Chapter 5

FEATURE EXTRACTION
5 FEATURE EXTRACTION

Feature extraction is a vital step in efficient pattern recognition. It is the process of extracting the dominant characteristics or properties of an object. Properties thus extracted are called features of the object. The set of features that are extracted from the character should have properties of good discriminative power, good descriptive power and be computationally feasible uniformly over the entire search space.

In order to provide accurate recognition of individuals, constructing the iris code is our final process. After being able to localize the iris, 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.

The template that is generated in the feature encoding process will also need a corresponding matching metric, which gives a measure of similarity between two iris templates. This metric 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.

In this section we propose a method that measures the quality of each feature of the biometric signature and takes into account this information to limit the comparable features in the computation of the similarity between iris signatures. In section 5.1 we discussed the Standard methods such as Statistical Measures, GLCM and Wavelet transforms, and section 5.2 describes the proposed method and also we discussed
the classification and results & classifier in section 5.3 respectively. Experiments led us to conclude that this method significantly decreases the error rates in the recognition of noisy iris images.

5.1 Standard Methods

5.1.1 Statistical Measures

Statistical features are considered for iris recognition process are [79] :-

- **Mean**

\[ x_k = \sum (R1 + R2) \]  

(5.1)

R1 R2, regions in the segmented iris. Then mean \( x_k \) can be calculated as

\[ \text{Mean} = \frac{\sum_{k=1}^{n} x_k}{n} \]  

(5.2)

- **Variance**

\[ S^2 = \frac{\sum_{k=1}^{n} (x_k - \bar{x})^2}{n - 1} \]  

(5.3)

- **Standard Deviation**

\[ S = \sqrt{\frac{\sum_{k=1}^{n} (x_k - \bar{x})^2}{n - 1}} \]  

(5.4)

where \( \bar{x} \) is the mean

These extracted Features are stored in the database for identification process. Using these features an image can be viewed as a feature vector.
\[
\vec{(F_c)} = (x^c, m^c, y^c, s^c, d^c, ...) 
\] (5.5)

where \(c=(R1+R2)\)

\(x^c\) = Mean of the \(c^{th}\) region

\(m^c\) = Median of the \(c^{th}\) region

\(y^c\) = Mode of the \(c^{th}\) region

\(s^c\) = Standard Deviation of the \(c^{th}\) region

\(d^c\) = Variance of the \(c^{th}\) region

5.1.2 GLCM

GLCM (gray-level co-occurrence matrix), also known as the gray-level spatial dependence matrix [80], is a statistical measure used to characterize the texture of an image by calculating how often pairs of pixel, with specific values and in a specified spatial relationship occur in an image and then by extracting statistical measures from this matrix. By default, the spatial relationship is defined as the pixel of interest and the pixel to its immediate right (horizontally adjacent), but one can specify other spatial relationships between the two pixels. Each element \((i, j)\) in the resultant GLCM is simply the sum of the number of times that the pixel with value \(i\) occurred in the specified spatial relationship to a pixel with value \(j\) in the input image. Initially, the dynamic range of the given image is scaled to reduce the number of intensity values. The number of gray levels determines the size of the GLCM. The gray-level co-occurrence matrix can reveal certain properties about the spatial distribution of the gray levels in the texture image. For example, if most of the entries in the GLCM are concentrated along the diagonal, the texture is coarse with respect to the specified offset. However, a single GLCM might not be enough to describe the textual features
of the input image. For example, a single horizontal offset might not be sensitive to
texture with a vertical orientation. For this reason, gray co-matrix can create multiple
GLCMs for a single input image. Various textural features have been defined based
on the work done by Haralick [81][82]. To create multiple GLCMs, specify an array
of offsets to the gray co-matrix function. These offsets define pixel relationships of
varying direction and distance. For example, one can define an array of offsets that
specify four directions (horizontal, vertical and two diagonals) and four distances. The
statistics are calculated from these GLCMs and then subtracting the database GLCM
with input GLCM then the threshold value is to be set for the comparison of database
image with respect to input image. The statistical parameters that can be derived for
GLCM are contrast, entropy, energy, homogeneity and Dissimilarity.

- Contrast measures the local variations in the gray-level co-occurrence matrix
- Entropy is high when the elements of GLCM have relatively equal values.
  Low when the elements are closer to either 0 or 1.
- Energy provides the sum of squared elements in the GLCM.
- Homogeneity measures the closeness of the distribution of elements in the
  GLCM to the GLCM diagonal.
- Dissimilarity is similar to contrast; it is high when the local region has a
  high contrast.

\[
\text{Contrast} = \sum_{i, k=1}^{n-1} P_{i,j} (i - j)^2 \quad (5.6)
\]

\[
\text{Entropy} = \sum_{i, k=1}^{n-1} P_{i,j} (-ln P_{i,j}) \quad (5.7)
\]
• **Energy**

\[
Energy = \sum_i \sum_j P(i, j)^2 \tag{5.8}
\]

• **Homogeneity**

\[
Homogeneity = \frac{1}{n} \sum_{i,j=0}^{n-1} \frac{P_{i,j}}{1 + (i - j)^2} \tag{5.9}
\]

• **Dissimilarity**

\[
Dissimilarity = \sum_{i,j=0}^{n-1} P_{i,j} |i - j| \tag{5.10}
\]

\( P_{i,j} \) is the normalized co-occurrence matrix., \( N \) is the number of rows, and \( \sigma_i \) and \( \sigma_j \) are the standard deviation of row and column. \( \mu_i \) and \( \mu_j \) are the mean of row and column.

### 5.1.3 Haar Wavelet Transforms

Wavelets can be used to decompose the data in the iris region into components that appear at different resolutions. Wavelets have the advantage over traditional Fourier transform in that the frequency data is localized, allowing features which occur at the same position and resolution to be matched up. A number of wavelet filters, also called a bank of wavelets, is applied to the 2D iris region, one for each resolution with each wavelet a scaled version of some basis function. The output of applying the wavelets is then encoded in order to provide a compact and discriminating representation of the iris pattern.

A fundamental goal of data compression is to reduce the bit rate for transmission or storage while maintaining an acceptable fidelity or image quality. Compression can be achieved by transforming the data, projecting it on a basis of functions, and then encoding this transform. Because of the nature of the image signal and the mechanisms of human vision, the transform used must accept non stationary and be well localized in both the space and frequency domains. The basic idea of the wavelet transform is to represent any arbitrary function as a superposition of wavelets. Any
such superposition decomposes into different scale levels, where each level is then further decomposed with a resolution adapted to the level. Decomposing images with the wavelet transform yields a multi-resolution from detailed images to approximation images in each level. If images of size N x M are taken then it is decomposed up to $K^{th}$ level where $K= 1, 2, 3$ etc. as illustrated in Figure 5.1. The quadrants (sub-images) within the image indicated as LH, HL, and HH represent detailed images for horizontal, vertical, and diagonal orientation, respectively in the first level. The sub-image LL corresponds to an approximation image that is further decomposed, resulting in two-level wavelet decomposition.

**Figure 5.1 – Three Level Wavelet Transforms**

Haar wavelet as a transformation on the given image essentially does an averaging and differencing of a pixel with its neighborhood. Initially, averaging and differencing process is carried out row wise and then it is followed by the similar operation column wise. In the first stage of Haar wavelet transform $P(z)$, the original data of size $N$ is compressed by a factor of 2 because $P(z)$ is determined by $N/2$ coefficients. At scale 4 or 8 or some larger number, we should be able to take our approximation $P(z)$ at scale 2 and split it into two parts, one being approximation at scale 4 and the other being detail needed to pass from scale 4 to 2. Continue in such a way that the
scale 2^k are determined by \( N / 2^k \) numbers \([83-90]\). Some of the advantages of Haar wavelet Transforms [HWT] are as follows.

1. Best performance in terms of computation time.
2. Computation speed is high.
3. Simplicity
4. HWT is efficient compression method.
5. It is memory efficient, since it can be calculated in-place without a temporary array.

### 5.2 Proposed New Method

The main limitation is that the first generation wavelet works well for infinite or periodic signals but it is not clear how one should modify it for use in a bounded domain. In many applications, the domain of interest is not infinite, and signals are not periodic. Furthermore, even 1-D signals are often not sampled regularly. In higher dimension, domains are often have boundaries, and often the metric is not flat, i.e., we need to analyze functions on manifolds or surfaces.

The big issue is how to keep the "nice" properties of wavelets, namely time-frequency localization and fast algorithms, while being able to extend beyond simple geometries. The answer is to give up translation and dilation. The construction must therefore not use any Fourier analysis. Instead, the calculation will be entirely based on a new approach called The Lifting Scheme.

#### 5.2.1 Lifting Wavelet Transforms

The lifting scheme is an algorithm to calculate wavelet transform in an efficient way \([91]\). It is also a generic method to create so-called second generation wavelets. The
main idea is to build a new set of biorthogonal wavelet filters starting from the known orthogonal wavelet filters. The new biorthogonal filters at the synthesis \((G_s(z), H_s(z))\) and analysis side \((G_a(z), H_a(z))\) can be designed as:

\[
G_s^{\text{new}}(z) = G(z) + H(z)S(z^2)
\]
\[
H_s(z) = H(z)
\]
\[
G_a(z) = G(z)
\]
\[
H_a^{\text{new}}(z) = H(z) - H(z)S(z^{-2})
\]

where \(G(z), H(z)\) are filters corresponding to known orthogonal filters and \(S(z)\) is a Laurent polynomial and the procedure is called lifting operation.

By choosing an appropriate \(S(z)\), one can modify the known wavelet to a new wavelet with better properties. One such main property that can be modified is the number of vanishing moments of the wavelet. Vanishing moment of the wavelet is defined as the maximum value of \(N\) for which,

\[
\int t^N \psi(t) dt = 0.
\]

It is well known that the number of vanishing moments of wavelet \(\psi(t)\) is equal to maximum value of \(N\) for which

\[
\frac{d^N G(z)}{dz} = 0 \text{ at } z = 1.
\]

In this work, proposed laurent polynomial \(S(z)\) for iris feature extraction is (for the sake of simplicity, only 1-d version is given):

\[
S(z) = \frac{-1}{8} [z - z^{-1}]
\]
This results in new wavelet to have two vanishing moments as opposed to that of Haar wavelet with vanishing moment one. With filters corresponding to Haar wavelet being, 

\begin{align*}
G(z) &= -\frac{1}{\sqrt{2}} + \frac{1}{\sqrt{2}} z^{-1} \\
H(z) &= \frac{1}{\sqrt{2}} + \frac{1}{\sqrt{2}} z^{-1}
\end{align*}

the resulting new filter at synthesis side is, 

\begin{align*}
G_{\text{new}}(z) &= G(z) + H(z)S(z^2) \\
&= \left( -\frac{1}{\sqrt{2}} + \frac{1}{\sqrt{2}} z^{-1} \right) + \left( \frac{1}{\sqrt{2}} + \frac{1}{\sqrt{2}} z^{-1} \right) \left( -\frac{1}{8} [z^2 - z^{-2}] \right) \\
&= -\frac{1}{\sqrt{2}} + \frac{1}{\sqrt{2}} z^{-1} + \frac{1}{8\sqrt{2}} z^{-2} + \frac{1}{8\sqrt{2}} z^{-2} + \frac{1}{8\sqrt{2}} z^{-2} + \frac{1}{8\sqrt{2}} z^{-3}.
\end{align*}

Similarly filter at the analysis side, 

\begin{align*}
H_{\text{new}}(z) &= \frac{1}{\sqrt{2}} + \frac{1}{\sqrt{2}} z^{-1} + \frac{1}{8\sqrt{2}} z^{-2} + \frac{1}{8\sqrt{2}} z^{-2} + \frac{1}{8\sqrt{2}} z^{-2} + \frac{1}{8\sqrt{2}} z^{-3}.
\end{align*}

Implementation of lifting operation uses in-place computation techniques to reduce computation time an approach is described below.

Predict and Update: The lifting scheme is an efficient implementation of the filtering operations. At the \(j^{th}\) level, input data set is transformed into two other sets: the low-resolution part \(\lambda_j\) and the high resolution part \(\gamma_j\). This is obtained first by just splitting the data set into two separate data subsets (usually called the lazy wavelet transform). The next step is to recombine these two sets in several subsequent lifting steps which decor relate the two signals.

A dual lifting step can be seen as a prediction: the data \(\gamma_j\) are ”predicted” from the data \(\lambda_j\). When the signals are still highly correlated, then such a prediction will usually be very good, and we can store only the part of \(\gamma_j\) that differs from its prediction (the prediction error). Thus \(\gamma_j\) is replaced by \(\gamma_j - P(\lambda_j)\), where \(P\) represents the prediction operator.
Thus, lifting scheme contains three [92-94] steps to decompose signal, that is, Split, Predict and Update, as shown in above figure. The original signal is \( s[n] \). It is transformed into approached signal in low frequency \( c[n] \) and detail signal \( d[n] \).

**Split**: In this step, the original signal \( s[n] \) is split into two subsets which do not overlap with each other: \( se[n] \) (even sequence) and \( so[n] \) (odd sequence), that is

\[
S_e[n] = S[2n] \tag{5.16}
\]

\[
S_o[n] = S[2n + 1]
\]
Figure 5.3 – Block Diagram of Predict and Update Lifting Steps.

**Predict**: If the original signal is locally coherent, the subsets $s_{e}[n]$ and $s_{o}[n]$ are also coherent, so one subset can be predicted by another. Commonly we use even sequence to predict odd sequence,

$$d[n] = s_{o}[n] - P(s_{e})[n]$$

(5.17)

Where $P$ is the predict operator and reflects the degree of correlation of data. $P(s_{e})[n]$ implies that the value of $d[n]$ can be predicted by the value of $s_{e}[n]$.

**Update**: $c[n]$ is the approach signal which has been decomposed. One of the important features is that its average value should be equal to the average value of original signal $s[n]$. So we can use detail subset $d[n]$ to update the signal $s_{e}[n]$, expressed by $c[n]$,

$$c[n] = s_{e}[n] + U(d)[n]$$

(5.18)

The decomposition of wavelet can be written as

$$
\begin{bmatrix}
\lambda(z) \\
\gamma(z)
\end{bmatrix} = M(z)
\begin{bmatrix}
S_{e}[z] \\
z^{-1}S_{o}[z]
\end{bmatrix}
$$

Where $M(z)$ is polyphase matrix, given as
\[ M(z) = \begin{bmatrix} 1 & s(z) \\ 0 & 1 \end{bmatrix} \begin{bmatrix} h_e[z] & h_0[z] \\ g_e[z] & g_0[z] \end{bmatrix} \]

where \( s(z) \) is the Update filter and is given as

\[ S(z) = \frac{-1}{8} [z - z^{-1}] \]

Where \( h_e(z) \) and \( g_e(z) \) are the FIR filters.

If there are \( 2^n \) data elements, the first step of the forward transform \([95-96]\) will produce \( 2^n - 1 \) averages and \( 2^n - 1 \) differences (between the prediction and the actual odd element value). These differences are referred to as wavelet coefficients.

The split phase that starts each forward transform step moves the odd elements to the second half of the array, leaving the even elements in the lower half. At the end of the transform step the odd elements are replaced by the differences and the even elements are replaced by the averages. The even elements become the input for the next step, which again starts with the split phase. The first element in the array contains the data average. The differences (coefficients) are ordered by increasing frequency.

### 5.2.2 Contourlet Transforms

Although the wavelet transform is powerful in representing images containing smooth areas separated with edges, it cannot perform well when the edges are smooth curves. Moreover it can capture limited directional information. A major drawback of two-dimensional wavelets is their limited capability in capturing directional information which has a significant role in analysis of the images, including feature extraction and classification.

Typically, a separable 2-D wavelet transform provides:
• **multi resolution**: which is the ability to visualize the transform with varying resolution from coarse to fine.

• **localization**: which is the ability of the basis elements to be localized in both the spacial and frequency domains.

• **critical sampling**: which is the ability for the basis elements to have little redundancy.

However, it is not capable of providing:

• **directionality**: which is having basis elements defined in a variety of directions.

• **anisotropy**: which is having basis elements defined in various aspect ratios and shapes.

To overcome this deficiency, and to capture the intrinsic geometrical structures in iris pattern, wavelet methods such as contourlet transform needs to be applied. The contourlet transform can effectively overcome the disadvantages of conventional wavelet: Contourlet transform is a multi-scale and multi-direction framework of discrete image. The ability of the contourlet transform for noise reduction is also better than the wavelet transform. In addition, contourlets represent edges better than wavelets. Therefore, the contourlet transform is adopted in this work. In this transform, the multiscale analysis and the multi-direction analysis are separated in a serial way. The contourlet transform captures the intrinsic geometrical structures of an iris image. It decomposes the iris image into a set of directional subbands with texture details captured in different orientations at various scales. Discriminant analysis is used to determine the optimal threshold for the selection of dominant directional energy components. Only dominant directional energy components are employed as elements of the input feature vector. The input feature vectors are compared with the template feature vectors for identification.
Contourlet transform (CT):

Contourlet transform (CT) allows for different and flexible number of directions at each scale. CT is constructed by combining two distinct decomposition stages [97], a multi scale decomposition followed by directional decomposition. The grouping of wavelet coefficients suggests that one can obtain a sparse image expansion by applying a multi-scale transform followed by a local directional transform. It gathers the nearby basis functions at the same scale into linear structures. In essence, a wavelet-like transform is used for edge (points) detection, and then a local directional transform for contour segments detection. A double filter bank structure is used in CT in which the Laplacian pyramid (LP) [98] is used to capture the point discontinuities, and a directional filter bank (DFB) [99] to link point discontinuities into linear structures. The combination of this double filter bank is named pyramidal directional filter bank (PDFB) as shown in Figure 5.4.

![Figure 5.4 – Two level Contourlet decomposition](image)
Laplacian Pyramid:

Multiscale data representation is a powerful idea. It captures data in a hierarchical manner where each level corresponds to a reduced-resolution approximation. One way of achieving a multi scale decomposition is to use a Laplacian pyramid (LP) as introduced by Burt and Adelson [100]. Figure 5.5. shows this decomposition process, where H and G are called (low pass) analysis and synthesis filters, respectively, and M is the sampling matrix. LP in the PDFB uses orthogonal filters and down sampling by two is taken in each dimension. The LP decomposition at each level generates a down sampled low pass version of the original and the difference between the original and the prediction, resulting in a band pass image.

However, the LP has the advantage over the critically sampled wavelet scheme that each pyramid level generates only one bandpass signal, even for multidimensional cases. This property makes it easy to apply many multiresolution algorithms using a coarse-to-fine strategy to the LP. Therefore the LP permits further subband decomposition to be applied on its bandpass images. A possible scheme is a pyramidal decomposition where the bandpass images of the LP are fed into directional filter banks. The filtering and downsampling operation for the LP yields the coarse approximation signal.

\[
c[n] = \sum_{h \in \mathbb{Z}^d} x[k]h[Mn - k] = \langle x, \bar{h}[-Mn] \rangle
\]  
(5.19)

where we denote \( \bar{h}[n] = h[n] \). The upsampling and filtering operation results in

\[
p[n] = \sum_{h \in \mathbb{Z}^d} c[k]g[n - Mk] = \sum_{h \in \mathbb{Z}^d} \langle x, \bar{h}[-Mk] \rangle g[n - Mk].
\]  
(5.20)

It is simple with low computational complexity due to its single filtering channel and has higher dimension. LP is a multiscale decomposition of the \( L^2(R^2) \) space in
Figure 5.5 – Laplacian Pyramid

to a series of increasing resolution.

\[ L^2(R^2) = V_{j0} \sum_{j=0}^{w} W_j \]  \hspace{1cm} (5.21)

where \(V_{j0}\) is the approximation at scale \(2^j\) and multi resolution \(W_j\) contains the added detail to the finer scale \(2^{j-1}\). By using \(L\) appropriate low pass filters, \(L\) low pass approximations of the image are created. The difference between each approximation and its subsequent down sampled low pass version is a band pass image. The result is a Laplacian pyramid with \(L+1\) equal size levels; one coarse image approximation and \(L\) band pass images.

**Directional Filter Bank :**

Filter banks (FB) are powerful tools in digital signal processing. They provide an efficient and structured method for decomposing and analyzing discrete signals. The directional filter bank (DFB) is a critically sampled filter bank \([101],[102],[103]\) that can decompose images into any power of two’s number of directions. The DFB is efficiently implemented via a \(l\)-level tree-structured decomposition that leads to \(2^l\) subbands with wedge-shaped frequency partition.
For the 2-D sequence, the \((nxM)\) fold down sampled sequence \(x_d(n)\) is defined as

\[
x_d(n) = x(Mn)
\]  

(5.22)

DFB is applied to the difference signal or \(W_{j-1}\) the subspaces.

\[
\theta_{j,k}^l(t) = \sum_{m \in \mathbb{Z}^2} h_k^l[m - M] \phi_{j,m}(t)
\]

(5.23)

The family \(\theta_{j,k}^l(t)\) is an orthonormal basis of a directional subspace \(v_{j,k}^l\)

**Powers of contourlet transform:**

To capture smooth contours in images, the representation should contain basis functions with variety of shapes, in particular with different aspect ratios. A major challenge in capturing geometry and directionality in images comes from the discrete
nature of the data, the input is typically sampled images defined on rectangular grids. Because of pixelization, the smooth contours on sampled images are not obvious. For these reasons, unlike other transforms that were initially developed in the continuous domain and then discretized for sampled data, the new approach starts with a discrete-domain construction and then investigate its convergence to an expansion in the continuous-domain. This construction results in a flexible multi-resolution, local, and directional image expansion using contour segments. Directionality and anisotropy are the important characteristics of contourlet transform. Directionality indicates having basis function in many directions. Conventional wavelet has basis functions only in three directions. The anisotropy property means the basis functions appear at various aspect ratios whereas as conventional wavelets are separable functions and thus their aspect ratio is one. Due to these properties CT can efficiently handle 2D singularities, edges in an image. This property is utilized in this paper for extracting directional features for various pyramidal and directional filters.

LP in the CT uses orthogonal filters and down sampling by two in each dimension. The low pass filter G in the LP uniquely define an orthogonal scaling function $\psi(t)$.

$$\phi(t) = 2 \sum_{m \in \mathbb{Z}^2} g(n) \phi(2t - n) \quad (5.24)$$

$$\phi_{j,n} = 2^{-j} \phi \left[ \frac{t - 2^j}{2^j} \right] \quad (5.25)$$

where $(\phi_{j,n})_{n \in \mathbb{Z}^2}$ is an orthonormal basis of $v_j$. for all $j \in \mathbb{Z}$ The sequence of nested subspaces $(v_j)_{j \in \mathbb{Z}}$ satisfies the shift invariance and scale invariance properties.$v_j$ is a subspace defined on a uniform grid with intervals $2^j \times 2^j$ the approximates the image at the resolution $2^j$. The difference image in the LP carry the details $W_j$ to increase the resolution of an image approximation.
\[ V_{j-1} = V_j \oplus W_j \]  

(5.26)

**Feature vector:**

Directional information present in the iris image can be exploited as feature vector. The original image is decomposed into eight directional subband outputs using the DFB at three different scales and the energy of each block can be obtained from the decomposed image. The energy \( E_{mn} \) of the image block associated with subband is defined as

\[ E_{mn} = \sum_{x,y \in m} |I_{mn}(x,y)| \]  

(5.27)

\( I_{mn}(x, y) \) denote the image coefficient at position \((x, y)\) of image block \(m\) corresponding to subband \(n\). Each energy value is calculated from the image block corresponding to the subband. To extract dominant directional energy, it is necessary to select a threshold. Normalized energy value is used instead of energy value to avoid threshold inaccuracies due to spatial intensity variations across the image.

In our experiments three-level contourlet decomposition is adopted. The resultant of the third level co-efficient gives the large reduction in the prominent features. The normalized image obtained form the localized iris image is decomposed by the PDFB. The contourlet transforms of the image as shown in Figure 5.7.
Once the features are extracted using Statistical measures, GLCM, Wavelet Transforms, Lifting Wavelet Transform and finally Contourlet transforms, an iris image is transformed into a unique representation within the feature space (Feature vector). In order to make the decision of acceptance or refusal, a distance is calculated to measure the closeness of match. The extracted features of the iris are compared with distance between the feature vectors of two iris images. The distance measures have
been considered and maximum of the distance between iris images of the same person in the database is considered as the threshold.

5.3.1 Euclidean Measures:

Euclidean Measures: The Euclidean distance is one way of defining the closeness of match between two iris feature templates. It is calculated by measuring the norm between two vectors \( X \) and \( Y \) respectively of two images under consideration

\[
EM_1 = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2 + ...} \quad (5.28)
\]

5.3.2 Distance Measure:

The Square of the difference between the maximum value of input (Max1) and database image (Max2) is then compared with absolute value of the difference value.

\[
DM = \frac{Max(Max_1 - Max_2)}{2} \quad (5.29)
\]

5.3.3 Separable Power:

Separable Power: The separability power method is determined by

\[
d = \frac{|\mu_1 - \mu_2|}{\sqrt{\sigma_1^2 + \sigma_1^2}} \quad (5.30)
\]

where \( \mu_1 \) and \( \sigma_1 \) are the mean and standard deviation of the distance of the codes belonging to the same person, and \( \mu_2 \) and \( \sigma_1 \) are the mean and standard deviation of the distance of the codes belonging to different persons.
### Table 5.1 – Time consumption of The Various Algorithms

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Localization Time (secs)</th>
<th>Feature Extraction Time (m secs)</th>
<th>Comparison Time (m secs)</th>
<th>Total Time (secs)</th>
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<td>Statistical Measures</td>
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<td>10</td>
<td>5.128</td>
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<td>Lifting wavelet</td>
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<td>42</td>
<td>4.238</td>
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<td>Contourlet transform</td>
<td>2.2</td>
<td>215</td>
<td>25</td>
<td>2.440</td>
</tr>
</tbody>
</table>

#### 5.4 Results of the Proposed Algorithm for Iris Recognition

It is evident from the working, that the algorithm is simple and efficient. The efficiency of this algorithm is in fact very high compared to the currently existing systems. These results are actually proved by means of tests performed on thousands of samples.

- **Execution speed**: Hough Transform is a very processor hungry method which requires enormous time to compute even with modern microprocessors. This is because redundant analysis is high in this method making computation requirement higher. Localization takes about 120 secs using this algorithm and in comparison, the current algorithm does the same job in less than 5 seconds.

- **Correct Segmentation Ratio**: The Hough Transform is only efficient if a high number of votes fall in the right bin, so that the bin can be easily detected amid the background noise. So the bin must not be too small, else some votes will fall in the neighboring bins, thus reducing these visibility of the main bin. Also, when the number
of parameters is more than two, the average number of votes cast in a single bin is very low, reducing its efficiency. Also, Hough Transform can only detect lines/circles but not their thickness thus increasing chances of false detections. Therefore the best success rate obtained is 87% in the Hough approach whereas the current approach brings this efficiency to nearly 99.78%.

- **Need for Approximate Radius**: The approximate value of radius is needed for the Hough transform to work properly. This causes huge problems, as human pupils often have a large variation in radii. But the current method uses this as an enhancement rather than a requirement and works perfectly fine in its absence.

- **Failure on Large Images and Small Embedded Processors**: As the computation involved is cumbersome, the process seriously fails in the case of large images with high computational requirement (limited to less than 200 x 200). It is also not possible to implement the Hough approach on small embedded processors due to the complexity involved.

- **Error Ratio**: The best error ratio obtained using the conventional wavelet approach is only about 99% under ideal condition, whereas the current algorithm achieves about 99.97% of efficiency.

- **Time Consumption**: As a result of the repeated “shift and compare” approach - the time consumption is huge. Therefore the current algorithm is a good solution performing a single comparison.

### 5.4.1 Salient Features

Authentication of samples is a relatively easy task compared to the identification of a person, which is very time consuming and cumbersome. Identification also has very high probability of error when compared to the “one to one” authentication
check. For performing an identification check, any algorithm needs the following basic features:

- Comparing with all samples in the database, implies a large number of comparisons of the order of billions.
- Time consumed in each comparison must be very small while performing billions of comparisons as, an increase of even a millisecond can cause several hours of difference when billions of comparisons are involved.
- The current algorithm maybe deemed the best for this approach as it involves both the above features-
  - False acceptance ratio is under 1% in the current algorithm.
  - Stands high in the list, in terms of the “Time consumed” parameter.

5.4.2 A Comparative Study With Other Algorithms - where it stands

Experiments suggest that the current algorithm has a very good recognition ratio in both the stages and also the time consumed in both stages is very good compared to other algorithms.

Enrollment Error Ratio

An important error that requires foremost attention is the failure to enroll. This indicates the system’s inability to correctly enroll a new individual into the database. This mainly occurs due to the system’s inability to perform the localization process correctly. Even the most famous algorithms like the Daugmans algorithm have a considerable amount of error in this stage - but the current method has 0.1% enrollment error as verified on all datasets.
<table>
<thead>
<tr>
<th>Algorithm</th>
<th>FER</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daugman Algorithm</td>
<td>1.5%</td>
</tr>
<tr>
<td>Current Method</td>
<td>0.1%</td>
</tr>
<tr>
<td>Wildes</td>
<td>1.75%</td>
</tr>
<tr>
<td>Jiali Cui’s</td>
<td>0.92%</td>
</tr>
<tr>
<td>Christal Tisse et. all</td>
<td>8%</td>
</tr>
</tbody>
</table>

**Table 5.2 – Enrollment Error of Various Algorithms**

![Bar chart comparing FER of various algorithms](chart.png)

**Figure 5.8 – Comparison of FER**
Correct Recognition Ratio

The most important parameter that sets a system apart from others is the final correct recognition ratio. This is calculated with the consideration of both - False acceptance ratio (FAR) and False rejection ratio (FRR). The correct recognition ratio of Daugmann’s algorithm is the highest with about 99%. The current algorithm achieves a correct recognition ratio of about 99.97%.

**Figure 5.9 – Comparison of CRR**
<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Correct Recognition Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Current Method</strong></td>
<td><strong>99.86 %</strong></td>
</tr>
<tr>
<td>Daugman Algorithm</td>
<td>99.37%</td>
</tr>
<tr>
<td>Wildes</td>
<td>98 %</td>
</tr>
<tr>
<td>Boles and Bolashash</td>
<td>92.64%</td>
</tr>
<tr>
<td>Li Ma and yang</td>
<td>94.9%</td>
</tr>
<tr>
<td>Roy and Bhattacharya</td>
<td>99.56%</td>
</tr>
<tr>
<td>Ma and Pan</td>
<td>99.6%</td>
</tr>
<tr>
<td>Liu and Bowyer</td>
<td>97.08%</td>
</tr>
<tr>
<td>Hong and zhuang</td>
<td>99.14%</td>
</tr>
<tr>
<td>Wen-Shiung et.all</td>
<td>95.62%</td>
</tr>
<tr>
<td>Chrital Tisse et.all</td>
<td>89%</td>
</tr>
<tr>
<td>Donald et.all</td>
<td>83.7%</td>
</tr>
<tr>
<td>Shinyoung Lim et.all</td>
<td>97.6%</td>
</tr>
<tr>
<td>Avilla and Reillo</td>
<td>97.89%</td>
</tr>
<tr>
<td>Rahib and Koray</td>
<td>98.62%</td>
</tr>
<tr>
<td>Masek</td>
<td>83.92%</td>
</tr>
<tr>
<td>Gaurav and Mayank</td>
<td>90%</td>
</tr>
</tbody>
</table>

**Table 5.3 – Correct Recognition Ratios of Various Algorithms**
Table 5.4 – Time Consumption of The Various Methods

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Localization Time (secs)</th>
<th>Feature Extraction Time (m secs)</th>
<th>Comparison Time (m secs)</th>
<th>Total Time (secs)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daugman Algorithm</td>
<td>8.7</td>
<td>682.5</td>
<td>54</td>
<td>9.436</td>
</tr>
<tr>
<td>Current Method</td>
<td>2.2</td>
<td>215</td>
<td>25</td>
<td>2.440</td>
</tr>
<tr>
<td>Wildes</td>
<td>8.3</td>
<td>210</td>
<td>401</td>
<td>8.911</td>
</tr>
<tr>
<td>Boles and Boashash</td>
<td>-</td>
<td>170.3</td>
<td>11</td>
<td>181.3</td>
</tr>
<tr>
<td>Roy and Bhattacharya</td>
<td>203</td>
<td>80.3</td>
<td>167.2</td>
<td>203.24</td>
</tr>
<tr>
<td>Ma and Pan</td>
<td>-</td>
<td>260.2</td>
<td>8.7</td>
<td>-</td>
</tr>
<tr>
<td>Donald et.all</td>
<td>-</td>
<td>14.5</td>
<td>15.4</td>
<td>-</td>
</tr>
</tbody>
</table>

Time Consumption

Despite the high efficiency of the algorithm, the time consumed by the algorithm is very less in the localization stage and also in the recognition stage. This puts it ahead of most other algorithms in terms of execution speed.

Experimental Results

In order to obtain a correct idea of the false recognition ratios and errors in identification, tests were conducted with over 35,000 samples for checking the authentication as well as identification errors. The results of each section are summarized below.
FAR and FRR

All authentication systems suffer from two forms of error. False acceptance happens when the biometric system authenticates an impostor. False rejection occurs when the system has rejected a valid user. A biometric system’s accuracy is determined by combining the ratios of false acceptance and rejection.

If we wish to protect sensitive data with a biometric system, we must tune the system to reduce the number of false acceptances. However, a system that’s highly calibrated to reduce false acceptances may also increase false rejections, resulting in more administrator intervention. So, a balance between acceptance and rejection ratios is very essential.

False Acceptance Ratio

False acceptance is the instance of a security system incorrectly verifying or identifying an unauthorized person. Also referred to as a type II error, a false acceptance typically is considered the most serious of biometric security errors as it gives unauthorized users access to systems that expressly are trying to keep them out. The false acceptance ratio, or FAR, is the measure of the likelihood that the biometric security system will incorrectly accept an access attempt by an unauthorized user. A system’s FAR typically is stated as the ratio of the number of false acceptances divided by the number of identification attempts.

\[
FAR(\%) = \frac{\text{Number of incidence of false acceptance}}{\text{Total number of tests performed}} \times 100 \quad (5.31)
\]
False Rejection Ratio

False rejection is the instance of a security system failing to verify or identify an authorized person. Also referred to as a type I error, a false rejection does not necessarily indicate a flaw in the biometric system; for example, in a fingerprint-based system, an incorrectly aligned finger on the scanner or dirt on the scanner can result in the scanner misreading the fingerprint, causing a false rejection of the authorized user. The false rejection ratio, or FRR, is the measure of the likelihood that the biometric security system will incorrectly reject an access attempt by an authorized user. A system’s FRR typically is stated as the ratio of the number of false rejections divided by the number of identification attempts.

\[
FRR(\%) = \frac{\text{Number of incidence of false rejections}}{\text{Total number of tests performed}} \times 100 \quad (5.32)
\]

FAR-FRR Performance of The System

Recognition performance was evaluated using the False acceptance ratio (FAR) and False rejection ratio (FRR), with results summarized as in Table 5.5. The threshold kept at a value of 80% yielded the best possible combination of FAR and FRR. The threshold value which is more than 80% is set to 0.45.
<table>
<thead>
<tr>
<th>IRIS DATABASE</th>
<th>FAR</th>
<th>FRR</th>
</tr>
</thead>
<tbody>
<tr>
<td>CASIA version 1</td>
<td>0.002%</td>
<td>0.10%</td>
</tr>
<tr>
<td>CASIA version 2</td>
<td>0.037%</td>
<td>0.23%</td>
</tr>
<tr>
<td>CASIA version 3</td>
<td>0.039%</td>
<td>0.29%</td>
</tr>
<tr>
<td>MMU Version 1</td>
<td>0.015%</td>
<td>0.1%</td>
</tr>
<tr>
<td>UPOL</td>
<td>0.027%</td>
<td>0.2%</td>
</tr>
</tbody>
</table>

Table 5.5 – Comparison of FAR-FRR

5.5 Summary

In this chapter we discussed our feature selection proposal, that is based on the analysis of the predominant noisy regions of the images captured in each specific imaging environment to select the features with highest discriminating capacity. Finally, our iris division and classification strategies were detailed. Moreover, we stress the independence between all of these methods and the particular feature extraction i.e Lifting and Contourlet and comparison used by the iris recognition strategy, which is obviously a strong point, regarding its applicability. In short, it is our belief that each of the proposals described in this chapter is propitious for the application in less constrained imaging capture environments, and contributes to increase the range of domains where iris recognition can be applied.