MULTISCALE EDGE DETECTION USING WAVELET MAXIMA FOR IRIS LOCALIZATION

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Keywords: Biometrics, iris localization, multiscale edge detection, wavelet maxima, Hough transform.

Abstract

Automated personal identification based on biometrics has been receiving extensive attention over the past decade. Iris recognition, as an emerging biometric recognition approach, is becoming a very active topic in both research and practical applications and is regarded as the most reliable and accurate biometric identification system available. Common problems include variations in lighting, poor image quality, noise and interference caused by eyelashes while feature extraction and classification steps rely heavily on the rich textural details of the iris to provide a unique digital signature for an individual. As a result, the stability and integrity of a system depends on effective localization of the iris to generate the iris-code. A new localization method is presented in this paper to undertake these problems. Multiscale edge detection using wavelet maxima is discussed as a preprocessing technique that detects a precise and effective edge for localization and which greatly reduces the search space for the Hough transform, thus improving the overall performance. Linear Hough transform has been used for eyelids isolating, and an adaptive thresholding has been used for eyelashes isolating. A large number of experiments on the CASIA iris database demonstrate the validity and the effectiveness of the proposed approach.

1 Introduction

The recent advances of information technology and the increasing requirement for security have led to a rapid development of intelligent personal identification systems based on biometrics [10]. Biometrics employs physiological or behavioural characteristics to accurately identify each subject. Commonly used biometric features include face, fingerprints, voice, facial, iris, retina, gait, palm-prints, hand geometry, etc.

The use of biometric indicia for identification purposes requires that a particular biometric factor be unique for each individual that it can be readily measured, and that it is invariant over time. Biometrics such as signatures, photographs, fingerprints, voiceprints and retinal blood vessel patterns all have significant drawbacks. Although signatures and photographs are cheap and easy to obtain and store, they are impossible to identify automatically with assurance, and are easily forged. Electronically recorded voiceprints are susceptible to changes in a person's voice, and they can be counterfeited. Fingerprints or handprints require physical contact, and they also can be counterfeited and marred by artefacts.

Human iris on the other hand is an internal organ of the eye and as well protected from the external environment, yet it is easily visible from within one meter of distance makes it a perfect biometric for an identification system with the ease of speed, reliability and automation.

Iris recognition technology combines computer vision, pattern recognition, statistical inference, and optics. Its purpose is real-time, high confidence recognition of a person's identity by mathematical analysis of the random patterns that are visible within the iris of an eye from some distance. Because the iris is a protected internal organ whose random texture is stable throughout life, it can serve as a kind of a living password that one need not remember but can always present. Because the randomness of iris patterns has very high dimensionality, recognition decisions are made with confidence levels high enough to support rapid and reliable exhaustive searches through national-sized databases [11].

The iris is a thin circular diaphragm, which lies between the cornea and the lens of the human eye. A front-on view of the iris is shown in Figure 1. The iris is perforated close to its centre by a circular aperture known as the pupil. The function of the iris is to control the amount of light entering through the pupil, and this is done by the sphincter and the dilator muscles, which adjust the size of the pupil [10].

Iris enjoys further practical advantages over fingerprints and other biometrics for the purposes of automatic recognition, including the ease of registering its image at some distance from the subject without physical contact. Compared with other biometric features (such as face, voice, etc.), the iris is more stable and reliable for identification [8].

Furthermore, since the iris is an externally visible organ, iris-based personal identification systems can be noninvasive to their users, which is of great importance for practical applications. All these desirable properties (i.e., uniqueness, stability, and noninvasiveness) make iris recognition a particularly promising solution to security in the near future.

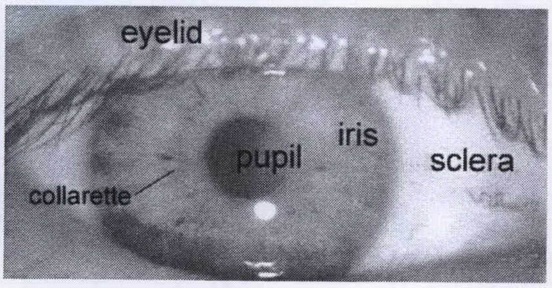


Figure 1: A front-on view of the human eye.

A typical iris recognition system generally consists of the following basic modules:

I. image acquisition, iris location, and pre-processing,
II. Iris texture feature extraction and signature encoding,
III. Iris signature matching for recognition or verification.

The speed and performance of an iris recognition system is crucial and it is limited by the results of iris localization to a great extent. Iris localization includes finding the iris boundaries (inner and outer) and the eyelids (lower and upper). So far, there are two classic iris location algorithms which have been proposed by Daugman [1] and Wildes [6]. Daugman makes use of an integro-differential operator for locating the circular iris and pupil regions, and also the arcs of the upper and lower eyelids. Wildes also used the first derivatives of intensity values followed by a thresholding of the result. From the edge map, votes are then cast in Hough space for the parameters of circles passing through each edge point, a maximum point in the Hough space will correspond to the radius and centre coordinates of the circle best defined by the edge points. Wildes also makes use of the parabolic Hough transform to detect the eyelids.

All existing methods for use in iris localization have been based on local scale which provides limited information about edge point's variations. On the other hand, a multiscale edge detection approach can provide a significantly more information on edges at varying scales, with a smaller number of texture points producing local maxima, which enable us to find the real geometrical edges of the image.

In this paper, we propose a novel approach for iris localization using a multiscale edge detection approach based on wavelet maxima. First we detect the multiscale edge map using the information extracted from the wavelet coefficients. This allows us to obtain finer edges for pupil and iris circles. A Hough transform is then used to localise the iris and the pupil. The eyelids are isolated using the horizontal multiscale edges with a linear Hough transform while the eyelashes are isolated using a thresholding technique.

The rest of the paper is organised as follows: Section 2 briefly describes the principle of iris localisation. Section 3 describes the proposed method including the principles of multiscale edge detection using the wavelet transform. Section 4 is concerned with the results and their analysis and while section 5 concludes the 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 [2]. 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.

The localization step is crucial to the success of an iris recognition system, since data that is falsely represented as iris pattern data will corrupt the biometric templates generated, resulting in poor recognition rates.

3 Proposed Method

An important issue in multiscale analysis is to relate the local properties of the signal to the evolution of the transform values when the scale varies [5].

3.1 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 [1,6,7,9]. However, a problem with smoothing arises: how much and which smoothing should one chooses? A strong smoothing will lead to the detection of less point while a lighter one will be more permissive. That is why S. Mallat defined, in his work with S. Zhong [4], the concept of multiscales 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.

3.2 Wavelet transform properties

A multiscale edge detection can be formalized through a wavelet transform as defined in [3]. In [4,5] the authors explained the main properties of a wavelet transform and showed how the maxima of a wavelet transform relate the sharper variation points of the image.

3.3 Proposed algorithm

A) In our work, we have used the algorithm described in [4] to obtain the wavelet decomposition using a pair of discrete filters H, G as shown in Table1.

H	*G*
0	0
0	0
0.125	0
0.375	-2.0
0.375	2.0
0.125	0
0	0

Table 1: Response of filters H, G.

At each scale s, the proposed algorithm decomposes an eye image I(x, y) into a smoothed image I(x, y, s) and $W_v(x\ y, s)$ and $W_h(x, y, s)$ wavelet coefficients. The algorithm is as follows:

s=0
while (s < S)

$$W_h(x, y, s) = \frac{1}{\lambda_s} . I(x, y, s) * (G_s, D)$$

$$W_v(x\ y, s) = \frac{1}{\lambda_s} . I(x, y, s) * (D, G_s)$$

$$I(x, y, s+1) = I(x, y, s) * (H_s, H_s)$$

s = s+1
end of while.

- We denote by D the Dirac filter whose impulse response is equal to 1 at 0 and 0 otherwise.
- We denote by A * (H, L) a separable convolution of the rows and columns, respectively, of image A with 1-D filters H and L.
- We denote by S the number of scales.
- I(x, y, s) the image smoothed at scale s.
- G_s, H_s are discrete filters obtained by appending 2^s-1 zeros between consecutive coefficients of H and G.
- λ_s , as explained in [4] due to discretization, the wavelet modulus maxima of a step edge does not have the same amplitude at all scales as they should in a continuous model. The constants λ_s compensates for this discrete effect. The values of λ_s are given in Table 2.
- $W_h(x, y, s)$ and $W_v(x, y, s)$ can be viewed as the two components of the gradient vector of the analyzed image I(x,y) smoothed by a lowpass filter.

s	λ_s
1	1.50
2	1.12
3	1.03
4	1.01
5	1.00

Table 2: Normalization coefficient λ_s .for s >5, λ_s =1.

Figure 2 clearly shows the application of the algorithm on an eye image where it can be observed that the edges of the image in both horizontal and vertical directions and at different scales are efficiently computed.

From Figure 2 it can be observed that there is 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.

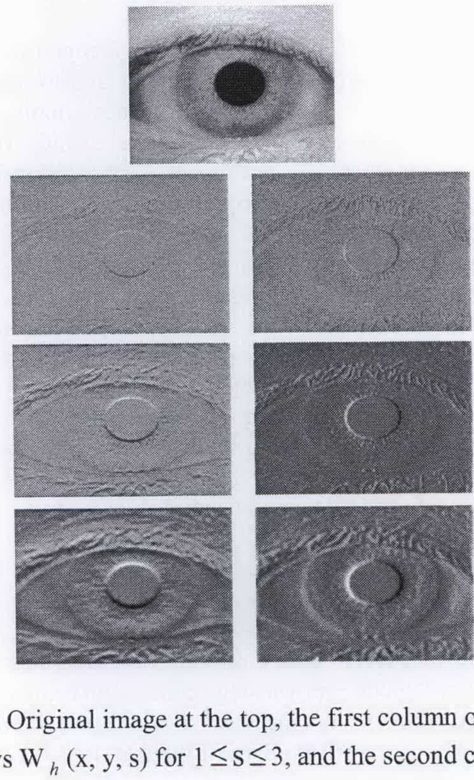


Figure 2: Original image at the top, the first column on the left shows $W_h(x, y, s)$ for $1 \leq s \leq 3$, and the second column on the right shows $W_v(x,y,s)$ for $1 \leq s \leq 3$.

B) After computing the two components of the wavelet transform, we compute the modulus at each scale as:

$$M(x, y, s) = \sqrt{|w_h(x,y,s)|^2 + |w_v(x,y,s)|^2} \quad (1)$$

The sharp variation points of the original image convoluted with a smoothed function at each scale are the points (x, y), where the modulus M(x, y, s) has a local maxima in the direction of the gradient given by:

$$A(x, y, s) = \arctan\left(w_v(x,y,s) \Big/ w_h(x,y,s) \right) \quad (2)$$

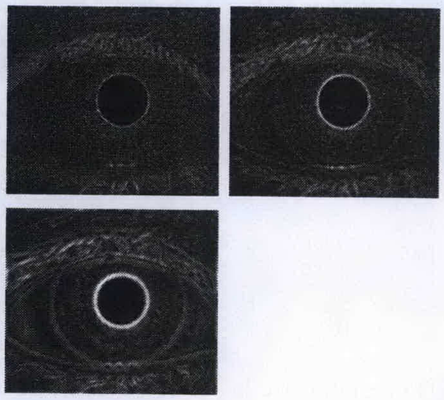


Figure 3: Modulus M(x, y, s) for s=1(top left), s=2(right) S=3(bottom left).

C) A thresholding operation is then applied to the modulus M(x, y, s). This is carried out on the modulus maxima MAX(M(x, y, s)) and then multiplied by a factor to obtain a threshold value that yields an edge map (with 1 and 0 values). The threshold value T is computed as follows:

$$T = \alpha * MAX(M(x, y, s)). \quad (3)$$

Therefore all values of M(x, y, s) greater or equal to T are considered edge points, α takes different values (the first value for pupil edge detecting and the second value for outer boundary edge detection)

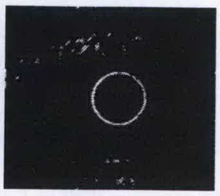


Figure 4: pupil edge detection using the horizontal and vertical coefficients W_v and W_h.

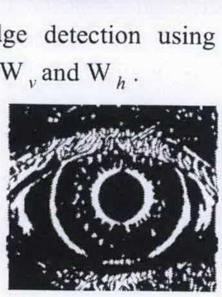


Figure 5: outer boundary edge detection using only the vertical coefficients W_v.

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 [6]

D) After the thresholding operation a circular Hough transform is used to detect the pupil and iris circles.

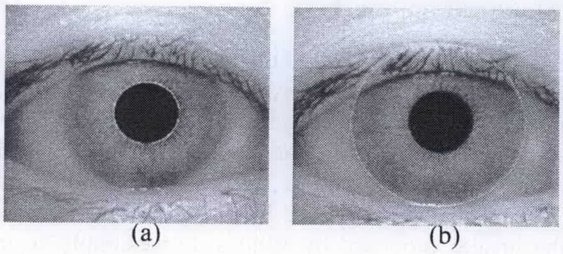


Figure 6: Iris localized: (a) pupil detected, (b) outer circle detected.

E) Eyelids were isolated by first fitting a line to the upper and lower eyelid using the linear Hough transform. Horizontal coefficients W_h (x, y, s) are used to create an edge map in Figure 7 while the thresholding operation is used to isolate eyelashes. Eyelid and eyelash detection method proved to be successful as shown in Figure 8.

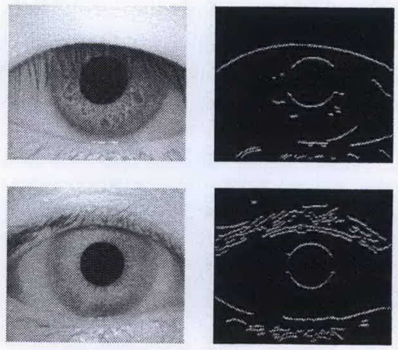


Figure 7: Edges for eyelids detection: the first column on the left shows the original images and the second column on the right shows the edges detected using the horizontal coefficients W_h (x, y, 3).

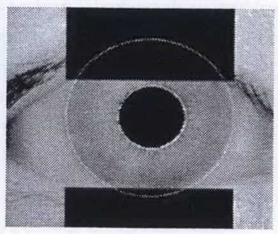


Figure 8: successful localization with eyelashes and eyelids isolating. Black regions denote detected eyelid and eyelash regions.

4 Results and Analysis

The proposed algorithm have been tested using the CASIA iris image database, which consists of 80 persons, 108 set eye images and 756 eye images. A perfect localization was obtained on all images. The results have been assessed and analysed regarding the following points:

4.1 Multiscale approach:

This approach can provide a complete and a stable description of signals; it is based on a wavelet formalization of multiscale approach. This characterization provides a new approach to classical iris edge detection problems since all existing research in iris localization is based either on the integro-differential method proposed by Daugman or the derivatives of the images proposed by Wildes. For example, a problem with Daugman's algorithm [1] is that it can fail in the presence of noise (i.e.., from reflections, .. etc) since the algorithm works only on a local scale basis.

However, in the proposed algorithm a multiscale approach provides more useful information about the sharp variations (images at each scale with a horizontal and a vertical decomposition Figure2), as demonstrated in [3,4] the scale defines the size of the neighbourhood where the signal changes are computed.

It is clear from Figure 9 that the proposed algorithm is capable to detect pupil and outer boundary circles even with poor quality iris images because of the efficient edge map detected from wavelet maxima.

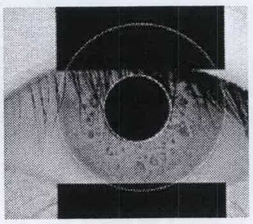
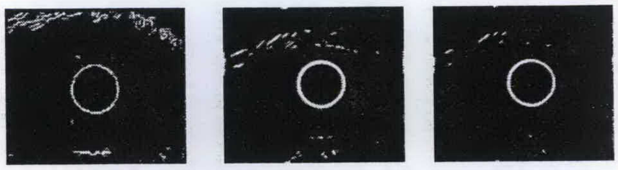


Figure 9: Poor quality iris image is efficiently localized. Eyelash and eyelid regions are detected and denoted as black.

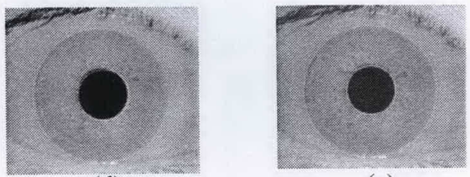
4.2 Threshold choice:

There are problems with threshold values to be chosen for edge detection. First this may result in critical edge points being removed, resulting in a failure to detect circles/arcs. Secondly, there is no precise criterion to choose a threshold value. Wildes [6] chose a hard threshold value and applied the Hough transform, but the choice of threshold was not based on solid grounds.

In the proposed algorithm the threshold value is selected by computing the maximum of the modulus at scale s which provides a solid criterion, because the sharp variation points of the image smoothed by h(x, y, s) are the pixels at locations (x, y), where the modulus M(x, y, s) has a local maxima in the direction of the gradient A(x, y, s) [3]. It can be clearly seen from Figure 10 that edges are well detected and the pupil is clearer as shown in (b) and (c) than edge and pupil in (a), as a result the pupil's circle is well localized as shown in (e). This is the reason why the proposed algorithm outperforms other algorithms which used a local scale and Canny edge detector.



(a) (b) (c)



(d) (e)

Figure 10: Edge influence in iris localization: (a) pupil edge map using Canny edge detector and threshold value (T1= 0.25 and T2=0.25), (b) and (c) pupil edge obtained with a multiscale edge detection using wavelet maxima for $\alpha = 0.4$ and $\alpha = 0.6$ respectively, (d) result of iris localization using Canny edge detector of example (a), (e) result of iris localization using multiscale edge detection (wavelet maxima) of example (c).

This analysis confirms and explains why this new method of multiscale edge detection using wavelet maxima for iris localization provides a precise detection of circles (iris and pupil) and a precise edge map obtained from the wavelet decomposition in the horizontal and vertical direction. This is turn greatly reduces the search space for the Hough transform, thereby improving overall performance.

5 Conclusion

A new method has been presented for iris localization. The algorithm is based on a multiscale edge detection using wavelet maxima and an adaptive thresholding which are very effective as a preprocessing step prior to the contour detection. This paper analyses the details of the wavelet maxima for edge detection proposed to localize iris in eye images. Experimental results have demonstrated that this approach is promising to improve iris localization for iris person identification.

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