this. Inaccuracy in the detection, modeling, and representation of these boundaries can cause different mappings of the iris pattern in its extracted description, and such differences could cause failures to match the iris patterns [1, 2].

A system is required to isolate and exclude these artifacts as well as detecting the circular iris region.

Many researchers have contributed their work in Segmentation and finding boundaries of pupil and Iris. Some of the popular techniques such Daugman’s Integro-differential, Hough transform and active contour methods are used for segmentation purpose.

2.1.1 Daugman's Integro-differential Operator

In order to localize an iris, Daugman proposed the Integro-differential operator. The operator assumes that pupil and limbus are circular contours and performs as a circular edge detector. Detecting the upper and lower eyelids are also performed using the Integro-differential operator by adjusting the contour search from circular to a designed accurate.
Chapter 2 - Segmentation and Normalization

\[
\max(r, x_0, y_0) \left| G_\sigma \ast \frac{\partial}{\partial r} \int_{(r, x_0, y_0)} \frac{I(x, y)}{2\pi r} \, ds \right|.
\] (2.1)

Where \(I(x, y)\) is an image, 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 \(r\) and center coordinates. The symbol \(\ast\) denotes convolution and \(G_\sigma(r)\) is a smoothing function such as a Gaussian of scale \(\sigma\). The operator behaves like a circular edge detector, blurred at a scale set by \(\sigma\) which searches iteratively for a maximum contour integral derivative with increasing radius at successively finer scales of analysis through the three parameter space of center coordinates and radius \((x_0, y_0)\) defining a path of contour integration.

2.1.2 Hough Transform

Hough transform is a standard image analysis tool for finding curves that can be defined in a parametrical form such as lines, polynomials and circles. The recognition of a global pattern is achieved using the local patterns. For instance, recognition of a circle can be achieved by considering the strong edges in an image as the local patterns and searching for the maximum value of a circular Hough transform. Wildes et. al., Kong and Zhang, Tisse et. al. and Ma et. al., had implemented Hough transform to localize irises [3-5].

The localization method, similar to Daugman's method, is also based on the first derivative of the image. R. P. Wildes had proposed an edge map of the image is first obtained by thresholding the magnitude of the image intensity gradient.

\[
|\nabla G(x, y) \ast I(x, y)|,
\] (2.2)

Where \(\nabla = \begin{bmatrix} \frac{\partial}{\partial x}, \frac{\partial}{\partial y} \end{bmatrix} \) and \(G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{(x-x_0)^2+(y-y_0)^2}{2\sigma^2}}\).

\(G(x, y)\) is a Gaussian smoothing function with scaling parameter \(\sigma\) to select the proper scale of edge analysis.
The edge map is then used in a voting process to maximize the defined Hough transform for the desired contour. Considering the obtained edge points as: 

\[(x_j, y_j), j = 1, 2, \ldots, n,\]

a Hough transform can be defined as:

\[H(x_c, y_c, r) = \sum_{j=1}^{n} h(x_j, y_j, x_c, y_c, r),\]  
(2.3)

\[h(x_j, y_j, x_c, y_c, r) = \begin{cases} 
1 & \text{if } g(x_j, y_j, x_c, y_c, r) = 0; \\
0 & \text{otherwise} 
\end{cases}\]  
(2.4)

The inner and outer boundaries are both modeled as circles and the parametric function \(g\) is defined as:

\[g(x_j, y_j, x_c, y_c, r) = (x_j - x_c)^2 + (y_j - y_c)^2 - r^2.\]  
(2.5)

Assuming a circle with the center \((x, y)\) and radius \(r\), the edge points that are located over the circle result in a zero value of the function. The value of \(g\) is then transformed to 1 by the \(h\) function, which represents the local pattern of the contour. The local patterns are then used in a voting procedure using the Hough transform, \(H\), in order to locate the correct inner and outer boundaries i.e. pupil and limbus.

The upper and lower parts, which have the horizontal edge information, are usually covered by the two eyelids. The horizontal edge information is used for detecting the upper and lower eyelids, which are modeled as parabolic arcs.

### 2.1.3 Discrete Circular Active Contours

N. J. Ritter and J. R. Cooper Ritter proposed an active contour model to localize iris in an image [6]. This model detects pupil and limbus by activating and controlling the active contour using two defined forces: internal and external forces. The internal forces are responsible to expand the contour into a perfect polygon with a radius \(\delta\) larger than the contour average radius. The internal force, \(F_{int,i}\), applied to each vertex, \(V_i\), defined as:

\[F_{int,i} = \bar{V}_i - V_i,\]  
(2.6)
Where, \( V_t \) is the expected position of the vertex in the perfect polygon, the position of \( V_t \) can be obtained with respect to \( C_r \). The average radius of the current contour, and the contour centre, \( C = (C_x, C_y) \). The center of a contour is defined as:

\[
C = (x_c, y_c) = \frac{1}{n} \sum_{i=1}^{n} V_i
\]  
(2.7)

Which is the average position of all contour vertices. The average radius of the contour is defined as:

\[
C_r = \frac{1}{n} \sum_{i=1}^{n} \| V_i - C \|
\]  
(2.8)

This is the average distance of all the vertices from the defined center point. The position of the vertices of the expected perfect polygon is then obtained as:

\[
\tilde{V}_i = (C_x + (C_r + \delta) \cos(2\pi i / n), C_y + (C_r + \delta) \sin(2\pi i / n)),
\]  
(2.9)

Where, \( n \) is the total number of vertices.

The internal forces are designed to expand the contour and keep it circular. The force model assumes that pupil and limbus are globally circular, rather than locally, to minimize the undesired deformations due to specular reflections and dark spots near the pupil boundary. The contour detection process of the model is based on the equilibrium of the defined internal forces with the external forces. The external forces are obtained from the gray level intensity values of the image and are designed to push the vertices inward. The magnitude of the external forces is defined as:

\[
\| F_{ext,i} \| = I(V_i) - I(V_i + \hat{F}_{ext,i}),
\]  
(2.10)

Where, \( I(V_i) \) is the gray level value of the nearest neighbor to \( V_i \), \( \hat{F}_{ext,i} \) is the direction of the external force for each vertex and it is defined as a unit vector given by:

\[
\hat{F}_{ext,i} = \frac{C - V_i}{\| C - V_i \|}
\]  
(2.11)
Therefore, the external force for each vertex can be defined as:

\[
F_{er,i} = \|F_{ex,i}\| F_{ex,i} \tag{2.12}
\]

The movement of the contour is based on the alignment of the internal and external forces over the contour vertices. Replacement of each vertex is obtained iteratively by:

\[
V_{i}(t+1) = V_{i}(t) + \beta F_{int,i} + (1 - \beta) F_{ext,i}. \tag{2.13}
\]

Where, \( \beta \) is a defined weight that controls the speed of the contour movement and sets the equilibrium condition of internal and external forces. The final equilibrium is achieved when the average radius and center of the contour becomes the same as the one in \( m \) iterations ago.

Many researchers have also affirmed the iris segmentation methods in their work. For example, the iris localization method proposed by Tisse et. al. is a combination of the Integro-differential and the Hough transform. The Hough transform is used for a fast tracking of the pupil center and then the Integro-differential is used to accurately locate inner and outer boundaries using a smaller search space [7].

2.1.4 Near Active Contour Segmentation Method

To detect inner (pupil) boundary, it is necessary to define the contour characteristics that the system aims to capture. It is common that inner (pupil) boundary is a closed, continuous and smooth curve, which is close to circular. \( N \) order to draw the better performance in the next phases of an iris recognition system, it is necessary to capture this contour with respect to a proper center point and a proper angular resolution. The center point of the contour is defined as the mean of the vertices, which can be defined as:

\[
C = (x_c, y_c) = \frac{1}{N} \sum_{i=1}^{N} V_i, \tag{2.14}
\]
Where, $N$ is the total number of vertices and $V_i$ is the $i^{th}$ vertex. The angular resolution of the contour is another important feature that should be considered. The continuity criterion is defined based on the angular resolution rather than the distance between the vertices which is common in general active contour models [8]. This resolution is chosen based on the average radius of pupils in the database of eye images. Considering the average radius of 45 pixels, the perimeter of a circle has around 285 pixels. In this case, a resolution of 400 angles is chosen in order to obtain outlines or edges that are pixel-wise continuous. The number of vertices is constant and each vertex represents a specific angle throughout the process. This condition can be considered as angular forces that bring the vertices in the right angular position with respect to the updated contour center.

Each vertex of a contour is represented by a vector, with a specific radius and direction with respect to the center point. In order to obtain a smooth curve with a close to circular shape, the internal forces are applied in the radial direction in a way to make the neighboring vertices have the same radius value in a proper angular range, $\Delta \theta$. The magnitude of an internal force applied to a single vertex is defined as:

$$|F_{int,i}| = \frac{1}{N} \left( \sum_{\Delta \theta} R_{\theta_i} \right) - R_i, \quad (2.15)$$

Where, $\Delta \theta$ represents the angular range, $N_{\Delta \theta}$ represents the number of vertices in the defined angular range and $R_i$. The internal forces are designed to push the vertices in order to have the same radius as the mean radius of the vertices in the angular range.

The external forces are designed to pull the curve toward the maximum measured circular gradient and are applied in the radial direction. The circular gradient of an image around a center point is obtained by applying the Integro-differential operator indifferent angles with the proper angular range [9].

The Daugman's Integro-differential operator, which is defined as:
Equation (2.16) integrates over the interval \([0, 2\pi]\), which is a complete circle. The external forces are then defined by the radial distance of each vertex from the maximum circular gradient. In order to obtain the inner and outer boundaries of pupil and iris the angular range is \(\Delta \theta = \frac{\pi}{10}\). Therefore, equation (2.16) can be modified and defined as:

\[
|F_{\text{ext},i}| = \arg \max_{(R_i)} \left| \frac{\partial}{\partial r} \int_{\frac{\theta + \Delta \theta}{2}}^{\frac{\theta - \Delta \theta}{2}} \frac{I(x, y)}{2\pi r} \, ds \right| - R_i
\]  

(2.17)

This external force which is based on gathering gradient information in the radial directions have the advantage that the contour would not stop in a local ridge or valley and the possibility of missing the pupil becomes very less [9].

This technique accelerates speed of the algorithm by limiting the search space and filters out the external forces that are pointing out to strong edges such as eyelids and eyelashes instead of the pupil boundary.

In addition, in order to speed up the algorithm, the external forces are calculated in only 128 angular directions and the rest of the values would be interpolated based on the near-circular assumption of the pupil boundary in the angular range \(\Delta \theta = \frac{\pi}{10}\).

Contour based is composition of internal and external force over the contour vertices and the replacement of each vertex in the radial direction is obtained iteratively by:

\[
R_{Vi}(n+1) = R_{Vi}(n) + F_{\text{int},i} + \alpha \times F_{\text{ext},i}
\]  

(2.18)

Where, \(R_{Vi}\) is the radius of vertex \(i\) and \(\alpha \in (0, 1)\) is a weight which controls the speed of contour movement and sets the equilibrium condition of internal and external forces. Lesser the values of \(\alpha\) yields the smoother contours, however the contour passes toward the maximum gradient area in a slow speed. On other hand if
there is increase in $\alpha$ value the effect of external forces and the contour vertices move toward the pupil boundary in a faster speed.

The value of $\alpha$ should be smaller than 1 to meet to the pupil boundary. If $\alpha$ is greater than 1, the contour would oscillate near the pupil boundary due to definition of the external forces.

At last it reaches to stability when the average radius and center of the contour become the same as the ones in the last iteration.

In this method, there are fixed number of vertices. Each vertex represents a specific angle throughout the iterations with respect to the updated contour center. This condition can be considered as angular forces that are responsible for readjusting the angular position of the vertices with respect to the updated center point.

2.1.4.1 Eyelid Model: Elliptic Eyelid contour

This contour model is derived from the assumption that an eyeball has a spherical shape. This hypothesis leads to an eyelid model based on the opening of the eye. The opening is defined as the angular position of an eyelid with respect to the center of the sphere. Assuming that an eyeball can be presented as a sphere [9].

$$x^2 + y^2 + z^2 = R_{eyeball}^2 \tag{2.19}$$

The figure 2.1 depicts view of an eyelid contour considering the spherical shape of an eyeball and the expected eyelid curve in a specific degree of eye opens. This plane can be defined as:

$$\tan(\phi) = \frac{y}{z} \tag{2.20}$$

The intersection curve simply becomes an ellipse curve:

$$x^2 + \frac{y^2}{\sin(\phi)^2} = R_{eyeball}^2 \tag{2.21}$$
This ellipse curve is transformed to the polar coordinates:

\[ x = r \sin(\theta), \quad y = r \cos(\theta), \]  

(2.22)

\[ r = \frac{R_{\text{eyeball}}}{\sqrt{\sin(\theta)^2 + \frac{\cos(\theta)^2}{\sin(\phi)^2}}} \]  

(2.23)

### 2.1.4.2 Detection of Iris and Eyelid

The database provided by the Institute of Automation, Chinese Academy of Sciences (CASIA), the iris boundaries have insufficient contrast and global search techniques such as the Integro-differential operator are more suitable for the extraction process. However, even the global methods can result in incorrect detection because of noises such as strong boundaries of upper and lower eyelids.

The algorithm iteratively searches for iris and eyelids boundaries and excludes the detected eyelids areas for the next iteration. The process is designed with respect to the pupil center as the reference point and is performed by excluding the pixel values where the radius of iris is larger than the radius of either upper or lower eyelids.
2.1.5 Modified Roman Swiniarski’s Iris Segmentation Method

Authentication plays a very critical role in security related applications like ecommerce. There are a number of methods and techniques for accomplishing this key process. Biometrics is gaining increasing attention in these days. Security systems, having realized the value of biometrics, use biometrics for two basic purposes: to verify or identify users. The use of fingerprints, facial characteristics and other biometrics for identification is becoming more common [22].

The success of segmentation depends on the imaging quality of eye images. Images in the CASIA iris database collected by Institute of Automation, Chinese Academy of Sciences do not have mirror like reflections due to the use of near infra-red light for illumination [19-22]. At the outset to detect the pupil a linear threshold in the image,

\[ T(x, y) = \begin{cases} 
  f(x, y) > 40 : 1 \\
  f(x, y) \leq 40 : 0 
\end{cases} \]  

(2.24)

where, \( f(x, y) \) is the Input Image and \( T(x, y) \) threshold image. Pixels with intensity greater than the threshold value are set to 40, therefore converted to 1 (black). Pixels smaller than or equal to 40 are assigned to 0 (white). The next step is freeman’s chain code is applied to find regions of 8-connected pixels which are...
assigned with a value 1. The default connectivity is 8 for two dimensions, 26 for three dimensions from this concept we can find for all regions by using the following condition. For each region $r$ which is less than 2500 all pixels values are fixed to zero. The freeman's chain code is applied again in order to obtain the pupil part from the image. From this region, it is trivial to obtain its central moments. Finding the edges of the pupil involves the creation of two imaginary orthogonal lines passing through the centroid of the region. The boundaries of the binarized pupil are defined by the first pixel with intensity zero, from the center to the boundaries.

Finally this algorithm yields the pupil centre coordinate $(x, y)$ and the horizontal and vertical radiuses of the pupil $(rx, ry)$ as shown in the figure 2.3. This method is applied on CASIA database version 1.0 which is found effective and reliable.

![Figure 2.3: Pupil Centre detected with horizontal and vertical radius](image)

The second step of iris recognition is to isolate the actual iris region in a digital eye image. The iris region can be approximated by two circles, one for the iris/sclera boundary and another, interior to the first, for the iris/pupil boundary. The eyelids and eyelashes normally occlude the upper and lower parts of the iris region. Also, specular reflections can occur within the iris region corrupting the iris pattern.
A technique is required to isolate and exclude these artifacts as well as locating the circular iris region.

The basic problem comes from the anatomy of the eye and the fact that every person is different. Sometimes the eyelid may occlude part of the iris, as it will occur often with the Asians, and no full circularity may be assumed in this case. Other times due to variation in gaze direction the iris center will not match the pupil center, and we will have to deal with strips of iris of different width around the pupil. This method takes in consideration that areas of the iris at the right and left of the pupil are the ones that most often present visible to data extraction. The areas above and below the pupil also carry unique information, but it is very common that they are totally or partially occluded by eyelash or eyelid.

The strategy adopted for iris detection uses the information from pupil detection part to trace a horizontal imaginary line that crosses the whole image passing through the center of the pupil. Starting from the edges of the pupil, we analyze the signal composed by pixel intensity from the center of the image towards the border and try to detect sudden increases of intensity level.

Although the edge between the iris and the sclera is most of the times smooth, it is known that it always have greater intensity than iris pixels. Here the difference is notice by applying a linear contrast filter.

It is possible that some pixels inside the iris circle are very bright, causing a sudden rise in intensity. That could mislead the algorithm to detect that iris edge at that point. To avoid this situation we consider the intensity average of small windows and then detect when the sudden rises occur from these intervals by using the following steps for image $f(x,y)$.

1. Find the center $(x_{cp}, y_{cp})$ of the pupil and the horizontal pupil radius $r$
2. Apply a linear spatial filter on image $f(x,y)$: $G(x,y) = f(x,y) \alpha$.
3. Create vector $V = [v_1, v_2, ..., v_w]$ that holds pixel intensities of the imaginary row passing through the center of the pupil $r$. 

29
4. Create vector $R = [rx_{cp} + rx, rx_{cp} + r x + 1, \ldots, r_w]$ from the row that passes through the center of the pupil ($y_{cp}$) in contrasted iris image. Vector $R$ formed by the elements of the ($y_{cp}$) line that start at the right border of the pupil ($rx_{cp} + rx$) and proceed in the same fashion of the entire image.

5. Similar as stated above, create vector $L = [l_{x_p} - rx, l_{x_p} - rx - 1, \ldots, r]$ from row of contrasted iris image. The vector $L$ contains elements of pupil center line starting at the left border of the pupil and ending at the first element of that line.

6. For each side of the pupil (vector $R$ for the right side and vector $L$ for the left side):
   
   I. Calculate the average window vector $A = [a_1, \ldots, a_n]$ or $n = \|L\|$ is subdivided in $i$ windows of size $ws$ for all window $i^{th}$ elements $a_{i, ws \cdot ws - 1} \ldots a_{i, ws}$ will contain the average of that window.
   
   II. Identifying the boundaries of iris from both sides that is left and right with the first increase of values in $A_j (1 \leq j \leq n)$ that exceeds a set threshold $t$. In this experiment, a value of $t$ equal to 10 has shown to identify the correct location of the iris edge.

IrisBasis is the main attempt to reduce the dimensionality of the problem while focusing only on parts of the scene that effectively identify the individual. Also, restricts the mapping of the iris to areas known to have less influence of eyelashes and eyelids, the sides of the iris. Assuming that intra-class rotation of iris is practically void; the following approach is used to extract pixels of either side of the pupil and forming one reduced image of the iris.

The overall approach of this method is as follows: given image, desired number of IrisBasis rows and columns,

i. Retrieve pupil center and radius

ii. Retrieve iris endpoints
   
   a. Calculate height of pupil (twice the radius)
b. Calculate space between rows (s) as pupil height divided by desired number of IrisBasis rows.

c. Calculate index of the first target row as center of pupil – vertical pupil radius, assuming that first row is at the top of the image

iii. For each side of the pupil

Calculate baseline width as iris edge of current side – pupil edge of current side for all baselines, start from the top of the pupil, ends at the bottom of the pupil and spaced by s, perform the following steps

i. Calculate, using the equation of the circle, the (x,y) location of pixel that resides in the intersection of current baseline and circle centered at pupil center with radius equal to pupil horizontal radius.

ii. Map pixels that are under the baseline to vector B with number of elements equal to half of desired number of columns. Use an average filter of 3x3 pixels to calculate pixel intensity.

iii. Merge the both halves of Iris matrices side by side into one final Iris is obtained.
2.1.6 Implementation and Experimental Results

Figure 2.4: Sample of five Classes from CASIA Database Version 1.0.
Figure 2.5: Segmentation by Integro-Differential Operator for Five different classes.
Figure 2.6: Three different Classes of CASIA Database with Iris isolated. Each class shows three different cases of Iris.

CLASS - 017
017_1_1 017_2_1 017_2_4

CLASS - 076
076_1_1 076_2_1 076_1_1

CLASS - 103
103_1_1 103_2_1 103_2_4
2.2 Normalization

Once the iris region is successfully isolated from an eye image, the next phase is to transform this iris region so that it has fixed dimensions in order to perform comparisons.

Most normalization techniques are based on transforming iris into polar coordinates, known as unwrapping process. Pupil boundary and iris boundary are generally two non-concentric contours. The non-concentric condition leads to different choices of reference points for transforming an iris into polar coordinates.

Unwrapping iris using pupil center is proposed by Lim and Boles [10, 11]. Chung and Lee have used a technique equivalent to linearly-guessed centre. This technique starts from the iris center. Moreover, a contour-based unwrapping method is designed based on the assumption that iris textures would not tend to be in excessive radial toughness from pupil boundary to iris boundary [12].

Many researchers such as Tisse et. al., Boles et. al. and Ma et. al. has also used the fixed size polar transformation model. This technique seems to be suitable in bringing iris images into a standard form which would make easy to extract iris feature. However, the circular shape of an iris implies that there are different numbers of pixels over each radius [5, 7, 11].

2.2.1 Daugman's Cartesian to Polar Transform

Irices from different people may be captured in different size and, even for irises from the same eye; the size may change due to illumination variations and other factors. Such elastic deformation in iris texture will affect the results of iris matching. For the purpose of achieving more accurate recognition results, it is necessary to compensate for the iris deformation [13]. Daugman's had devised a model known as rubber sheet model which remaps each point within the iris region to a pair of polar coordinates.

Cartesian to Polar Transform is also known as rubber sheet model. This method transforms a localized iris texture from Cartesian to polar coordinates. This model assigns to each point in the iris, regardless of iris size in the image and of
pupillary dilation, a pair of dimensionless real coordinates \((r, \theta)\) where \(r\) lies in the unit interval \([0, 1]\) and \(\theta\) is the angular variable, cyclic over \([0, 2\pi]\). The normalization of the iris image \(I(x, y)\) from raw coordinates \((x, y)\) to a double dimensionless and nonconcentric coordinate system \((r, \theta)\) can be defined as:

\[
I(x(r, \theta), y(r, \theta)) \rightarrow I(r, \theta)
\]  
(2.25)

Where \(x(r, \theta)\) and \(y(r, \theta)\) are defined as linear combinations between the set of pupillary boundary points \((x_p(\theta), y_p(\theta))\) determined by the internal active contour, and the set of outer boundary points along the Iris \((x_s(\theta), y_s(\theta))\) determined by the external active contour describing the iris boundary [14].

Figure 2.7(a): An Iris Image of Class 014_1_3 from CASIA Database V1

Figure 2.7(b): Normalized Image of Class 014_1_3 using Cartesian to polar

2.2.2 R. P. Wildes' Image Registration

R. P. Wildes had proposed an image registration technique for normalizing iris textures. In this method, a newly captured image, \(I_a(u, v)\) would be aligned with an image in the database, \(I_d(u, v)\) that the comparison is performed. The
alignment process is a transformation using a choice of mapping function, 
\((U(x,y),V(x,y))\) which minimizes the function:

\[
\int_{x} \int_{y} (I_d(x,y) - I_d(x-u,y-v))^2 \, dx \, dy
\]  
(2.25)

The alignment process compensates for the rotation and scale variations. The
mapping function is constrained to capture a similarity transformation of image
coordinates \((x,y)\) to \((x',y')\), as defined below:

\[
\begin{pmatrix} x' \\ y' \end{pmatrix} = \begin{pmatrix} x \\ y \end{pmatrix} - s R(\phi) \begin{pmatrix} x \\ y \end{pmatrix},
\]  
(2.26)

With \(s\) as the scaling factor and \(R(\phi)\) a image matrix representing rotation
by \(\phi\). The parameters \(s\) and \(\phi\) are recovered by an iterative minimization procedure
[3].

R. P. Wildes normalization method is based on a different approach as
compared to Daugman’s method. In this method, normalization is performed in the
matching time. Comparing to Daugman’s method, the normalization method would
be time consuming in identification applications. However, for verification purposes
this method is capable of compensating unwanted factors such as variations in
rotation and scale.

2.2.3 Non-linear Normalization Model

The unwrapping method proposed by Daugman’s assumes that iris patterns
are linearly distributed in the radial direction, which allows the mapping procedure
into the interval \([0, 1]\). This technique depends on two main aspects:

1. The image acquisition process adjusts the pupil size to a correct radius range
by adjusting the illumination.

2. The feature extraction process is locally applied to many different positions of
the iris texture, which would compensate the local non-linear variations.

Non-linear normalization method was proposed by X. Yuan, P. Shi,
considers a nonlinear behavior of iris patterns due to changes of pupil size. In order
to unwrap an iris region correctly, a non-linear model and a linear normalization model are combined. The non-linear method, which is first applied to an iris image, is based on following three norms:

1. The pupil margin and iris origin (which correspond to the inner and outer boundaries of the iris) are concentric circles.
2. The margin of the pupil does not rotate significantly during pupil size changes.
3. The pupil shape does not change and remain circular when pupil size changes.

This model is defined by virtual arcs, which are named "fibers" following Harry Wyatts presented in his work, that connect a point on the pupil border to a point on the Iris [16].

The polar angle crossed by the arcs between these two points is $\frac{\pi}{2}$. The virtual arcs are defined based on normalized pupil sizes to a fixed value using a pre-defined $\lambda_{ref}$ which is gained by the mean of all $\lambda$ values defined as $\lambda = \frac{r}{R}$ in the iris database. The $r$ and $R$ represent the radius of pupil and Iris respectively. The reference annular region with $\lambda_{ref}$ is then linearly mapped into a fixed-size rectangle region of $m \times n$ by equally sampling $m$ points in each virtual concentric sampling circle with a fixed radial resolution.

### 2.2.4 Iris Unwrapping: Using Contour-Based Model

Transforming iris texture from Cartesian to polar coordinates, known as the unwrapping process, is one of the stages of an iris recognition algorithm, and has a significant impact on the overall performance of the system.

The main purpose of an iris texture is to control the amount of light entering the eye in different illumination conditions. The studies on physiology of iris illustrates that the response of the texture with respect to different intensities of light is non-linear due to the distribution of iris muscles controlling the pupil size [16].

An iris texture consists of two main muscles that are distributed in the angular and radial directions, known as the sphincter and dilator muscles,
respectively. In strong light conditions, in order to decrease the pupil diameter, the sphincter muscle contracts while the dilator muscle stays relaxed to adjust the light that enters the eye. However, in the conditions where the light is weak, the sphincter muscle relaxes and the dilator muscle contracts to increase the pupil diameter to allow more light to enter the eye. The two different illumination conditions, strong light and weak light, which cause the iris texture to perform in two different modes result in a non-linear behavior of the iris texture.

In Iris recognition system, studying the behavior of irises seems to be essential to be able to propose a correct normalization technique. In order to describe the importance of a normalization method more thoroughly, it could be helpful to highlight the uniqueness of each individual's iris and its stability over time as the bases of all iris recognition systems.

Assuming that each iris has unique patterns that do not change over time, it is desired to capture these patterns every time an image is taken from the eye. However, an iris texture is highly sensitive to illumination and the texture deforms to change the pupil diameter and control the amount of light entering the eye. The deformation of the texture also results in the deformation of the iris patterns. In order to obtain the unique patterns of the iris, it is desired to be able to track the changes of the iris to recover the unique patterns.

It is stated that the way an iris responds to illumination also varies from eye to eye due to different distributions of the muscles controlling the pupil.

Figure 2.8(a): Unwrapping using the pupil center (CP) and center point of Iris (CI)
Therefore, it seems more practical to study the behavior of a large number of
irises to obtain a normalization model that is optimal in capturing and tracking the
patterns.

In this thesis, different segmentation and normalization methods are studied
and implemented over irises in the CASIA database version 1.

Iris Center: the Unwrapping Reference Point

The center of an iris can be used as the reference point to unwrap the iris
texture. The possible advantage of this point is that limbus contour is fixed and does
not change over time. As depicted in figure 2.8(a) and (b) an unwrapping method
using iris center as the reference point.

Pupil Center: the Unwrapping Reference Point

Pupil center can also be considered as a proper choice for the reference point.
Lim et. al. and Boles et. al. algorithms are both based on pupil center as the
reference point. Unwrapping an iris with respect to this point seems to be
advantageous in extracting features from the areas near the pupil, where the iris
textures have more defined patterns, and may lead to acceptable recognition results.

Minimum Distance Unwrapping Method

An unwrapping method is examined based on the minimum distance of the
points over the pupil boundary from the ones over the Iris boundary. In this method,
N equally spaced points are chosen over the Iris boundary and the corresponding points over the pupil boundary have been selected based on the minimum distance criterion results in global and local minimum distance between the points over the two boundaries. It is noticed that the minimum distance method can cause irregular resolution over the pupil boundary due to different positioning of the pupil center with respect to Iris center.

**Contour-Based Method: Global Minimum**

Similar to the minimum distance method, an unwrapping method is studied based on the global minimum of the distances between the Iris and pupil boundaries. In this method, despite the minimum distance method, the points that are chosen over both of the borders are equally spaced and the positioning of the two borders are based on their global distance. The global minimum distance of the contour-based model is defined as:

\[
\arg\min_{(x_p(\theta_k), y_p(\theta_k))} \left( \int_0^{2\pi} \sqrt{((x_i - x_p(\theta))^2 + (y_i - y_p(\theta))^2} d(\theta) \right),
\]

(2.27)

Where, \((x_i, y_i)\) and \((x_p, y_p)\) are the borders of Iris and pupil respectively. \(\theta\) is defined as the angular offset for the pupil border in order to minimize the global minimum formulation.

The initial idea of both the minimum distance and the contour-based methods has arisen from the assumption that an iris texture tends to be in its most relaxed state in each pupil diameter. Therefore, it would make sense to adjust the points over the two boundaries in a way that the texture would not be in excessive radial tension. Moreover, both the minimum distance and the contour-based models have the advantage over the center based techniques in cases where the pupils are not perfectly circular.

In cases where the pupil borders are not perfect circles and have been detected by the active contour model, center-based models may not be as robust as contour based models with due to the sensitivity of the normalization to the correct choice of center point.
Linearly-Guessed Reference Point Method

In this method, the reference point is obtained own by a linear estimation using centers and radii of pupil and limbus as shown in the Figure 2.9. This method represents the unwrapping process should be performed by a point that the pupil center tends to reach when the pupil radius approaches to zero.

The limbus center and radius are considered as the starting state and the pupil center and radius are considered as a measurement in order to linearly guess the position of the pupil center when its radius is zero. This method is quite equivalent to the unwrapping method [17].

![Figure 2.9: Double-reference method equivalent linearly guessed center point](image)

2.2.5 Iris Normalization: Using Dynamic-Size Model

In addition to the above methods for transforming an iris image from Cartesian to polar coordinates, the concept of sampling frequency. As an example, the images provided by the CASIA database are 280×320, which can be considered as 280 x 320 samples from the area the image is taken. J. G. Daugman suggested capturing iris images with approximately 100 to 200 pixels in diameter and suggests that this resolution should not be less than 50 pixels over the iris diameter. However,
the image acquisition proposed by R. P. Wildes said capturing around 256 pixels in diameter.

Considering that the number of samples obtained from an iris is finite and statistics the mentioned minimum resolution criterion, another sampling issue arises at the time of transforming an iris from Cartesian to polar coordinates.

However, in the discrete form, the transformation comes across two main problems:

1. The polar samples do not perfectly match the Cartesian samples, so the polar values are required to be forecasted.
2. In each radius of the polar coordinates, there is different number of samples in the Cartesian coordinates, which can cause problems such as uncontrolled sampling, excessive interpolation and in some cases loss of information.

One of the most commonly used normalization methods is to transform an iris from Cartesian to polar coordinates with fixed radial and angular resolutions. The works presented in are based on a fixed-size transformation. However, as it has been described, the normalization process causes uncontrolled over-sampling, excessive interpolation and in some cases loss of information resolution is a linear factor of radius, which controls interpolation in each radial positioning and prevents loss of information [10, 18].

![Figure 2.10: A Fixed Normalization Approach for Isolated Iris](image)

512 Pixels

64 Pixels

Figure 2.10: A Fixed Normalization Approach for Isolated Iris
Figure 2.11: A rubber sheet model for four different classes of CASIA database Version 1.0.
2.3 Conclusion

The study has represented different approaches for Iris segmentation and Normalization. Iris Segmentation is an important step in iris recognition system. Properly detecting the inner and outer boundaries of iris texture is significantly important in all iris recognition systems. The popular methods like Daugman’s Integro-differential, Hough transform and active contour methods are useful in iris segmentation. An iris is normally segmented by detecting its inner (pupil) and outer (limbus) boundaries. Daugman’s Integro-differential not only detects the inner and outer boundaries, it also detects the upper and lower eyelids by adjusting the contour search from circular to a designed accurate.

Hough transform is a standard image analysis tool for finding curves that can be defined in a parametrical form such as lines, polynomials and circles.

The database provided by the Institute of Automation, Chinese Academy of Sciences (CASIA), the iris boundaries have insufficient contrast and global search techniques such as the Integro-differential operator are more suitable for the extraction process. However, even the global methods can result in incorrect detection because of noises such as strong boundaries of upper and lower eyelids.

Normalization is a process that changes the range of pixel intensity values. Sometimes, it is also called contrast stretching. The normalized iris image has low contrast and may have non-uniform brightness caused by the position of the light sources. Normalization techniques are based on transforming iris into polar coordinates, known as unwrapping process. Pupil boundary and Iris boundary are generally two non-concentric contours. The non-concentric condition leads to different choices of reference points for transforming an iris into polar coordinates. Proper choice of reference point is very important where the radial and angular information would be defined with respect to reference point.

Most normalization techniques are based on transforming iris into polar coordinates, known as unwrapping process. The non-concentric condition leads to different choices of reference points for transforming an iris into polar coordinates. Daugman’s normalization method is well known method and the same is also called as the rubber sheet model.
Chapter 2 - Segmentation and Normalization

References


