An effective and fast iris recognition system based on a combined multiscale feature extraction technique

Makram Nabti, Lahouari Ghouti and Ahmed Bouridane

Institute for Electronics, Communications and Information Technology (ECIT), School of Electronics, Electrical Engineering and Computer Science, Queen's University Belfast, Northern Ireland, BT7 1NN UK

Department of Information and Computer Science, King Fahd University of Petroleum and Minerals, Dhahran 31261, Saudi Arabia.

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Abstract

The randomness of iris pattern makes it one of the most reliable biometric traits. On the other hand, the complex iris image structure and the various sources of intra-class variations result in the difficulty of iris representation. Although, a number of iris recognition methods have been proposed, it has been found that several accurate iris recognition algorithms use multiscale techniques, which provide a well-suited representation for iris recognition. In this paper and after a thorough analysis and summarization, a multiscale edge detection approach has been employed as a pre-processing step to efficiently localize the iris followed by a new feature extraction technique which is based on a combination of some multiscale feature extraction techniques. This combination uses special Gabor filters and wavelet maxima components. Finally, a promising feature vector representation using moment invariants is proposed. This has resulted in a compact and efficient feature vector. In addition, a fast matching scheme based on exclusive OR operation to compute bits similarity is proposed where the result experimentation was carried out using CASIA database. The experimental results have shown that the proposed system yields attractive performances and could be used for personal identification in an efficient and effective manner and comparable to the best iris recognition algorithm found in the current literature.

Keywords: Biometrics; Iris recognition; Multiscale edge detection; Wavelet maxima; Gabor filters bank; Moment invariants

1. Introduction

Biometric technology deals with recognizing the identity of individuals based on their unique physical or behavioural characteristics [1]. Physical characteristics such as fingerprint, palm print, hand geometry and iris patterns or behavioural characteristics such as typing pattern and hand-written signature present unique information about a person and can be used in authentication applications.

The developments in science and technology have made it possible to use biometrics in applications where it is required to establish or confirm the identity of individuals. Applications such as passenger control in airports, access control in restricted areas, border control, database access and financial services are some of the examples where the biometric technology has been applied for more reliable identification and verification.

In the field of financial services, biometric technology has shown a great potential in offering more comfort to customers while increasing their security. As an example, banking services and payments based on biometrics are going to be much safer, faster and easier than the existing methods based on credit and debit cards. Proposed forms of payments such as pay and touch scheme based on fingerprint or smart cards with stored iris information on them are examples of such applications. Although there are still some concerns about using biometrics in the mass consumer applications due to information protection issues, it is believed that the technology will find its way to be widely used in many different applications.

Moreover, access control applications such as database access and computer login also benefit from the new offered technologies. Compared to passwords, biometric technologies offer more secure and comfortable accessibility and have dealt with problems such as forgetting or hacking passwords. For instance, the new login method based on combination of a password with its typing pattern has been an innovative proposal where knowing the password itself would not be
Sanchez-Avila [12] provided a partial implementation of the plex plane. The resulting 2048-component iris code was used for iris pattern matching. Each phasor filters resulted in 1024 complex-valued phasors which denote multiscale Gabor filters to demodulate texture phase structure. A major progress has been made in iris recognition. Multi-resolution based techniques have played a very important role in developing iris feature extracting methods. In previous methods, local and general characteristics of iris patterns are exploited to represent individual distinctiveness. As the representative methods for extracting iris features, there are quadrature 2D Gabor wavelets which are introduced by Daugman [5,10,15] and wavelet based methods which are proposed by many researchers [13,22]. The Gabor wavelet representation can capture salient visual properties such as spatial localization, orientation selectivity, and spatial frequency [23]. Therefore, sufficient [2]. The method is based on typing pattern of a person by measuring the delays between the typing instances, which can be seen as a behavioural characteristic similar to handwritten signature. Considerations of reliability and invasiveness suggest that the human iris is a particularly interesting structure on which to base a biometric approach for personnel verification and identification. From the point of view of reliability, the special patterns that are visually apparent in the human iris are highly distinctive to an individual, the appearance of any one iris suffers little from day to day variation. In addition, the method is non-invasive since the iris is an overt body that can be imaged at a comfortable distance from a subject with the use of extant machine vision technology. Owing to these features of reliability and non-invasiveness, iris recognition is a promising approach to biometric based verification and identification of people [3].

In general, the process of iris recognition system consists of: (i) image acquisition, (ii) Preprocessing the iris image including iris localization, image normalization and polar transformation, (iii) iris Feature extraction and (iv) iris matching.

Iris patterns are formed by combined layers of pigmented epithelial cells, muscles for controlling the pupil, a stromal layer consisting of connective tissue, blood vessels and an anterior border layer [4,1]. The physiological complexity of the organ results in the random patterns of the iris, which are statistically unique and suitable for biometric measurements [5]. In addition, iris patterns are stable over time and only minor changes happen to them throughout an individual’s life [6]. It is also an internal organ, located behind the cornea and aqueous humor and is well protected from the external environment. This characteristics such as being protected from the environment and having more reliable stability over time, compared to other popular biometrics, have well justified the ongoing research and investments on iris recognition by various researchers and industries around the world. Compared to other biometric systems, iris recognition has been in the limelight for high-security biometric applications.

1.1. Related work

Research in the area of iris recognition has been receiving considerable attention and a number of techniques and algorithms have been proposed over the last few years.

Flom and Safir first proposed the concept of automated iris recognition in 1987 [7]. Since then, a number of researchers have worked on iris representation and matching and have achieved great progress [1,8–10]. Daugman [4,11] made use of multiscalar Gabor filters to demodulate texture phase structure information of the iris. Filtering an iris image with a family of filters resulted in 1024 complex-valued phasors which denote the phase structure of the iris at different scales. Each phasor was then quantized to one of the four quadrants in the complex plane. The resulting 2048-component iris code was used to describe an iris. The difference between a pair of iris codes was measured by their Hamming distance. Sanchez-Reillo and Sanchez-Avila [12] provided a partial implementation of the algorithm by Daugman. Wildes [13] represented the iris texture with a Laplacian pyramid constructed with four different resolution levels and used the normalized correlation to determine whether the input image and the model image are from the same class. Boles and Boashash [14] calculated a zero-crossing representation of one-dimensional (1D) wavelet transform at various resolution levels of a concentric circle on an iris image to characterize the texture of the iris. Iris matching was based on two dissimilarity functions. In [15], Sanchez-Avila et al. further developed the iris representation method by Boles and Boashash [14]. They made an attempt to use different similarity measures for matching, such as Euclidean distance and Hamming distance. Lim et al. [16] decomposed an iris image into four levels using 2D Haar wavelet transform and quantized the fourth-level high-frequency information to form an 87-bit code. A modified competitive learning neural network (LVQ) was adopted for classification. Tisse et al. [17] analyzed the iris characteristics using the analytic image constructed by the original image and its Hilbert transform. Emergent frequency functions for feature extraction were in essence samples of the phase gradient fields of the analytic image’s dominant components [18,19]. Similar to the matching scheme of Daugman, they sampled binary emergent frequency functions to form a feature vector and used Hamming distance for matching. Kumar et al. [20] utilized correlation filters to measure the consistency of iris images from the same eye. The correlation filter of each class was designed using the two-dimensional (2D) Fourier transform of training images. If the correlation output (the inverse Fourier transform of the product of the input image’s Fourier transform and the correlation filter) exhibited a sharp peak, the input image was determined to be from an authorized subject, otherwise an impostor one. Bae et al. [9] projected the iris signals onto a bank of basis vectors derived by independent component analysis and quantized the resulting projection coefficients as features. In another approach by Ma et al., Multichannel [8] and Even Symmetry Gabor filters [5] are used to capture local texture information of the iris, which are used to construct a fixed length feature vector. Nearest feature line method is used for iris matching. In [21] a set of one-dimensional intensity signals is constructed to effectively characterize the most important information of the original two-dimensional image using a particular class of wavelets; a position sequence of local sharp variation points in such signals is recorded as features. And fast matching scheme based on exclusive OR operation is used to compute the similarity between a pair of position sequences.

A major progress has been made in iris recognition. Multi-resolution based techniques have played a very important role in developing iris feature extracting methods. In previous methods, local and general characteristics of iris patterns are exploited to represent individual distinctiveness. As the representative methods for extracting iris features, there are quadrature 2D Gabor wavelets which are introduced by Daugman [5,10,15] and wavelet based methods which are proposed by many researchers [13,22]. The Gabor wavelet representation can capture salient visual properties such as spatial localization, orientation selectivity, and spatial frequency [23]. Therefore,
the Gabor wavelets have been used in image processing for feature extraction and texture analysis. The wavelet transform is a very powerful tool for texture discrimination [24]. It is a linear operation that decomposes a signal into components that appear at different scales. This transform is based on the convolution of the signal with a dilated filter. However, the question of what kind of features should be extracted from the iris region? It is clear that the extracted features should meet at least the following requirements:

- **Significant**: so that the iris image signature is an effective representation of the original iris image.
- **Compact**: so that the similarity measurement could be computed quickly.
- **Fast**: we have to process a large collection of images. Also we might have to extract features from query images on line as well.

This paper contributes towards a more realizable solution to these problems.

### 1.2. Outline

In this paper, we first present a new method for iris preprocessing (localization step) which is a crucial step to the success of any iris recognition system, since data that is falsely represented as iris pattern data will corrupt the biometric templates generated, thus resulting in poor recognition rates. This method introduces a multiscale approach for edge detection by using wavelet maxima modulus for efficiently detecting the iris region for use in the feature extraction stage. Once this done, a combined feature extraction scheme using a special Gabor filters bank and wavelet maxima components to extract all texture information from orientations in horizontal and vertical details is proposed. The feature vector representation proposed by using first statistical measurement (mean and variance) and a set of moment invariants will enable us to determine the best representation in order to obtain a significant iris code. For the matching process, a Hamming distance has been used and a series of experiments are performed to evaluate the proposed algorithm. Moreover, in order to demonstrate that the proposed scheme is most suitable for extracting iris features, we have to carry out an extensive quantitative analysis among some existing methods and detailed discussions on the overall experimental results are discussed.

The remainder of this paper is organized as follows. Section 2 provides a description of the localization step while the normalization step is illustrated in Section 3. Detailed description of feature extraction method and matching are given in Sections 4 and 5, respectively. Experimental results and discussions are reported in Section 6. Section 7 concludes this paper.

### 2. Iris localization

The iris is an annular part between the pupil (inner boundary) and the sclera (outer boundary). Both the inner boundary and the outer boundary of a typical iris can approximately be considered as circles. However, the two circles are usually not concentric [5]. Iris localization by definition means to isolate the actual iris region in a digital eye image by detecting the inner and outer boundary of the iris. The eyelids and eyelashes normally occlude the upper and lower parts of the iris region. A technique is required to isolate and exclude these artefacts as well as locating the circular iris region.

#### 2.1. Multiscale edge detection

Since an edge separates two different regions, an edge point is a point where the local intensity of the image varies rapidly—more rapidly than in the neighbour points which are close from the edge: such a point could therefore be characterized as a local maximum of the gradient of the image intensity. The problem is that such a characterization is to be applied to differentiable images, and above all that it also detects all noise points. All techniques used so far to resolve the problem are based on smoothing the image first [13–15,24]. However, a problem with smoothing arises: how much and which smoothing should one chooses? A strong smoothing will lead to the detection of less points while a lighter one will be more permissive. That is why S. Mallat defined, in his work with Zhong [25], the concept of multiscale contours. In this case every edge point of an image is characterized by a whole chain of the scale-space plane: the longer the chains are, the more important is the smoothing we impose, and the smaller number of edge points we will get. In addition, this allows us to extract useful information about the regularity of the image at the edge point it characterizes. This can be very attractive in terms of a finer characterisation of edge map.

#### 2.2. Wavelet transform properties

Multiscale edge detection can be formalized through a wavelet transform as defined in Ref. [26]. Edges in images can be mathematically defined as local singularities. Until recently, the Fourier transforms was the main mathematical tool for analyzing singularities. However, the Fourier transform is global and not well adapted to local singularities. It is hard to find the location and spatial distribution of singularities with Fourier transforms. On the other hand, wavelet analysis is a local analysis; it is especially suitable for time-frequency analysis [26], which is essential for singularity detection. This was a major motivation for the study of the wavelet transform in mathematics and in applied domains. With the growth of wavelet theory, the wavelet transforms have been found to be remarkable mathematical tools to analyze the singularities including the edges, and further, to detect them effectively. This idea is similar to that of Canny’s approach which selects a Gaussian function as a smoothing function; while the wavelet-based approach chooses a wavelet function. Mallat et al. [25,27] proved that the maxima of the wavelet transform modulus can detect the location of the irregular structures. One and two-dimensional signals can be reconstructed, with a good approximation, from the local maxima of their wavelet transform modulus.
The wavelet transform characterizes the local regularity of signals by decomposing signals into elementary building blocks that are well localized both in space and frequency. This not only explains the underlying mechanism of classical edge detectors, but also indicates a way of constructing optimal edge detectors under specific working conditions. A remarkable property of the wavelet transform is its ability to characterize the local regularity of functions. For an image \( f(x, y) \), its edges correspond to singularities of \( f(x, y) \), and thus are related to the local maxima of the wavelet transform modulus. Therefore, the wavelet transform is an effective method for edge detection.

2.3. Multiscale iris edge detection

The resolution of an image is directly related to the appropriate scale for edge detection. High resolution and a small scale will result in noisy and discontinuous edges; low resolution and a large scale will result in undetected edges. The scale controls the significance of edges to be shown. Edges of higher significance are more likely to be preserved by the wavelet transform across the scales. Edges of lower significance are more likely to disappear when the scale increases.

Assume \( f(x, y) \) is a given image of size \( M \times N \). At each scale \( j \) with \( j > 0 \) and \( S_{0}f = f(x, y) \). The wavelet transform decomposes \( S_{j-1}f \) into three wavelet bands: a lowpass band \( S_{j}f \), a horizontal high-pass band \( W_{H}^{j}f \) and a vertical high-pass band \( W_{V}^{j}f \). The three wavelet bands \( (S_{j}f, W_{H}^{j}f, W_{V}^{j}f) \) at scale \( j \) are of size \( M \times N \), which is the same as the original image, and all filters used at scale \( j \) \((j > 0)\) are up-sampled by a factor of \( 2^{j} \) compared with those at scale zero. In addition, the smoothing function used in the construction of a wavelet reduces the effect of noise. Thus, the smoothing and edge detection steps are combined together to achieve the optimal result.

The method of multiscale edge detection is used to find the edges. This wavelet is non sub-sampled wavelet decomposition and essentially implements the discretized gradient of the image at different scales. At each level of wavelet transform the modulus \( M_{j}f \) of the gradients can be computed by

\[
M_{j}f = \sqrt{|W_{H}^{j}f|^{2} + |W_{V}^{j}f|^{2}}.
\]

And the associated phase \( A_{j}f \) is obtained by

\[
A_{j}f = \tan^{-1}(W_{V}^{j}f / W_{H}^{j}f).
\]

The sharp variation points of the image \( f(x, y) \) smoothed by \( S_{j}f \) (\( f(x, y) S_{j}f \)) are the points \((x, y)\), where the modulus \( M_{j}f \) has a local maxima in the direction of the gradient given by \( A_{j}f \) (Fig. 1). From Fig. 2, it can be observed that there is
Fig. 3. Iris localized: (a) pupil edge map, (b) pupil detected, and (c) outer circle detected.

Fig. 4. Edges for eyelids detection: the first column on the left shows the original images and the second column on the right shows the edges detected using the horizontal coefficients $W_h(x, y, 3)$.

significant information about edge information in an eye image, with $W_h(x, y, s)$ eyelids and that the horizontal pupil’s lines are clearer than outer boundary circle, and with $W_v(x, y, s)$ useful information about both pupil and outer boundary circles.

2.4. Detecting pupil and iris boundaries

To detect the iris and pupil boundaries an edge map has been detected first by using a multiscale edge detection (Fig. 3).

The use of vertical coefficients for outer boundary edge detection will reduce the influence of the eyelids when performing a circular Hough transform because the eyelids are usually horizontally aligned [13].

The Hough transform locates contours in an $n$-dimensional parameter space by examining whether they lie on curves of specified shape. For the iris outer or pupillary boundaries and a set of recovered edge points $(x_i, y_i)$, $i = 1, \ldots, n$, a Hough transform is defined by

$$H(x_c, y_c, r) = \sum_{i=1}^{n} h(x_i, y_i, x_c, y_c, r),$$

where $H(x_c, y_c, r)$ shows a circle through a point, the coordinates $x_c, y_c, r$ define a circle by the following equation:

$$x_c^2 + y_c^2 + r^2 = 0.$$  \hspace{1cm} (3.1)

In the case of edge detection for iris boundaries Figs. 3b and c the above equation becomes:

$$(x_i - x_c)^2 + (y_i - y_c)^2 - r^2 = 0.$$  \hspace{1cm} (3.2)

2.5. Isolating eyelids and eyelashes

Eyelids and eyelashes are isolated from the detected iris image by considering them as noise because they degrade the performance of the system. The eyelids are isolated by first fitting a line to the upper and lower eyelid using the linear Hough transform. A horizontal line is then drawn which intersects with the first line at the iris edge that is closest to the pupil. A second horizontal line allows the maximum isolation of eyelid regions. A multiscale edge detection is then used to create the edge map (Fig. 4), and only the horizontal gradient information is taken. If the maximum in the Hough space is lower than a set threshold, then no line is fitted, since this corresponds to non-occluding eyelids. Also, the lines are restricted to lie exterior to the pupil region and interior to the iris region. A thresholding operation is followed for detecting Eyelashes (Fig. 5).

3. Iris normalization

Once the iris region is segmented, the next stage is to normalize this part so as to enable the generation of the iriscode and their comparisons. Since the variations in the eye, like optical size of the iris, position of pupil in the iris, and the iris orientation change from person to person, it is required to normalize the iris image so that the representation is common to all, with similar dimensions.

The normalization process involves unwrapping the iris and converting it into its polar equivalent. It is done using Daugman’s Rubber sheet model (Fig. 6). The center of the pupil is considered as the reference point and a remapping formula is used to convert the points on the Cartesian scale to the polar scale. In this model a number of data points are selected along each radial line and this is defined as the radial resolution. The number of radial lines going around the iris region is defined as the angular resolution as in Figs. 7 and 8.
4. Feature extraction

The iris has an interesting structure and presents plentiful texture information. So, it is attractive to search representation methods which can capture local crucial information in an iris. The distinctive spatial characteristics of the human iris are manifest at a variety of scales [3]. For example, distinguishing structures range from the overall shape of the iris to the distribution of tiny crypts and detailed texture. To capture this range of spatial detail, it is advantageous to make use of a multiscale representation. Some works have used multiresolution techniques for iris feature extraction [13–15] and have proven a high recognition accuracy. At the same time, however, it has been observed that each multiresolution technique has its specification and situation in which it is suitable; for example, a Gabor filter bank has been shown to be most known multiresolution method used for iris feature extraction and Daugman [15] in his proposed iris recognition system demonstrated the highest accuracy by using Gabor filters. However, from the point of view of texture analysis one can observe that Gabor filter based methods analyse pretty well the texture orientations. In this paper, we have investigated the use of wavelet maxima components as a multiresolution technique alternative for iris feature extraction. In this context, we have analysed iris textures in both horizontal and vertical directions especially that the iris has a rich structure with a very complex textures so that it makes sense to analyse the iris texture by combining all information extracted form iris region by considering all orientations in terms of horizontal and vertical details.

To demonstrate this, we propose a new and combined multiresolution iris feature extraction scheme by analysing the iris using first wavelet maxima components and then applying a special Gabor filter bank to extract all dominant features.

4.1. Wavelet maxima components

Wavelet decomposition provides a very good approximation of images and natural setting for the multi-level analysis. Since wavelet transform maxima provide useful information about textures and edges analysis [26], we propose to use it here as a fast feature extraction by using the wavelet components. Wavelet maxima have been shown to work well in detecting
edges which are likely key features in a query; moreover this method provides useful information about texture features by using horizontal and vertical details.

As described in Ref. [25] to obtain the wavelet decomposition a pair of discrete filters \( H, G \) has been used (Table 1).

At each scale \( s \), the algorithm decomposes the iris image \( I(x, y) \) into \( I(x, y, s) \), \( W_h(x, y, s) \) and \( W_v(x, y, s) \) as shown in Figs. 9 and 10.

- \( I(x, y, s) \): the image smoothed at scale \( s \).
- \( W_h(x, y, s) \) and \( W_v(x, y, s) \) can be viewed as the two components of the gradient vector of the analyzed image \( I(x, y) \) in horizontal and vertical direction, respectively.

In each scale \( s \) where \( S \) is the number of scales or decomposition, image \( I(x, y) \) is smoothed by a low-pass filter:

\[
s = 0, \\
I(x, y, s + 1) = I(x, y, s) (H_s, H_s). \\
\]

And horizontal and vertical details are obtained, respectively, by

\[
W_h(x, y, s) = \frac{1}{\lambda_s} I(x, y, s) (G_s, D), \\
W_v(x, y, s) = \frac{1}{\lambda_s} I(x, y, s) (D, G_s). \\
\]

- We denote by \( D \) the Dirac filter whose impulse response is equal to 1 at 0 and 0 otherwise.

<table>
<thead>
<tr>
<th>Table 1</th>
<th>Response to filters ( H, G )</th>
</tr>
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<tbody>
<tr>
<td>( H )</td>
<td>0</td>
</tr>
<tr>
<td>( G )</td>
<td>0</td>
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Fig. 9. Wavelet maxima vertical component at scale 2 with intensities along specified column.

Fig. 10. Wavelet maxima horizontal component at scale 2 with intensities along specified column.

- We denote by \( A(H, L) \) the separable convolution of the rows and columns, respectively, of the image \( A \) with the \( 1 - d \) filters \( H \) and \( L \).

- \( G_s, H_s \) are the discrete filters obtained by putting \( 2^s - 1 \) zeros between consecutive coefficients of \( H \) and \( G \).

- \( \lambda_s \), as explained in Ref. [25] due to discretization, the wavelet modulus maxima of a step edge do not have the same amplitude at all scales as they should in a continuous model.

The constants \( \lambda_s \) compensate for this discrete effect.

### 4.2. Special Gabor filter bank

The two-dimensional Gabor Wavelets function \( g(x, y) \) and its Fourier transform \( G(u, v) \) can be defined as follows [28]:

\[
g(x, y) = \frac{1}{2\pi \sigma_x \sigma_y} \exp \left[ -\frac{1}{2} \left( \frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2} \right) + 2\pi Wx \right], \quad (7)
\]

\[
G(u, v) = \exp \left[ -\frac{1}{2} \left( \frac{(u - W)^2}{\sigma_u^2} + \frac{v^2}{\sigma_v^2} \right) \right], \quad (8)
\]

where \( \sigma_u = 1/2\pi \sigma_x \) and \( \sigma_v = 1/2\pi \sigma_y \). A Gabor function can form a complete but non-orthogonal basis set and by expanding a signal using this basis provides a localized frequency description. A class of self-similar functions, referred to as Gabor wavelets in the following discussion, is now considered. Let \( g(x, y) \) be the mother similar functions, referred to as Gabor wavelet, then this self-similar filter dictionary can be obtained by appropriate dilations and rotations of \( g(x, y) \) through the generating function:

\[
g_{mn}(x, y) = a^{-m} g(x', y'), \quad (9)
\]

\[
x' = a^{-m} (x \cos \theta + y \sin \theta), \quad (9.1)
\]

\[
y' = a^{-m} (-x \sin \theta + y \cos \theta), \quad (9.2)
\]

where \( a > 1 \), \( m, n \) = integer and \( \theta = n\pi/k \) is the orientation \( k \) is the number of orientations) and \( a^{-m} \) is the scale factor.
The non-orthogonality of the Gabor wavelets implies that there is redundant information in the filtered images, and the following strategy is used to reduce this redundancy [28]. Let \( U_l \) and \( U_h \) denote the lower and upper centre frequencies of interest. Let \( K \) be the number of orientations and \( S \) be the number of scales in the multiresolution decomposition. Then the design strategy is to ensure that the half-peak magnitude support of the filter responses in the frequency spectrum touch each other as shown in Fig. 11 This results in the following formulas for computing the filter parameters \( \sigma_u \) and \( \sigma_v \) (and thus \( \sigma_x \) and \( \sigma_y \)).

\[
a = (U_h/U_l)^{-1/(S-1)},
\]

\[
\sigma_u = \frac{(a-1)U_h}{(a+1)\sqrt{2\ln 2}},
\]

\[
\sigma_v = \tan\left(\frac{\pi}{2K}\right)\left[U_h - 2 \ln \left(\frac{\sigma_u^2}{U_h}\right)\right] \times \left[2 \ln 2 - \frac{(2 \ln 2)^2 \sigma_u^2}{U_h^2}\right]^{-1/2},
\]

where \( W = U_h \), and \( m = 0, 1, \ldots, S - 1 \). In order to eliminate the sensitivity of the filter response to absolute intensity values, the real (even) components of the 2D Gabor filters are biased by adding a constant to make them zero mean.

4.3. Proposed method

1. Compute wavelet maxima components in horizontal and vertical directions using five scales.
2. For each component, special Gabor filter bank is applied with 4 scales and 6 orientations to obtain \((4 \times 6) \times 5 \times 2 = 120 \times 2 = 240 \) filtered image.
3. The feature vector is presented by using two different techniques, the first is a statistical measure (mean and variance) and the second experience is moment invariants (Fig. 12).

4.4. Template generation

4.4.1. Statistical features

A feature vector can be constructed. For each filtered image the statistical features of the image are computed such as the mean and the variance (or standard deviation) \( \mu_{mn} \) and \( \sigma_{mn} \). In the experiments, we show that the best results are obtained if four scales \( (S = 4) \) and six orientations \( (K = 6) \) are used. The resulting feature vector is as follows:

\[
f = [\mu_{0,0}, \sigma_{0,0}, \mu_{0,1}, \sigma_{0,1}, \ldots, \mu_{3,5}, \sigma_{3,5}].
\]
After applying wavelet maxima components in the normalized iris image and for each filtered image in both horizontal and vertical direction for the five scales, a special Gabor filter bank has been used with four scales and six orientations, so that:

- For the horizontal details: wavelet maxima (five images) → Gabor filters \((4 \times 6 \times 5) = 120\) images.
- For the vertical details: wavelet maxima (five images) → Gabor filters \((4 \times 6 \times 5) = 120\) images.

With statistical features, mean and variance are calculated for each image from \((120 \times 2) = 240\) images to obtain a feature vector of 480 elements.

### 4.4.2. Moments invariant

The theory of moments provides an interesting series expansion for representing objects. This is also suitable to mapping the filtered image to vectors so that their similarity distance can be measured [29].

Certain functions of moments are invariant to geometric transformation such as translation, scaling, and rotation. Such features are useful in identification of objects with unique signatures regardless of their location, size, and orientation [29].

A set of seven 2D moment invariants that are insensitive to translation, scaling, rotation have been computed for each image analysed by wavelet maxima horizontal and vertical component and Gabor filters. 240 filtered images have been obtained, for each image from those a seven element row vector containing the moment invariants just defined means our feature vector has a size \((240 \times 7) = 1680\) elements.

### 5. Matching

It is very important to present the obtained vector in a binary code because it is easier to determine the difference between two binary code-words than between two number vectors. In fact, Boolean vectors are always easier to compare and to manipulate.

We have applied a Hamming Distance matching algorithm for the recognition of two samples. It is basically an exclusive OR (XOR) function between two bit patterns. Hamming Distance is a measure, which delineate the differences, of iris codes. Every bit of presented iris code is compared to the every bit of referenced iris code, if the two bits are the same, e.g. two 1’s or two 0’s, the system assigns a value ‘0’ to that comparison and if the two bits are different, the system assigns a value ‘1’ to that comparison. The formula for iris matching is shown as follows:

\[
\text{HD} = \frac{1}{N} \sum P_i \oplus R_i ,
\]

where \(N\) is the dimension of feature vector, \(P_i\) is the \(i\)th component of the presented feature vector while \(R_i\) is the \(i\)th component of the referenced feature vector. The match ratio between two iris templates is given by

\[
\text{Ratio} = \left( \frac{T_z}{T_b} \right) \times 100 ,
\]

where \(T_z\) is total number of zeros calculated by Hamming distance vector and \(T_b\) is the total number of bits in iris template.

### 6. Experimental results and analysis

To demonstrate the usefulness of the proposed new method for identifying individuals from an iris image sequence using our combined multiresolution techniques and multiscale edge detection, we have implemented the algorithm described above and a series of experiments to evaluate its performance have been extensively carried out. In addition, we have compared the performance of proposed method against some existing methods for iris recognition and detailed discussions on the overall experimental results are given.

#### 6.1. Database

The Chinese Academy of Sciences—Institute of Automation (CASIA) eye image database [30] containing 756 greyscale eye images with 108 unique eyes or classes and seven different images of each unique eye have been used in the experimentation. Images from each class are taken from two sessions with one month interval between sessions. The images were captured especially for iris recognition research using specialised digital optics developed by the National Laboratory of Pattern Recognition, China. The eye images are mainly from persons of Asian decent, whose eyes are characterised by irises that are densely pigmented, and with dark eyelashes.

#### 6.2. Multiscale edge detection

The proposed multiscale technique provides a new approach to classical iris edge detection problems. In addition, in the proposed algorithm the multiscale approach provides more useful information about the sharp variations (images at each scale with a horizontal and a vertical decomposition, as shown in Fig. 2 and demonstrated in [25] where the scale defines the size of the neighbourhood where the signal changes are computed. This approach yields a good localization a necessary step to achieve higher recognition accuracy. Extensive experimentation and its analysis have shown that the proposed method outperforms existing and similar techniques with an accuracy of 99.6% (Fig. 13).

#### 6.3. Combined multiresolution feature extraction techniques

In our new approach, we have introduced the combined multiresolution techniques based feature extraction which provides more significant iris textured information. The combination has been done by taking into account the iris structure and the nature of texture. The visual appearance of the iris is a direct result of its multilayered structure [3]. Therefore, from this structure the iris texture should be defined in all directions and orientations. Some existing methods in iris recognition have used multiscale approach to present iris features. However each of these methods belongs to one class of iris representation classes.
such as: phase-based methods [5,11], zero-crossing representation [14,31], texture analysis [13,16] and intensity variation analysis [9,22]. Although, these techniques have been successful, they come with their own drawbacks in the sense that they all attempt to analyse/quantify iris texture from their own specified criterion such that if this criterion fails the performance is greatly affected. To address this problem, we have attempted to analyse and quantify iris texture from a number of criteria which are combined together so that to improve the efficiency of the recognition. In other words, we are interested in investigating a method to balance this problem by combining all textures.

In our proposed approach, it has demonstrated that the combined multiscale techniques are effective and robust to analyse iris textures and to achieve a high system performance (Table 3).

### 6.4. Template presentation

We have used two different experiments to present the feature vector. First statistical features (mean and variances) have been used as feature vector elements with 480 elements obtained. The other experiment has used seven moment invariants that are insensitive to translation, scaling, rotation so that a feature vector of 1680 elements is obtained. From the experimental results (Table 2), it has been found that the performance accuracy is higher when using the seven moment invariants than the accuracy with statistical features. From this result one can conclude that moment invariants are more useful in identification and significantly represent images more efficiently; they are compact and can be easily used to compute similar distances. In addition, these moments are invariant to all affine transformations (namely translation, scaling and rotation).

### 6.5. Comparison with existing methods

The methods proposed by Daugman [5], Wildes et al. [13], Boles and Boashash [14], Ma and Tan [21] are the best known among existing schemes for iris recognition. Furthermore, they characterize local details of the iris based on phase, texture analysis, zero-crossing and local sharp variation representation. Therefore, we have chosen to compare the performance of our proposed algorithm against that of these ones. The method by Wildes et al. only works in verification mode [13], therefore we have not compared its performance because our method is proposed for an identification mode of operation.

From the results shown in Table 3, one can observe that Daugman’s method and our proposed one yield the best performances, followed by Tan’s method [21] and Boles [14]. This is because that these methods very well describe the texture features of the iris. Daugman’s method is slightly better than the proposed method in identification mode. Daugman demodulated phase information of each small local region using multiscale quadrature wavelets, and then quantized the resulting phasor denoted by a complex-valued coefficient to one of the four quadrants in the complex plane. To achieve high accuracy, the size of each local region must be small enough, which results in a high dimensionality of the feature vector (2048 components). As such, his method captures much more information in much smaller local regions. This makes his method slightly better than ours. Boles [14] and Ma [21] used a kind of one dimensional ordinal measures. So these two methods lose much information compared with 2D ordinal representations, which directly lead to a worsening of their performances when compared to ours method. Boles and Boashash [14] only employed extremely little information along a virtual circle on the iris to represent the whole iris, which results in a relatively low accuracy, in Ma [21] method the current features are local features, so it may be easily affected by iris localization, noise and the iris deformation caused by pupil movements.

Table 4 illustrates the computational cost of the methods described in [5,14,21] and the current algorithm. The above experiments are carried out in Matlab 6.0 since the method of Boles [14] are based on 1D signal analysis, they cost less time than others in feature extraction. Our proposed approach for feature extraction is faster than Daugman’s method and Ma and Tan’s method because it uses a compact feature vector representation with a high recognition rate.

<table>
<thead>
<tr>
<th>Methods</th>
<th>Correct recognition rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daugman</td>
<td>99.90</td>
</tr>
<tr>
<td>Ma and Tan</td>
<td>99.23</td>
</tr>
<tr>
<td>Boles et boashashe</td>
<td>93.2</td>
</tr>
<tr>
<td>Proposed method (statistical features)</td>
<td>99.52</td>
</tr>
<tr>
<td>Proposed method (moment invariants)</td>
<td>99.60</td>
</tr>
</tbody>
</table>

Table 2

<table>
<thead>
<tr>
<th>Feature vector representation</th>
<th>Statistical features</th>
<th>Moment invariants</th>
</tr>
</thead>
<tbody>
<tr>
<td>Feature vector size (bits)</td>
<td>480</td>
<td>1680</td>
</tr>
<tr>
<td>Correct recognition rate (%)</td>
<td>99.60</td>
<td>99.52</td>
</tr>
</tbody>
</table>

![Fig. 13. Success rate of iris localization.](image-url)
6.6. Discussion and future work

From the above analysis and comparisons, one can draw the following conclusions:

- In our proposed approach a multiscale approach has allowed us to detect the edges for a precise and effective iris region localization. This approach used modulus wavelet maxima to define pupil and iris edges. This, in turn, greatly reduces the search space for the Hough transform, thereby improving overall performance.
- The combined special Gabor filters with wavelet maxima components provide more textured information, since wavelet maxima allow us to efficiently detect the horizontal and vertical details through scale’s variation and when the proposed special Gabor filters are applied on these components at different orientations and scales, more and precise information can be obtained thus improving the performance of the recognition accuracy.
- The moment invariants are useful and are efficient to represent iris features since they are sensitive to translation, scaling and rotation and as such they provide a complete, compact and significant feature vector which can improve the matching stage while making it faster.

The experimental results show that our proposed method to analyze iris textures is attractive and very promising. Future work will include:

- Local variations analysis to precisely capture local fine changes of the iris so as to increase the recognition accuracy.
- Investigating combined local and global textures analysis for more efficient and robust iris recognition.

7. Conclusion

In this paper, we have introduced a novel efficient multiscale approach for human iris recognition based on combined feature extraction methods by considering both the textural and topological features of an iris image which is invariant to translation, scale and rotation. The proposed algorithm yields superior performance when compared to the algorithms of Boles [14] and Tan [21], with lower complexity and high recognition rate, using lower complexity with Daugman’s method [5] using CASIA database.

All experimental results have demonstrated that the proposed method achieves high performance in both speed and accuracy. This confirms that combined multiresolution feature extraction techniques truthfully perform iris recognition accuracy and our analysis and understanding are rational and practical.

References


About the Author—MAKRAM NABTI received the “Ingenieur d’Etat” degree in Computer Science from Ecole Polytechnique of Algiers, Algeria, in 2003. From 2003 to 2005, he worked in the Algerian National Centre for Research and Development as a research developer in information systems and forensic and security applications where he developed a national information system for security in April 2005. In September 2005, he joined Queen’s University of Belfast, Belfast, UK as a Ph.D. student in Computer Science. He is currently working in biometrics for forensic and security. His research interests are in the areas of biometrics, security and digital signal/image processing. Makram Nabti is a student member of IEEE Signal Processing, Communications and Computer Societies, member of IET, and a researcher in the Speech and Vision Systems group at the Institute of Electronics, Communications and Information Technology (ECTT), QUB.

About the Author—AHMED BOURLIDANE received the “Ingenieur d’Etat” degree in electronics from “Ecole Nationale Polytechnique” of Algiers (ENPA), Algeria, in 1982, the M.Phil. degree in electrical engineering (VLSI design for signal processing) from the University of Newcastle-Upon-Tyne, U.K., in 1988, and the Ph.D. degree in electrical engineering (computer vision) from the University of Nottingham, U.K., in 1992. From 1992 to 1996, he worked as a Research Developer in telesurveillance and access control applications. In 1994, he joined Queen’s University Belfast, Belfast, U.K., initially as Lecturer in computer architecture and image processing. He is now a Reader in computer science, and his research interests are in imaging for forensics and security, biometrics, homeland security, image/video watermarking and cryptography. He has authored and coauthored more than 130 publications. Dr. Bouridane is a Senior Member of IEEE Signal Processing, Circuits and Systems, and Computer Societies.