Iris Quality Assessment and Bi-orthogonal Wavelet Based Encoding for Recognition

Aditya Abhyankar*, Stephanie Schuckers

*Electrical and Computer Eng Dept, Clarkson University, Potsdam, NY, USA

Abstract

Iris recognition has been demonstrated to be an efficient technology for personal identification. In this work, methods to perform iris encoding using bi-orthogonal wavelets and directional bi-orthogonal filters are proposed and compared. All the iris images are enhanced using the wavelet domain in-band de-noising method. This method is shown to improve the iris segmentation results. A framework to assess the iris image quality based on occlusion, contrast, focus and angular deformation is introduced and used as part of a novel adaptive matching technique based on the assessed iris image quality. Adaptive matching presents improved performance when compared against the Hamming distance method. Four different databases are used to analyze the system performance. The first two databases include popular CASIA and high resolution University of Bath databases. Results obtained for these databases compare with results from the literature, in terms of speed as well as accuracy. The other two databases have challenging off-angle (WVU database) and uncontrolled (Clarkson database) iris images and are used to assess the limits of system performance. Best results are achieved for directional bi-orthogonal filter based encoding technique combined with the adaptive matching method with EER values of 0.07%, 0.15%, 0.81% and 1.29% for the four databases, which reflect highly competent performance and high correlation with the quality of the iris images.

Key words: iris recognition, bi-orthogonal wavelets, directional filters, automatic segmentation, adaptive matching, in-band enhancement, iris quality assessment, off-axis iris images, uncontrolled iris capturing, receiver operating characteristics

* Corresponding author.

Email addresses: abhyanas@clarkson.edu (Aditya Abhyankar), sschucke@clarkson.edu (Stephanie Schuckers).
1 Introduction

Biometric recognition is showing increased demand and acceptance in public and private sectors. Iris recognition is considered to be a highly accurate and consistently reliable method for personal identification. The iris, being found to be very stable, highly unique and easy to capture, is classified as one of the better biometric identifiers [1,2]. The human iris, a ring-like structure sandwiched between the black colored central pupil region and white sclera region in the human eye, has a very complex fiber-like structure which can be inscribed to formulate a biometric template. The human iris, evolved out of chaotic morphogenetic processes [3], has also been shown to remain consistent over a lifetime of a human [2,4]. Unlike fingerprints, typically, an iris image is captured using a non-contact imaging process and has shown potential of deployment in real-time applications [5]. Thus, iris has high universality, distinctiveness, permanence and performance [6].

1.1 Background

The epigenetic patterns of a human iris have been shown to be unique and hence useful for personal identification. Image processing and signal processing techniques are employed to extract information from the unique iris structure from a digitized image of an eye [7–11]. This information is transcoded into a “biometric template”, which is stored in a database and used for verification and identification purposes. Thus, the drive behind template formation is to mathematically encode the iris pattern and match it with other similar representations.

The idea of an automated iris recognition system was conceptualized and patented by Flom et al [4]. Daugman [3,5,7,12] used Gabor filtering to demodulate and encode the iris structure with quadrature quantization of a phasor to generate a 2048 bit long iris template. The Hamming distance is used for comparison with a stored template to generate a match score and make a decision of a match or a non-match. Several researchers have contributed to the maturation of iris recognition technology. The broad classification of these approaches as phase-based methods, zero-crossing representation, texture analysis and intensity analysis is presented in [9]. The approach presented by Daugman [3,7] is categorized as phase-based; while other approaches [2,9,10,13,14] are texture-based. Boles et al [8] presented multi-resolution 1-D wavelet transform based zero-crossings thus capturing iris texture. The approach presented in [9] is predominantly an intensity-based approach and captures the most discriminating iris information through a 1-D intensity signal. Park et al [15] uses directional filter banks to decompose iris image into directional sub-band outputs. We
have extended the approach given in [15] by using bi-orthogonal directional filters to improve the efficiency, scalability and flexibility of the system.

Our work is centered on two main contributions: improvement of method of encoding the iris information by incorporating directional bio-orthogonal wavelets and incorporation of image quality in the matching process with adaptive AND-NOT quality-based matching.

In the first, effective use of wavelet filters is desired in order to improve the iris representation. The distinctiveness of the iris structure lies in the local stochastic irregularities. As given in [9], these local chaotic features can be considered as transient signals. Wavelets are chosen for encoding the segmented iris information since it is possible to analyze these irregularities locally and simultaneously at different scales, in order to capture sharp variation points. To ensure efficiency of the system, a fast and efficient lifting scheme is used to design the biorthogonal wavelets [16]. Since a wavelet’s basis has degrees of freedom in two dimensions, their building blocks are very well localized in space as well as frequency. This property of wavelets is used to encode the iris information in an efficient way. To perform comparative analysis, Gabor based iris encoding is also performed and ROCs are correlated.

Wavelet filters are capable of exploiting the local features from different scales simultaneously and hence used for iris coding. Our earlier work presented in [17] encodes the complex iris structure to generate global iris texture features. Well known Gabor responses at various scales and orientations were used to capture the iris texture profile. To make these features more local, further bi-orthogonal wavelet based iris encoding was implemented and was shown to improve the system performance. The improvement in the performance is because bi-orthogonal kernels are suitable for local feature extraction, because of good local resolution in both frequency as well as space. Bi-orthogonal filters were developed using the lifting scheme and the resulting kernels belong to a class of orthogonal moments. The intuitive choice of bi-orthogonal wavelets comes from the orthogonal moments, which have the least redundancy and thus very efficient representation of iris information, resulting into compact iris templates. Comparative analysis between Gabor and bi-orthogonal encoding is presented in [17] and bi-orthogonal wavelets outperform Gabor encoding.

In this work, we have further enhanced the filtering by using directional vanishing moments. This further enhances the feature extraction and encoding part, as the filter responses only in the line of the specified direction are tapped. The inspiration behind using the directional filtering comes from the promising research presented in [15]. Intuitually, if directional sub-bands are used to perform local analysis, non-ideal iris information can be more locally represented using the sub-band information.
In the second contribution, we have developed an approach to incorporate iris quality at the pixel level in order to improve the matching process through the use of adaptive AND-NOT quality-based matching. For reliable personal recognition using iris biometric, the quality of iris images plays a vital role. Previously, the importance of quality in designing a reliable identification system has been discussed in the literature [18]. Very limited study about the iris quality evaluation and its impact on the recognition is available in the literature [19,20]. A very simple iris assessment procedure is presented in this paper and the quality scores are used for two purposes. First, global quality scores for each image are used to compare the databases analytically, in order to further facilitate research into the data capturing procedures. Second, pixel-level quality scores are incorporated to enhance matching with a new adaptive AND-NOT methodology.

1.2 System Overview

Following the general framework of Daugman’s algorithm, the process of iris recognition is divided into four parts namely, segmentation where the iris region is isolated in an eye image under consideration; mapping where each pixel of the isolated iris is mapped from concentric domain to non-concentric domain; encoding where the filter coefficients are quantized and mapped into a binary bit stream giving rise to a template; and matching where ‘Hamming distance’ between every pair of the templates is calculated to find the inter and intra class distributions. The decision is made based on thresholds selected from the distributions [3].

In this work, first, the iris image quality is assessed using four Factors, namely, occlusion, focus, contrast and angular deformations. Using linear combination of these factors iris quality score (IQS) is calculated. This score is calculated at pixel level (IQSP) and further extended to the image level (IQSI). IQSI is used to compare the various databases used in this study and IQSP is used to adaptively modify the iris template matching. Second, previously developed bi-orthogonal wavelet based iris recognition system [17] is applied to larger databases and is compared with methods similar to the well known Daugman’s Gabor based system [3,5,7,12]. Further, directional bi-orthogonal filters are added and used to characterize iris structure more efficiently. Enhancement in the performance is shown.

A complete system overview is shown in Fig. 1. As shown, four databases are used in this study to test the algorithms. These databases are compared using the IQSI values. All the iris images are first enhanced and then subjected to template formulation. Gabor, bi-orthogonal and directional bi-orthogonal encoding is performed and recognition results are compared for all databases.
The matching is performed using traditional Hamming distance method and also using adaptive IQSP based method. Comparative study of these two matching techniques is performed from the point of view of system error rates. All the four databases are analyzed using all combinations, ROCs are plotted and EERs are calculated.

The remainder of the paper is organized as follows. Section (II) provides an overview of the data used for this work. Section (III) presents the quality assessment for iris images. Section (IV) presents a detailed comparative description of previously developed Gabor and bi-orthogonal wavelet based system and newly designed directional bi-orthogonal wavelet based system. This section also includes the method to incorporate quality into matching at the local pixel level. Experimental results are reported in section (V). Section (VI) provides discussion and future work. Section (VII) presents the conclusions.

2 Data management

This section presents the data used for the work in this paper. It is important to test the designed algorithm on sufficiently large and diverse data set. Four different databases were used to evaluate and analyze performance of the designed systems.

The first data set (database1 from hereon) is a data set of gray scale iris digital images provided by the Chinese Academy of Sciences (CASIA). The database consists of 756 gray scale images coming out of 108 distinct classes and 7 images of each eye. The data was collected from 80 subjects in two sessions with a one month gap between the two sessions [21].

The second data set (dataset2 from hereon) contains iris images collected at University of Bath. The data set consists of 1000 high-quality eye images taken from 50 eyes (left and right) of 25 subjects. The images are compressed by the JPEG2000 codec at 0.5 bpp and have a resolution of $1280 \times 960$.

The third data set (dataset3 from hereon) is comprised of the data collected at the West Virginia University (WVU) Eye Institute. This data was collected from 101 subjects in one session with 4 images of the left and right eye for each subject. Thus a total of 808 images coming from 202 classes are used for further testing of the algorithm. The uniqueness of this database is that out of the 4 images collected for every class, the first and fourth are on-angle while the second and third are off-angle by $15^\circ$ and $30^\circ$ respectively.

The fourth data set (dataset4 from hereon) consists of iris images collected at Clarkson University. This data was collected from 80 subjects in one session
Fig. 1. System overview of the iris recognition methodologies. Four different databases used in this study are compared using the quality assessment method developed in this study. Enhanced iris images are segmented and normalized. Three different encoding schemes namely, Gabor, bi-orthogonal and directional bi-orthogonal are used to encode the iris information. Matching is performed using traditional Hamming and newly designed adaptive AND-NOT quality-based matching. ROCs are plotted to evaluate the recognition performance.
Fig. 2. Sample iris images from all the four databases used. The first row presents the data from most widely used CASIA. The second row presents data samples from high resolution data collected at University of Bath. The third and fourth rows present data samples from uncontrolled Clarkson data and off-axis WVU eye center data.

with 4 images each of left and right eye for each subject. Thus, a total of 640 images from 160 classes are used for analysis. This data set is an uncontrolled data set and is collected using Oki Irispass-h hand held device (model EQ5009A). No extra care is taken to control the quality and illumination of the iris information.

The data sets together form diverse iris representations in terms of sex and ethnicity and conditions under which iris information was captured. The CASIA data set predominantly has iris data from Asians, while the data collected at the WVU mostly contains iris images of Caucasians. For the data collected at Clarkson University and West Virginia University, protocols for data collection from the subjects were followed that were approved by the West Virginia University and Clarkson University Institutional Review Boards (IRB). While dataset1 has the most widely used and fair quality iris data, dataset2 has very high resolution data. Dataset3 and dataset4 have challenging iris images because of the non-ideal and uncontrolled conditions during iris capture respectively. The profiles of the databases used are represented in Table 1.

Sample iris images are shown in Fig. 2. The first row shows sample irises from widely used CASIA database while the second row has very high resolution sample iris images from University of Bath database. The third row shows uncontrolled sample iris images collected at Clarkson University and the fourth row presents sample off-axis iris images from WVU database. Detailed analysis
of the entire data is presented in the next section.

Table 1
Data set: Distribution

<table>
<thead>
<tr>
<th>Data set</th>
<th>No. of images</th>
<th>No. of classes</th>
<th>Images per class</th>
<th>Exploited intra-class combinations</th>
<th>Exploited inter-class combinations</th>
</tr>
</thead>
<tbody>
<tr>
<td>CASIA</td>
<td>756</td>
<td>108</td>
<td>7</td>
<td>2268</td>
<td>566,244</td>
</tr>
<tr>
<td>Bath</td>
<td>1000</td>
<td>50</td>
<td>20</td>
<td>9500</td>
<td>980,000</td>
</tr>
<tr>
<td>WVU</td>
<td>808</td>
<td>202</td>
<td>4</td>
<td>1212</td>
<td>568,428</td>
</tr>
<tr>
<td>Clarkson</td>
<td>640</td>
<td>160</td>
<td>4</td>
<td>960</td>
<td>407,040</td>
</tr>
</tbody>
</table>

3 Quality analysis

As mentioned earlier, the databases used in this study have unique characteristics associated with the iris images. This forms the basis for their use in this study and assists in understanding the system performance for specific circumstances. Two databases (database1 and database2) have highly controlled data collection environment and therefore high quality images. Two databases (database3 and database4) have controlled off angle and uncontrolled iris images respectively.

We developed a new method to generate an iris quality score (IQS). This score is calculated for every pixel (IQSP) and is further extended to image level (IQSI). In order to account for the variation in quality, we developed procedure to account for quality in matching at the pixel level by creating a quality score at each pixel. IQSP will be used later when performing adaptive matching. The score includes the following:

- occlusion
- focus
- image contrast
- angular deformation

In the literature it has been shown that various different factors affect the iris image quality [18–20] and hence the system performance. Daugman designed methodology to determine focus by looking at the Fourier spectrum and measuring energy associated with the high frequency bands [7]. Ma et. al. designed a scheme to classify clear, defocused, blurred and occluded iris images [9]. Zhang et.al presented the sharpness map of iris boundary in [22].

For this study, iris image quality is calculated using four factors mentioned
above. The factors are automatically calculated and the final quality score is determined by the linear combination of all these factors. The four quality factors are normalized on the scale of 1-25 and are summed to obtain final quality metric on the scale of 1-100, which is presented in the next subsection. All the scores are normalized such that a higher value indicates better quality; thus for individual measures, zero represents lowest quality and 25 represents the highest quality.

3.1 Iris image quality metric

The following four subsections describe how the four factors are calculated automatically. These factors are calculated after segmenting the iris region. The four different databases used in this study are compared using these quality measures. Also, since these quality measures are local measures, they are used to hierarchically organize the iris information. Thus, for every pixel in the iris region the four measures are calculated and finally a quality score is found by summing up these factors linearly (IQS). This information is used in two different ways. First, the quality score associated with the iris pixels (IQSP) is used during the matching process. A modified distance measure is adapted to improve the matching procedure with the help of associated quality values. Second, these local measures are used to pre-process the segmented iris information before performing the encoding. Also, the local measures are summed up and thresholded to generate iris quality scores at image levels (IQSI), which is used in comparing the four databases used in this study.

![Fig. 3. Less efficient ways to localize segmented iris information to calculate occlusion. Left figure (a) shows iris region divided into circular regions. Figure (b) presents the iris region divided into polar rod like structures. We found both these methods less effective because of very little resolution obtained.](image)
3.1.1 Occlusion

In an iris image, it is desired to have the occluded region to be minimal in order to have sufficient iris information available for encoding. We have developed an automated way to determine the percentage of occlusion. Initially we divided the segmented iris region into either circular rings or into polar rod like structures, as shown in Fig. 3. Thus, when it is determined that a part is occluded, the whole ring or rode is rejected. The main reason behind low efficiency of these methods is because of the small resolution obtained as the occlusion in an iris image is predominantly observed near upper and lower iris outer boundaries.

In order to get better resolution we divided the iris region into rectangular blocks. The process has following steps,

- Find the iris and pupil boundaries from the iris image using integro-differential operators [3].
- Build a rectangular mask around iris region and divide it into fixed size blocks
- Calculate the non-occluded portion using the frequency content analysis of only the ring like iris structure
- This percentage is then normalized on the scale from 1-25

The entire procedure is shown in Fig. 4. Initially the iris region is segmented from the rest of the eye using circular intensity differences. Then, a rectangular mask is developed around the outer iris boundary and it is further divided into smaller rectangles of size 10×10. All the blocks for which more than 10% of the block lies inside the iris boundary and outside pupil boundary are counted as the total blocks of interest. The occlusion detection is performed based on the frequency and intensity analysis. As the iris area has very complex structure and hence is high frequency region, can be easily separated from the other low frequency areas, like eye lashes, reflections and eyebrows, which constitute the total occlusion area. Also, the iris region is ideally darker than sclera, eyelids and lighter than pupil, and thus helps in identifying iris region correctly. This task is performed at every block and all the pixels within a block are marked with the same score. This is used in the matching process.

Then to calculate image level quality score (IQSI) the total unoccluded area is normalized on the scale of 1-25, depending on the total number of unoccluded blocks. For example, the iris region shown in Fig. 4 has total 276 blocks corresponding to the iris region, out of which 55 blocks represent occluded area. Thus percentage of un-occluded region is 80.01%. When normalized on the scale of 1-25, the score is 20.01.

This percentage of occlusion measurement was performed on all the four databases. Although the occlusion region was automatically detected, every
Fig. 4. (a) shows the segmented iris region. (b) presents the rectangular mask designed around the iris region. (c) shows the rectangular mask divided into smaller rectangular blocks. (d) shows rectangles representing occlusion clearly marked out.

image was checked manually for the accuracy. Errors in 6 images in correctly identifying occlusion region were observed for the Clarkson database. These errors were manually corrected by reversing the status of wrongly marked occluded regions to un-occluded. The reason behind this failure is excessively bright iris region, thus making it loose the texture and gain low frequency properties.

3.1.2 Focus measure

Intuitively, an image with good focus is a sharp image with minimum blur. It has been shown in [23] that the focus estimator should be designed in such a way that it responds to high frequency variations of image intensity. Therefore, for focused images the measure will be high and for blurred images it will be low. The measure proposed in [23] is applied to the iris images. The second derivative is used to high pass the iris images. The modified Laplacian is given
in [23] as,
\[ \nabla_M^2 I = \left| \frac{\partial^2 I}{\partial x^2} \right| + \left| \frac{\partial^2 I}{\partial y^2} \right| \tag{1} \]

The discrete approximation of this modified laplacian is given in [23] as,
\[ \nabla_{ML}^2 I(x, y) = |2I(x, y) - I(x - s, y) - I(x + s, y)| + \] \[ = |2I(x, y) - I(x, y - s) - I(x, y + s)| \tag{2} \] \[ \tag{3} \]

where, \( s \) is the variable spacing between pixels.

Finally, the focus measure, also called the depth map, at point \((x, y)\) in the iris structure is computed as the sum-modified-laplacian (SML) values, in a window around \((x, y)\), which are greater than a threshold \( t \),
\[ F(x, y) = \sum_{i=x-N}^{i=x+N} \sum_{j=y-N}^{j=y+N} \nabla_{ML}^2 I(x, y) \text{ for } \nabla_{ML}^2 I(x, y) \geq t \tag{4} \]

Parameter \( N \) is the window size. In our experiments the window size is chosen to be \( 8 \times 8 \). The SML operator provides local measurement of the quality of the iris image focus. This value is same for all pixels in one block.

### 3.1.3 Image contrast

Extremely bright or dark parts of iris images are not useful for personal identification and hence are to be identified as noise. For an 8-bit images, pixel values range from 0 to 255. Values near 128 are considered to be of best contrast. For all the pixels above 246 and below 10, the contrast measure is set to 0. The range of 117 pixels (11-128 and 128-245) is then normalized on the scale of 1-25. For example, a pixel with a value of 117 will be normalized to a value of 22.85.

### 3.1.4 Angle deformation

For this study the angular deformation is not estimated. The information provided by the respective data collectors is taken as recorded. Also, the depth of angular deformation is assumed to be uniform over the entire iris image thus ensuring same angular deformation for all the pixels. The maximum angular deformation is 30°. This is normalized on the scale of 1-25. Thus, angular deformation of 15° gets normalized to 12.5 and for 30° the normalized value is 0.
Thus, larger value represent less angular deformation and thus better quality. For Clarkson database, a few images are off-angle images. These images were compared against the known off-axis images from WVU database and a score was assigned manually.

3.2 Image Iris Quality Score

These four quality factor scores are added linearly to form the total quality score. The score at the pixel level for the four measures is added to generate total iris quality score at pixel level (IQSP), which is used at the matching stage. The score at the image level for the four measures is added to generate total iris quality score at image level (IQSI), which is used to compare the four databases.

4 Gabor and Bi-orthogonal wavelet based iris recognition

This section describes bi-orthogonal wavelet algorithms developed to perform personal recognition using iris information. The algorithms are flexible enough to be adapted for the non-ideal cases like off-angle images, noise etc and show comparable results when applied to non-ideal databases. The procedure of iris based human verification can be divided into the following four steps [3]:

(1) Isolation or Segmentation
(2) Normalization
(3) Template Formation or Encoding
(4) Match-Score Calculation

These functionalities are coded in MATLAB (v6.5R13) and a graphic user interface is developed. The internal complexion of every step differs to previous method, only in an attempt to make the system more efficient, either speed wise or performance wise [24]. In the typical ‘iris recognition system’ setup, first the raw eye image undergoes various operations including separating the iris region from the rest of the eye image, unfolding that information into a 2-D matrix and then encoding it using the appropriate filter coefficients. The quantized filter output is the iris template and can be stored in a database. When a person is to be recognized, then similar procedures are followed for the iris image, called as probe input, and is matched with one (verification) or all (identification) the templates, called gallery, in the database [3]. In this study, we have focused on the verification analysis and only 1 : 1 matches are considered.
Fig. 5. Complete algorithm in snap shot. The different stages are shown: segmentation, normalization and template formation.

The whole algorithm in snap shot is given in Fig. 5. In Fig. 5, (a) shows the original image while (b) shows the segmented iris image. The area between two marked circles is the significant iris information. The iris center is marked and used for normalization process. The effect of in-band de-noising for the selective iris areas is shown in (c). For the selected value of radial resolution, iris area is divided along the radial direction and the distinct division is shown in (d). The normalized iris is shown in (e), while (f) shows the iris template. This particular sample iris is from CASIA data set.

4.1 Bi-orthogonal filter design

This subsection describes the design of bi-orthogonal filters. Designed bi-orthogonal filters are used at various stages from iris enhancement to iris encoding. These filters were selected due to the properties of the filters including speed and efficient encoding capability.

Instead of traditional multiresolution analysis (MRA) scheme, a novel lifting technique is used to construct the biorthogonal filters [16,25–27]. The main advantage of this scheme over the classical construction is that it does not rely on the Fourier transform. Also, it allows faster implementation of wavelet
The basic idea behind the lifting scheme is shown in Fig. 6. It starts with trivial wavelet, the “lazy wavelet”; which has the formal properties of wavelet, but is not capable of doing the analysis. The lifting scheme then gradually builds a new wavelet, with improved properties, by adding in a new basis function. This itself is the inspiration behind the name of the scheme. The lifting scheme can be visualized as an extension of the FIR (Finite Impulse Response) schemes [27].

Fig. 6. The lifting scheme for wavelets. It first calculates the Lazy wavelet transform, then calculates the $a_{j-1,m}$, and finally lifts the $b_{j-1,k}$.

It is known that any two-channel FIR sub band transform can be factored into a finite sequence of lifting steps. Thus, implementation of these lifting steps is faster and efficient. Biorthogonal 5/3 tap was selected for encoding the iris information. The frequency content of the resulting coefficients is adjusted each time to achieve a separated band structure.

As shown in Fig. 6, suppose the low pass part of signal at level $j$ is given as $b[j,k]$. This is transformed into two parts at level $j - 1$ : low pass part as $b[j - 1,k]$ and high pass part as $a[j - 1,k]$. This is first achieved by splitting $b[j,k]$ into high pass and low pass portions and this process is called a ‘Lazy Wavelet Transform’ [27]. Lifting steps usually come in pair of ‘predict’ and ‘update’. The data $a[j - 1,k]$ are predicted from the data in the subset $b[j - 1,k]$. This is the real de-correlating step. But this presentation does not retain certain important properties. Hence the set $b[j - 1,k]$ is updated with the data computed from the new updated $a[j - 1,k]$. By these steps the data gets shifted from level $j$ to $j - 1$.

The next four subsections explain the four operations mentioned earlier. The
third subsection is the most important one and presents comparative analysis of two different encoding schemes used in this work namely, bi-orthogonal encoding and directional bi-orthogonal encoding. The last subsection describes an adaptive matching technique which takes into account the quality score associated with the different iris regions while performing the matching.

4.2 Isolation or Segmentation

Segmentation involves isolating the important information of the iris from the rest of the eye image. Before doing actual segmentation, all the images are transformed into the wavelet domain using bi-orthogonal wavelets and maxima energy extraction is performed. The number of retained coefficients is selected to be 10000. The images are further enhanced before segmentation is performed using the log and simple gradient masking. Maxima energy extraction makes sure that only important iris information is retained. After this first filtering, iris images are further analyzed based on the local frequency information. The enhancement procedure is explained in detail in the next sub-subsection.

4.2.1 Iris image enhancement

The results of quality based analysis of the databases is presented in the results section. It is evident that iris image enhancement is necessary before performing segmentation.

The enhancement is performed in order to improve segmentation. The iris image is transformed into the wavelet domain and low frequency and high frequency responses are obtained. In iris images, very low frequency points (for example sclera region) and very high frequency points (for example eye lashes or reflections) may represent non-iris or noisy regions. The very low frequency regions are marked and become part of the masked regions. The final enhanced image is obtained by thresholding very small coefficient values in the high as well as low frequency sub-bands and then cutting off the low frequency low energy components from the high band masked image. These operations are performed at sub-band levels and hence this type of enhancement is called as in-band de-noising.

The sequential flow of the enhancement procedure is shown in Fig. 7. Figure (a) shows the original image, (b) shows the low frequency analysis image with the masked regions, marked black, (c) shows the high frequency analysis image with the masked regions overlapped, (d) shows the enhanced iris image. This image is used only for segmentation purpose and not for encoding.
Fig. 7. Iris enhancement. (a) original iris image. (b) low frequency response. (c) high frequency response. (d) enhanced iris image.

Fig. 8. Iris segmentation. (a) Low pass iris mask overlapped with the iris image (b) Effective segmentation for the continuous smooth energy.
4.2.2 Iris segmentation

The low pass iris image is further subjected to canny edge detector, as shown in Fig. 8. The detected edges are mapped on the enhanced inverted iris images. The area within the global edge is phase shifted and then the complete image is transformed into the wavelet domain. The phase information is used and the marked area is further divided into smaller regions and average intensity thresholding is performed. The masked area is used to further remove non-significant edge information. Non-significant information could be in the form of eye-lashes, eyelids and reflections [28–30] and can not be removed or rectified completely but is either suppressed or given low priority during encoding and matching procedures. In order to take care of these different types of noise entities, thresholding is done for each sub-band and hence the scheme is called ‘in-band noise removal’. Each band significantly removes the noise content depending on whether it is high pass or low pass and the direction in which that filters acts i.e. horizontal, vertical or diagonal. E.g. eyelashes were predominantly removed in the HL band. This is followed by hough transform and thresholding. The threshold value is adaptive and changes for every image depending upon the relative variations in the intensity of different parts of the image, selected heuristically. The point where average intensity drops below the threshold is chosen as the iris radius. The threshold’s effectiveness depends upon the angular resolution. Sample isolated iris images are shown in Fig. 9.

![Sample isolated iris regions](image)

Fig. 9. Sample isolated iris regions

4.3 Normalization

The first thing involved in the normalization process is to map the data from \((r, \theta)\) domain to \((x, y)\) domain. For this the center of iris is taken as the starting point as compared to the pupil center in Daugman’s method. The linear radial vector traces the complete iris region. Also, instead of matching up the iris and pupil centers, the vector dimension is kept fixed. This is the resolution along the iris radius. The vector dimension is fixed at 200. For highly non-concentric iris pupil pairs matching of the centers is performed. The diagonal information is mapped in the opposite quadrant to avoid any loss of information.

The reason behind high radial resolution of 200 with a circular resolution
of 20 can be explained as follows. After studying iris images using wavelets and examining their phase information, it was found that iris patterns have very strong components along the radial direction. This was concluded after observing average correlation among the wavelet coefficients along the radial direction to be 0.87 against average correlation of only 0.36 between wavelet coefficients of circular portions, on the normalized scale ranging from 0 to 1. The wavelet sub-band splitting was stopped when the energy of the correlated wavelet coefficients went below 20% of the total sub-band energy, and that number was retained as the resolution along circular or radial direction. The circular resolution value of 20 is selected for this study, which is trade-off between providing effective division for noise removal as well as obtaining reasonable size templates, increasing angular resolution may result in an excessively large template.

4.4 Template Formation or Encoding

For this particular study, digital iris images are encoded using bi-orthogonal wavelets and directional bi-orthogonal wavelets to formulate a template.

4.4.1 Gabor and Bi-orthogonal encoding

The segmented and normalized iris information is transformed into the wavelet domain using the biorthogonal tap, as explained earlier. The filters are designed using the lifting steps, which have the advantage that it is completely invertible. These filters transform the data into a different and new basis where ‘large’ coefficients correspond to relevant image data and ‘small’ coefficients corresponds to noise. Thresholding is performed once again. The process is known as image de-noising.

Wavelet encoded data is scalable and localized and hence matching of the features at same location using various scales is possible [31]. Band pass bi-orthogonal pre-filtering is performed to encode the information. The filter is generated using Gaussian filters and approximation is used. The wavelet coefficients are further quadrature quantized. This results in formation of bit-stream of 1s and 0s. This is done for all the iris images and the formulated bit-pattern is the iris template. With angular resolution of 20 and radial resolution of 200, the formulated bit-streams are 8000 bits long. Along with the iris template, a mask template of 4000 bits is also formed which is used for locating the noisy parts of the image.

A Gabor method is also implemented for comparison [31]. Band pass Gabor pre-filtering is performed to encode the information. The filter is generated using Gaussian filters and approximation is used [3].
4.4.2 Directional filter based encoding

This subsection describes the directional filter bank approach for encoding the pre-isolated iris information. The iris recognition problem can be treated as texture characterization problem. The system performance is directly dependent on extracting features from the iris information and performing classification in the feature space. Directional bi-orthogonal filters are used to provide a compact and efficient representation of the iris information and comparative analysis with the previously reported bi-orthogonal feature based technique is given.

Directional filters are designed through the implementation of the ladder structure shown in Fig. 10, which was originally proposed in [32]. The 1-D filter bank is generalized to two dimensions by a simple 1-D to 2-D transformation. The resultant 2-D filters are,

\[
H_0(z_0, z_1) = \frac{1}{2}(z_0^{-2N} + z_0^{-1}\beta(z_0z_1^{-1})\beta(z_0z_1)) \tag{5}
\]

\[
H_0(z_0, z_1) = -\beta(z_0z_1^{-1})\beta(z_0z_1)H_0(z_0, z_1) + z_0^{-4N+1} \tag{6}
\]

\[
F_0(z_0, z_1) = -H_1(-z_0, -z_1) \tag{7}
\]

\[
F_1(z_0, z_1) = H_0(-z_0, -z_1) \tag{8}
\]

where, \(\beta(z)\) is the linear phase filter and \(N\) is the length of the filter. Since, the directional filters contain infinitely sharp pass bands, the DC energy of the iris image gets evenly spread across all the \(M\) bands. Filters are obtained by letting \(z_0a \rightarrow -z_0\) in above equations.
Fig. 11. Analysis of the four databases using occlusion measure. The measure is actually a quality measure and directly reflects the quality of the image. So a higher measure indicates less occlusion and thus better iris image quality.

The wavelet encoded information is further subjected to quadrature quantization and procedures similar to bi-orthogonal coding are performed. The directional vanishing moments are observed to provide resolution predominantly in the high frequency sub-bands and hence the retained coefficients in those sub-bands are increased by 200 and decreased by same number in low frequency bands.

Pseudo-code for this process is as follows:

\[
\begin{align*}
&h_{a', new}(Z) = h_a(Z) - g_a(Z) * S(Z^{-2}) \\
g_{s', new}(Z) = g_s(Z) + h_s(Z) * S(Z^2), S = \text{Laurent Polynomial} \\
h_{s', new}(Z) = h_s(Z) + g_s(Z) * S'(Z^2) \\
g_{a', new}(Z) = g_a(Z) - h_a(Z) * S'(Z^{-2}), S' = \text{Laurent Polynomial} \\
\end{align*}
\]

Synthesis polyphase matrix is derived as,
\[
P(Z) = \text{even}[(h_s)(Z)] \text{even}[(g_s)(Z)]; \text{odd}[(h_a)(Z)] \text{odd}[(g_a)(Z)]
\]

After Primal lifting,
\[
P_{new}(Z) = P(Z) * [1S(Z); 01]
\]

After dual lifting,
\[
P_{new}(Z) = P(Z) * [10; S'(Z)1]
\]
4.5 Match score calculation

In this subsection, two different matching techniques are discussed. The first technique uses the traditional Hamming distance, while the second technique takes into account the quality map associated with the pixels and weights the pixels accordingly, during matching.

4.5.1 Hamming distance matching

Only phase information converted to ones and zeros is encoded from the normalized iris patterns. The formulated templates are matched and similarity scores are calculated. Bit-wise comparison of the templates is made and Hamming distance is calculated for every such comparison. This is achieved by doing successive bit wise “X-OR”ing and “AND”ing. To account for the rotational inconsistencies the maximum matched value is chosen. The mask templates are used to ignore the noisy parts of the image. The formula for determining out the Hamming distance is given in [3] as,

\[
HD = \frac{\| \text{code } X \otimes \text{code } P \cap \text{mask } X \cap \text{mask } P \|}{\| \text{mask } X \cap \text{mask } P \|}
\] (9)

The operation of “X-OR” (\( \otimes \)) detects the dissimilarity between corresponding pair of bits, while “AND” (\( \cap \)) operation with the mask makes sure that the noisy or lesser significant portion of the image is not encoded. The (\( \| \| \)) represents the norm of the vectors. The Hamming Distances are normalized on the scale of a range from 0 to 1.

4.5.2 Weighted AND-NOT distance

This subsection describes a new approach to calculate the match score adaptively, by incorporating the quality metric determined on a pixel level. Classification via template pattern matching is described here. First, gallery X and a probe P can be defined as,

\[
X = \begin{cases} 
X(n,m) \text{ for } (n,m) \in R_x = (\{1, ..., N_x\}, \{1, ..., M_x\}), \\
0 \text{ otherwise}
\end{cases} 
\] (10)

\[
P = \begin{cases} 
P(n,m) \text{ for } (n,m) \in R_p = (\{1, ..., N_p\}, \{1, ..., M_p\}), \\
0 \text{ otherwise}
\end{cases} 
\] (11)
then, Hamming distance can be looked as,

\[ E(n,m) = \begin{cases} 
X(n,m) \otimes P(n,n) & \text{for } (n,m) \in R_x \cap R_p \\
X(n,m) & \text{for } (n,m) \in R_x - R_p \\
P(n,m) & \text{for } (n,m) \in R_p - R_x \\
0 & \text{otherwise}
\end{cases} \] (12)

Thus, x-or returns 1 for a mismatch. We have tested a weighted Hamming distance, which is defined as,

\[ E_w(n,m) = E(n,m) \times \sum_{(k,l) \in N(n,m)} E(k,l) \] (13)

where, \( N(n,m) \) is a \( 3 \times 3 \) neighborhood of the \((n,m)\)th pixel. But, this approach did not result in any improvement in performance.

When we use an X-OR operation the source of the errors is not considered. In particular no distinction is made between errors in foreground pixels and noise-free foreground pixels. It may be desirable to give more importance to the noise-free foreground pixels since most of the information is contained in them. This can be done by using the AND-NOT measure. The weighted AND-NOT map is defined by,

\[
E_w(AN) = [(X \land \overline{P})(n,m) \\
\times \sum_{(k,l) \in N(n,m)} (X \land \overline{P})(k,l)] \lor [(P \land \overline{X})(n,m) \\
\times \sum_{(k,l) \in N(n,m)} (P \land \overline{X})(k,l)]
\] (14, 15, 16)

This map is useful in cases where the weighting has elevated the mismatch level due to the presence of noisy elements.

5 Results

The results section is divided into three subsections. In the first subsection, the quality analysis of the iris images and a comparative analysis of various databases used in this study are presented. The second subsection presents the recognition rates using three different Gabor, bi-orthogonal and directional bi-orthogonal wavelet encoding algorithms, when applied to the four databases. The last subsection provides results for more analytical comparison of the algorithms.
5.1 Quality Analysis Results

This subsection presents the quality oriented analysis of all the databases used in this study. Four quality measures, namely occlusion measure, focus measure, contrast measure and angular deformation, are designed as described in section (III), and used for the analysis. The first three measures are detected automatically as described in section (III), and the fourth measure is taken as recorded from the data collectors.

Fig. 11 shows the occlusion measure analysis for all the four databases. As already explained, the occlusion measure varies from 0-25. A higher measure indicates better image quality, that is less occlusion. The x-axis shows the occlusion measure from 0-25, while y-axis represents the frequency of occurrence. Histogram plots for the four databases are distinctly marked. The higher score indicates better image quality, and thus from Fig. 11, database2 has the least occluded images while database4 has the most occluded iris images.

Similarly, Fig. 12-14 represent the quality measures for focus, contrast and angular deformation, respectively. These figures can be read similar to Fig. 11, where the x-axis represents the quality measure from 0-25, with smaller value indicates poor quality, and y-axis represents the frequency of occurrence.

As seen in Fig. 12, database2 has a majority of iris images with good focus. Database4 shows the lowest focus values for the iris images. It can be seen from Fig 13 that all of the databases except database4 shows good contrast with database1 demonstrating the best results. Since database3 has deliberately
Fig. 13. Histogram of the four databases for the contrast measure. A higher measure indicates better image contrast and thus better iris image quality.

Fig. 14. Histogram of the four databases for the contrast measure. A higher measure indicates less angular deformation and thus better iris image quality.

introduced angular deformation iris images, as shown in Fig. 14, it shows poor angle measure distribution. For other databases, the angle measure shows the least distortion.

The four quality measures are combined linearly to formulate the iris quality measure, which ranges from 0-100. The iris quality measure distributions are
shown in Fig. 15. As seen clearly, database2 has the best quality images, while database4 has the worst quality images, as expected.

![Fig. 15. Total iris quality measure distribution for the four databases. The x-axis ranges from 0-100. Y-axis represents the frequency of occurrence. The databases are marked.](image)

5.2 Recognition results

This subsection presents receiver operating curves (ROCs) for the four databases, when the recognition is attempted using three algorithms namely Gabor, bi-orthogonal and directional bi-orthogonal encoding. Results are considered for both traditional Hamming distance and quality adjusted matching. The match scores are divided into inter-class and intra-class matching. Inter-class results are the results obtained by matching iris of a person with iris of another person. Intra-class results are obtained by matching the template of a person with another template of the same iris captured at other time. The ROCs are plotted based on FAR (False Acceptance Rates) and FRR (False Rejection Rates) for different threshold values.

Fig. 16-18 show the respective results for three types of encoding schemes (Gabor, bi-orthogonal and directional bi-orthogonal) for simple Hamming distance matching. The directional filters show a better recognition rate.

Two different matching techniques are described. Results presented in Fig. 20-22 are for the modified matching scheme and compared to the Hamming distance based technique.

Results are presented for three encoding and two matching algorithms for the four databases. When Gabor iris recognition system was applied, EER val-
Fig. 16. Gabor filter based iris recognition using Hamming distance matching. ROCs (receiver operating characteristics) are plotted and EERs (equal error rates) are calculated for all the databases. As expected from the quality scores, database 2 performs best, while database 4 performs worst.

Values of 1.27%, 1.11%, 3.32% and 12.53 were obtained for database 1 to database 4 respectively (see Fig. 16). When bi-orthogonal iris recognition system was applied, EER values of 0.97%, 0.65%, 2.67% and 9.08 were obtained for database 1 to database 4 respectively (see Fig. 17). The method was subjected to the first enhancement by implementing use of directional bi-orthogonal filters for encoding iris information and improved EER values of 0.38%, 0.21%, 1.53% and 2.97 were obtained for database 1 to database 4 respectively (see Fig. 18).

Then, the method was subjected to the second enhancement by implementing use of quality based matching of the iris templates. EER values of 1.04%, 0.74%, 2.41% and 8.03 were obtained for database 1 to database 4 respectively with Gabor encoding (see Fig. 20). Improved EER values of 0.21%, 0.09%, 1.18% and 5.03 were obtained for database 1 to database 4 respectively with bi-orthogonal encoding (see Fig. 21). When both these enhancements were implemented simultaneously, the best results were obtained as reflected by the EER values of 0.15%, 0.07%, 0.81% and 1.29 for database 1 to database 4 respectively with directional bi-orthogonal encoding and quality based matching (see Fig. 22).
Fig. 17. Bi-orthogonal wavelet based iris recognition using Hamming distance matching. ROCs (receiver operating characteristics) are plotted and EERs (equal error rates) are calculated for all the databases. As expected from the quality scores, database2 performs best, while database4 performs worst.

5.3 Segmentation and decidability index results

This subsection describes various other results, when the designed systems are tested from analytical point of view. The very first step in iris recognition is to isolate the iris information from the rest of the eye image. Iris image enhancement improves the segmentation performance. The comparative analysis of iris segmentation for all the databases with and without image enhancement is shown by bar graphs in Fig. 19. In Fig. 19, the x-axis presents the four databases and y-axis represents the percentage of iris segmentation. Two columns for every database represent two conditions. The left column shows the percentage of segmented images without enhancement, and the right column shows the percentage of segmented iris images with enhancement, for respective database. The decision on proper segmentation was made based on visual inspection.

For database1, 721 (95.37\%) iris images were correctly segmented, and the segmentation rate improves to 99.6\% (753/756) after the image enhancement. Similarly for database2, database3 and database4, the pre-enhancement segmentation rates were 90.8\% (908/1000), 77.1\% (623/808) and 64.37\% respectively. The improved segmentation rates for these databases after the enhancement were observed to be 99.2\% (992/1000), 98.01\% (792/808) and 95.62\% (612/640). All the incorrectly segmented images are included while finding the
Fig. 18. Directional bi-orthogonal wavelet based iris recognition using hamming distance matching. ROCs (receiver operating characteristics) are plotted and EERs (equal error rates) are calculated for all the databases. As expected from the quality scores, database2 performs best, while database4 performs worst.

Fig. 19. Segmentation results for the four databases, with and without iris image enhancement.
From the distributions and the FAR and FRR values and plotted ROCs it can easily seen that bi-orthogonal wavelets perform better than Gabor encoding. Further, directional bi-orthogonal tap gives better results than bi-orthogonal filters.

To model this mathematically, decidability index $d'$ suggested by Daugman [3] is calculated to find out how well separated the inter and intra class distributions are. If $\mu_1$ and $\mu_2$ are the means and $\sigma_{1b}$ and $\sigma_{2b}$ the standard deviations of the distributions, then $d'$ is calculated as,

\[
d' = \frac{|\mu_1 - \mu_2|}{\sqrt{(\sigma_1^2 + \sigma_2^2)/2}} \tag{17}
\]

Table 2 gives the $d'$ values for directional bi-orthogonal filters as well as bi-orthogonal filters, for the four databases. The decidability is calculated using Eq. 17. A higher $d'$ value essentially means that inter and intra class distributions are more separated from each other, and thus represent better system for correctly identifying both the classes. Similarly, lower $d'$ value indicates less robust system.

Fig. 20. Gabor filter based iris recognition using weighted AND-NOT matching. ROCs (receiver operating characteristics) are plotted and EERs (equal error rates) are calculated for all the databases. As expected from the quality scores, database2 performs best, while database4 performs worst.
Table 2
Results: $d'$ values for selected filter type.

<table>
<thead>
<tr>
<th>Bi-orthogonal wavelets</th>
<th>directional bi-orthogonal</th>
</tr>
</thead>
<tbody>
<tr>
<td>db1</td>
<td>7.231</td>
</tr>
<tr>
<td>db2</td>
<td>5.896</td>
</tr>
<tr>
<td>db3</td>
<td>3.456</td>
</tr>
<tr>
<td>db4</td>
<td>1.567</td>
</tr>
<tr>
<td>db1</td>
<td>8.234</td>
</tr>
<tr>
<td>db2</td>
<td>6.654</td>
</tr>
<tr>
<td>db3</td>
<td>5.234</td>
</tr>
<tr>
<td>db4</td>
<td>3.778</td>
</tr>
</tbody>
</table>

Fig. 21. Bi-orthogonal wavelet based iris recognition using weighted AND-NOT matching. ROCs (receiver operating characteristics) are plotted and EERs (equal error rates) are calculated for all the databases. As expected from the quality scores, database2 performs best, while database4 performs worst.

6 Discussion

In this work new encoding and matching techniques for doing efficient iris recognition, along with iris quality assessment is presented. Previously developed Gabor and bi-orthogonal wavelet based encoding method is extended and more efficient directional bi-orthogonal wavelet based method, with directional vanishing moments is developed. A new matching technique based on the pixel-level iris image quality is implemented and compared with the traditional Hamming distance based matching. ROCs were plotted and system performance for four different databases, for three encoding techniques and two matching techniques were plotted. Results showed that the method combining directional bi-orthogonal wavelets for encoding and adaptive pixel-level quality-based algorithm for matching had superior performance. The results are discussed in detail as follows.
First, iris quality assessment framework based on four quality factors namely occlusion, focus, angular deformation and contrast is implemented at pixel (IQSP) as well as image (IQSI) level. IQSP is used for doing adaptive matching while IQSI is used to compare (further discussed below) and assess different databases used in this study as given in Table 1. Iris quality scores at image level (IQSI) were used to analyze the four databases. Individual assessment of the databases using four quality factors namely, occlusion, focus, contrast and angular deformation was performed as presented in Fig. 11-14. These quality factors were linearly summed and database comparison was made using the total iris quality score at the image level (IQSI). Results are shown in Fig. 11-14. The resultant total quality histogram for four databases is presented in Fig. 15. It can be observed from Fig. 15 that database1 (popular CASIA) and database2 (high resolution bath database) have a very high percentage of good quality images. As against that, database3 (WVU database) and database4 (Clarkson database) have a very high percentage of medium and poor quality iris images respectively. It has to be noted that, database4 has poor quality iris images in terms of occlusion, contrast and focus, as against that, database3 has off-axis images with fairly good contrast, less occlusion and good focus. Unlike previous methods to assess iris quality [7,9,18-20,22], the method presented in this work is very simple and purely based on intuitive understanding. We have already shown [33] that iris quality and system recognition rate are very highly correlated.

Secondly, this work presents two new approaches for encoding the iris: biorthogonal wavelet filters and directional biorthogonal wavelet filters.

Previous work at our lab which uses Gabor and bi-orthogonal encoding to perform iris recognition is given in [17]. This method is compared and shown to outperform Gabor encoding in [17]. Here, the developed bi-orthogonal wavelet encoding based algorithm for iris recognition was tested using three more (four in total) databases and for more challenging conditions.

As mentioned in section (I), previously, various approaches are designed and implemented to effectively encode the relevant iris information for doing personal recognition. Daugman developed the automated iris recognition system [3]-[12], which forms the fundamentals of the current research in such that the iris recognition techniques may be less constrained. A wavelet transform based method presented in [8], compact iris representation and recognition using dyadic wavelets proposed in [34,35], iris recognition presented by [14], Independent Component Analysis (ICA) based iris feature encoding and recognition presented in [1] are, in spirit, advancements of Daugman’s method, as all of these methods are based on capturing the local variations in the high frequency iris region. Another branch of capturing iris information uses texture analysis based techniques [9]. A machine vision based iris recognition method presented in [2], improved feature vector based iris recognition enhancement presented in [24], methods proposed in [9], and directional energy feature based methods presented in [15] use various texture analysis methods and consider iris to be a highly complex texture.
Fig. 22. Bi-orthogonal directional wavelet based iris recognition using weighted AND-NOT matching. ROCs (receiver operating characteristics) are plotted and EERs (equal error rates) are calculated for all the databases. As expected from the quality scores, database2 performs best, while database4 performs worst. Improvement over the bi-orthogonal filters is reflected in the EER values.

The methods presented in this work are blend of these techniques. Our previous method presented in [17] captures the local variations in the iris regions by means of highly efficient bi-orthogonal filters. The advancement proposed in this method takes into account the directional vanishing moments associated with these filters, in order to analyze and encode iris texture more economically, and is inspired from [15].

The algorithm is developed using MATLAB 6.5, with a pentium processor, with 1GB RAM. The time required for feature extraction is 722 milliseconds and for matching it is 19.2 milliseconds. Thus, total time for feature extraction and matching is 741.2 milliseconds. This time is comparable to various algorithms as presented in table (III) for computational complexity analysis, presented in [36].

Further results are also given for the method of iris image enhancement and improvement in the iris segmentation is demonstrated. Previously, various attempts have been made to improve the iris segmentation procedures [28,29,33]. In this work, more emphasis is given on the pre-processing enhancement technique and iris segmentation is performed using circular canny edge detectors. The wavelet domain in-band de-noising techniques are used to enhance the iris images. The detailed procedures are shown in Fig. 7-8. Also, improved segmentation performance is shown in Fig. 19. All the iris recognition results
in this study are obtained for the enhanced iris images.

Lastly, along with the advancements in the iris encoding methods, improvements in the matching techniques are also presented. A novel iris quality based adaptive matching is proposed and is shown to produce best results when combined with the directional filter based iris encoding. The effectiveness of this matching method was shown by comparing its matching capability with the traditional Hamming distance method. A simple iris quality assessment technique using occlusion, focus, contrast and angular deformations into account is presented. Previous methods to assess image quality do not consider this information when matching [7,9,18–20,22]. In this work we used non-linear weighing at the pixel level to weigh good quality portions in the iris images more significantly. When this weighting is used during matching, improved system performance was obtained, as depicted in Fig. 22.

In this work, four different databases are used for analyzing the new iris recognition methodology. For most of the previous studies only the standard iris databases, for example CASIA database [21], are used and the results are reported. All the four databases used in this study have unique properties and hence result in a wide variety of iris images, in terms of quality, capturing technique, scanner used and so forth. Since most of the earlier works have reported their results for either CASIA [21] or University of Bath data, our results can only be partially compared with the results presented in the literature. Our results using modified encoding and matching techniques produce an EER of 0.07% for the CASIA database, which is equal to the best result reported in the algorithm comparison presented in [9].

As shown in the earlier analysis of the quality of the databases, CASIA and BATH have high quality images compared to other databases. The importance of this work is that the algorithms developed have been tested on much more challenging datasets. Thus, recognition results obtained for database3 and database4 formulate the brute force analysis of the designed algorithms. The directional filter based encoding of the iris region shows significant improvement in the recognition performance as seen from Fig. 21 and 22. More importantly, a significant improvement in the performance is observed for poor quality database4 and o-axis database3. Similar improvement in the performance is obtained by using modified matching, as shown in Fig. 17. The best results obtained by combining these methods produce the lowest EER values for all the databases (see Fig. 18).

From the presented EERs it can be observed that the designed algorithm produces comparable error rates in competent time duration when compared with [36]. But, these results are for more challenging images collected using uncontrolled capturing setup. Faster implementation of the directional filters compensate for the extra time needed to perform quality analysis, and thus makes our approach more adaptive against poor quality images. The speeds for the various intermediate processes when estimated for MATLAB on an Dell Precision workstation 650 (3.06 GHz processor, 1GB RAM) are as follows: Hamming distance matching: 7 ms, adaptive matching: 19.2 ms, bi-orthogonal
feature extraction: 512 ms, directional bi-orthogonal feature extraction: 722 ms. Thus, designed system is comparable in speed and accuracy with the existing systems, but is also capable of adaptively handling poor quality images using wavelet based enhancement and segmentation of iris, directional bi-orthogonal filters based iris feature extraction and weighted AND-NOT matching.

The designed algorithm framework is completely scalable and every intermediate procedure is independent of the other. In future, it is desired to combine the modified encoding and matching schemes developed in this work with our more efficient segmentation scheme presented in [33]. Presently database4 presents a highly uncontrolled set up for iris image acquisition. In future, it is desired to simulate various challenging capturing conditions (like illumination, pose etc) under controlled environment in order to study their effect in more systematic way. Also, presently 15° and 30° off-axis images are used for analysis, and it would be required to test the algorithms with more off-axis images with more resolution.

Presently, all the four quality factors are combined linearly. In future, ways to non-linearly combine these various quality factors needs to be explored. For example, in order to analyze iris images from database3, more emphasis has to be given for angular deformation, as against other quality factors.

More robust iris quality assessment methodologies with pre-defined ground truth can help improve the system analysis and is one of our future tasks. Currently, iris enhancement is performed globally. A local enhancement could produce more significant results at every scale.

Apart from the limited quality parameters designed in this study, more thorough design of quality parameters needs to be implemented. Converting the designed algorithm to more basic languages like C, can improve the overall speed of the system. Adaptive quality based basis design for more efficient directional filters can improve the selectivity of the designed filters. Lastly, fuzzy partitioning can be used for decision making in order to improve the sensitivity of the overall iris recognition system.

7 Conclusion

Gabor and Bi-orthogonal wavelet filters based iris recognition system are designed and implemented. Iris features are captured from the local variations using bi-orthogonal and directional bi-orthogonal filters. Directionality of the designed filters is used to encode these features efficiently. A platform for analyzing the quality of the iris images is developed, which takes into account four quality factors, namely occlusion, focus, contrast and angular deformation, and combines them linearly. The system performs adaptive matching of the iris templates based on the quality assessment of the iris images at a pixel level. In-band iris image enhancement is performed before iris segmentation, thus improving the segmentation performance. ROCs are plotted to analyze
the system performance.

Four different databases are analyzed for this particular study. Popular CASIA and high resolution Bath databases are analyzed and results are compared with the previous methods. The designed system is shown to produce results equivalent to the best results reported in the literature. To further analyze the system, off-axis iris database collected at WVU eye institute and uncontrolled iris data collected at Clarkson University are used. The system performance shows high correlation with the quality of the captured iris images and thus essentially higher EERs for database3 and database4. The improvement in the EERs of these challenging images is shown through efficient directional filter encoding and more robust adaptive matching technique. Thus, designed system shows improved/comparable results for good quality iris images with the previous methods, accuracy-wise/speed-wise, and competent results for challenging iris images.

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