IRIS Image Edge Detection using Wavelets

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Abstract

Edge detection is a terminology in image processing and computer vision, particularly in the areas of feature detection and feature extraction, to refer to algorithms which aim at identifying points in a digital image at which the image brightness changes sharply or more formally has discontinuities. There are many ways to perform edge detection. However, the most may be grouped into two categories, gradient and Laplacian. The gradient method detects the edges by looking for the maximum and minimum in the first derivative of the image. The Laplacian method searches for zerocrossings in the second derivative of the image to find edges. Another method of detecting edges is using wavelets. Specifically a two-dimensional Haar wavelet transform of the image produces essentially edge maps of the vertical, horizontal, and diagonal edges in an image. Wavelet analysis is a local analysis; it is especially suitable for time frequency analysis, which is essential for singularity detection. This research focuses on Haar and Daubechies D4 wavelet transform to find an edge from an image. The proposed technique has been demonstrated for iris imagery and the reported results have been compared with Daubechies D4 wavelet based edge detection technique.

Keywords:

Haar,Wavelets,Edge Detection, IRIS Image Edge

1. Introduction

A 'wavelet' is a small wave which has its energy concentrated in time. It has an oscillating wavelike characteristic but also has the ability to allow simultaneous time and frequency analysis and it is a suitable tool for transient, non-stationary or time-varying phenomena[1].More technically, a wavelet is a mathematical function used to divide a given function or continuous-time signal into different scale components. Usually one can assign a frequency range to each scale component. Each scale component can then be studied with a resolution that matches its scale. A wavelet transform is the representation of a function by wavelets. The wavelets are scaled and translated copies (known as "daughter wavelets") of a finite-length or fast-decaying oscillating waveform (known as the "mother wavelet") [2]. Wavelet transforms have advantages over traditional Fourier transforms for representing functions that have discontinuities and sharp peaks, and for accurately deconstructing and reconstructing finite, non-periodic and/or non-stationary signals.The wavelet analysis procedure is to adopt a wavelet prototype function, called an 'analysing wavelet' or 'mother wavelet'. Temporal analysis is performed with a contracted, high frequency version of the prototype wavelet, while frequency analysis is performed with a dilated, low frequency version of the same wavelet. Mathematical formulation of signal expansion using wavelets gives Wavelet Transform (WT) pair, which is analogous to the Fourier Transform (FT) pair. Discrete-time and discrete-parameter version of WT is termed as Discrete Wavelet Transform (DWT). DWT can be viewed in a similar framework of Discrete Fourier Transform (DFT) with its efficient implementation through fast filterbank algorithms similar to Fast Fourier Transform (FFT) algorithms.

Wavelet theory has been developed as a unifying framework only recently, although similar ideas and constructions took place as early as the beginning of the century. The idea of looking at a signal at various scales and analyzing it with various resolutions has in fact emerged independently in many different fields of mathematics, physics and engineering. In mid-eighties, researchers of the 'French school' built strong mathematical foundation around the subject and named their work 'ondeletts' (wavelets). The need of simultaneous representation and localisation of both time and frequency for non-stationary signals (e.g. music, speech, images) led toward the evolution of wavelet transform from the popular Fourier transform. Different 'time-frequency representations' (TFR) are very informative in understanding and modelling of WT.

Fourier Transform(FT): A signal in the time domain is described by a function f(t), where t is usually a moment in time. When we apply the Fourier transform to the signal, we obtain a function F(ω) that takes as input a frequency, and outputs a complex number describing the strength of that frequency in the original signal. The real part is the strength of the cosine of that frequency, and the imaginary part is the strength of the sine.

One way to obtain the Fourier transform of a signal is to repeatedly correlate the sine and cosine wave with the signal. When the results high valued, the coefficients of the

Manuscript received December 5, 2025
Manuscript revised December 20, 2025
https://doi.org/10.22937/IJCSNS.2025.25.12.10

Fourier transform will be high. Where the signal or the wave is close to zero, the coefficients will be low. Consider music, which is continuously varying in pitch. Fourier analysis done on the entire song tells you which frequencies exist, but not where they are.

Fourier transform is a well-known mathematical tool to transform time-domain signal to frequency-domain for efficient extraction of information and it is reversible also. For a signal x(t), the FT is given by:

$$X(f)=\int_{-\infty}^{\infty} x(t)e^{-j2\pi ft}dt \quad (1)$$

Wavelet transforms are broadly divided into two classes: continuous, discrete. A continuous wavelet transform (CWT) is used to divide a continuous-time function into wavelets. Unlike Fourier transform, the continuous wavelet transform possesses the ability to construct a time-frequency representation of a signal that offers very good time and frequency localization. For a prototype function ψ (t) ε L2(R) called the mother wavelet, the family of functions can be obtained by shifting and scaling this ψ (t) as:

$$\Psi a,b(t)=\frac{1}{\sqrt{a}}\Psi\left(\frac{t-b}{a}\right),\text{where } a,b\varepsilon R(a>0) \quad (2)$$

The DHWT is obtained by applying a low or high pass filter along the rows of the source image and down sampling, then applying a low or high pass filter along the columns of the intermediate image and down sampling once more. Low pass operations are implemented as averages of adjacent pixel values and high pass operations arc implemented as differences between adjacent pixels values. Down sampling is performed without loss of information, so that the wavelet representation of the image is the same size as the source image

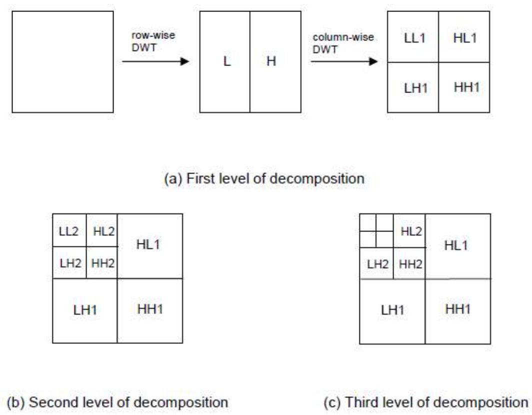

Figure 1 Three levels of decomposition in 2DWT

The Haar wavelet's mother wavelet function $\psi(t)$ can be described as

$$\Psi(t) = \begin{cases} 1 & 0 \le t \le 1/2, \\ -1 & 1/2 \le t \le 1, \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

And its scaling function $\varphi(t)$ can be described as

$$\emptyset(t) = \begin{cases} 1 & 0 \le t < 1, \\ 0 & \text{otherwise.} \end{cases} \quad (4)$$

Daubechies D4 wavelet transform: the Haar scaling and wavelet functions are calculated using two coefficients, h0, h1 and g0, g1, respectively. As the name suggests, the scaling and wavelet functions of the Daubechies D4 wavelet transform are calculated using four coefficients, h0, h1, h2, h3 and g0, g1, g2, g3.

The scaling function coefficient values are:

$$h_0=\frac{1+\sqrt{3}}{4\sqrt{2}} \quad (5)$$
$$h_1=\frac{3+\sqrt{3}}{4\sqrt{2}} \quad (6)$$
$$h_2=\frac{3-\sqrt{3}}{4\sqrt{2}} \quad (7)$$
$$h_3=\frac{1-\sqrt{3}}{4\sqrt{2}} \quad (8)$$

The wavelet function coefficient values are:

g0 = h3 g1 = -h2 g2 = h1 g3 = -h0 (9)

The scaling values, ai, and the wavelet values, ci are calculated by taking the inner product of the hj and gj coefficients and the signal. The equations for the scaling and wavelet inner products are shown below.

Daubechies D4 scaling function

ai=s[i]*h0+s[i+1]*h1+s[i+2]*h2+s[i+3]*h3 (10)

Daubechies D4 wavelet function

ci = s[i]*g0 + s[i+1]*g1 + s[i+2]*g2 + s[i+3]*g3 (11)

2. Existing Components of IRIS Edge Detection using Wavelets

In novel iris recognition system, Morphological operators are used for iris edge detection. Binary code representation via phase of Daubechies wavelet is gotten from each iris image and a minimum Euclidean distance classifier is applied for matching process[3].

The iris recognition system is combined from three major steps as follows:

Preprocessing: includes image capturing, image filtering and enhancement (optional) image iris localization, iris normalization, iris de-noising and enhancement.
Iris feature extraction.
Iris feature classification.

The first action of Preprocessing is to determine iris edges include inner (with pupil) and outer (with sclera) edges. Iris can be introduced as follows: a diaphragm with rich texture encircling a circular region (pupil). Both the inner boundary and the outer boundary of a typical iris can approximately be taken as circles but these two circles are usually not co-centric.There are two brilliant characteristics in iris which are useful in detection process. The more darkness of pupil region versus other parts and having medium gray level of iris district that limited between pupil (very low) and sclera (very high) levels. So a method for detecting these two boundariesare designed. Mathematical morphological operators with a suitable threshold are applied to iris images. The pupil and limbus centers with respect radiuses are calculated. The details of method are as follows.
Pupil Detection: Because the pupil is similar to a dark circular disk, pupil detection is equal to find the black circular region in the eye image.

Pre-Filtering and Enhancement [3]: First the captured image must be converted to grayscale format if it is not already an intensity image. Also, specular and corneal reflections can occur within the iris region corrupting the iris patterns and pupil darkness. A technique is required to isolate and exclude these artifacts as well as locating the circular iris region. When this spot happens in the pupil near from iris/pupil border, the detection of the inner boundary of iris fails. A grayscale images with 256 × 256 size is used in the process and a simple technique in order to eliminate artifacts on the eye image due to environmental light. The strategy is as

1. Evaluation the complement of image(the absolute Subtraction of each pixel's intensity from 255)
2. Filling holes in the intensity image. A hole is an area of dark pixels surrounded by lighter pixels. 4-connected background neighbors for input images is used which means a neighborhood whose neighbors are touching the central element on an (N-1)-dimensional surface, for the N-dimensional case.(N=2)
3. Evaluation again the complement of processed image.

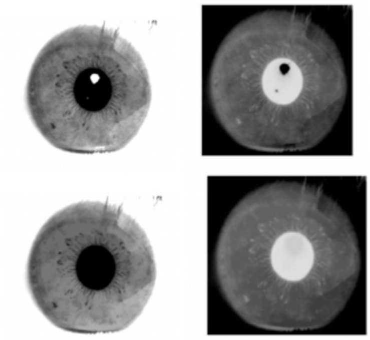

Figure 2.(a) Original image. (b) Complement of image.(c)Filling the holes. (d) Preprocessed image

Inner Edge Detection: The pupil edge detection is obtained from the preprocessed iris image. By a suitable threshold and a below strategy the inner edge of iris is detected.

1. Selecting two appropriate numbers that are indicated to two upper and lower thresholds (L,U).
2. For K=1:iteration number do as follows

   See te intensity of each pixel, if it is lower than the smaller L + K ,
   Convert is to 0 and if it is bigger thanU − K , covert it to 255.
   Otherwise filter the intensity to the lower one by a scaling factor.
3. The processed image is converted to a logical image that means a Black& White type image will be obtained.

At last, binary feature vector of length for every input image is generated. It is desirable to obtain an iris representation invariant to translation, scale, and rotation. In the algorithm, translation and scale invariance are achieved by normalizing the original image at the preprocessing step. Since features of this method are the selected coefficients of decomposition levels which are gotten via wavelet, there is no explicit relation between features and the original image. Therefore, getting approximate rotation invariance is achieved by unwrapping the iris disk at different initial angles.

3. NEW CLASS OF IRIS EDG DETECTION USING WAVLETS

The purpose of this research is to explain the working mechanism of edge detectors from the point of view of wavelet transforms and to develop a way to construct edge detector using wavelet transform. Input image is a gray scale Iris imagery where each pixel contains different intensity values of gray from 0 to 255. The image which is come from the previous block is used for the wavelet transform. Different wavelets(Haar and Daubechies D4) [4,5]are applied on the processed image which creates different subbands like LL,LH,HH and HL. When the Daubechies D4 wavelet transform is applied on the image,edge problem can be solved by any one of the three methods.

Treating the dataset as if it is periodic. The beginning of the data sequence repeats falling the end of the data sequence. Treating the data set as if it is mirrored at the ends.This means that the data is reflected from each end, as if a mirror were held up to each end of the data sequence. Gram-Schmidt orthogonalization. Gram-Schmidt orthogonalization calculates special scaling andc wavelet functions that are applied at the start and end of the dataset. Edge detector is the main block where the detection of the edge from the image has been performed. In this system, we use the LH,HH and HL subbands of the one –level decomposition because they have more detailed information of the dominant edges in the original image and an edge detector algorithm based on threshold value.
Output image is the edge image of the given image which is stored in the LL subband .This is what the solution to our problem.

A new wavelet based edge detection technique involves two main process to detect edges from iris imagery. Initially two different wavelet transforms such as Haar and daubechies D4 are applied to the the input image (Iris image) of size power of 2 . It creates four subbands LL,LH,HL and HH. Then an edge detector algorithm based on threshold value is applied to the LH,HL and HH subbands to produce edge image of the input image.The edge image is stored in the LL subband.

Haar wavelet transform: Each step in the forward Haar transform calculates a set of wavelet coefficients and a set of averages. If a data set s0, s1, sN-1 contains N elements, there will be N/2 averages and N/2 coefficient values. The averages are stored in the lower half of the N element array and the coefficients are stored in the upper half. The averages become the input for the next step in the wavelet calculation, where for iteration i+1, Ni+1 = Ni/2. The recursive iterations continue until a single average and a single coefficient are calculated. This replaces the original data set of N elements with an average, followed by a set of coefficients whose size is an increasing power of two (e.g., 20, 21, 22 ... N/2).

The Haar equations to calculate an average (ai) and a wavelet coefficient (ci) from an odd and even element in the data set are shown below:

ai = (s[i] + s[i+1])/2 (12)

ci = (s[i] - s[i+1])/2 (13)

In wavelet terminology the Haar average is calculated by the scaling function. The coefficient is calculated by the wavelet function. In the linear algebra view of the forward Haar transform, the first average is calculated by the inner product of the signal [s0, s1, ... sN-1] and the vector, of the same size, [0.5, 0.5, 0, 0, ..., 0]. This is the scaling vector. The first coefficient is calculated by the inner product of the signal and the vector [0.5, -0.5, 0, 0, ..., 0]. This is the wavelet vector.

The next average and coefficient are calculated by shifting the scaling and wavelet vectors by two and calculating the inner products. In the wavelet literature scaling and wavelet values are sometimes represented by hi and gi respectively. In the case of the Haar transform the scaling and wavelet values would be scaling function coefficients h0 = 0.5, h1 = 0.5 wavelet function coefficients g0 = 0.5, g1 = -0.5 . The scaling and wavelet values for the Haar transform are shown below in matrix form.

$$\begin{matrix} h_0 & h_1 & 0 & 0 & \cdots \\ g_0 & g_1 & 0 & 0 & \cdots \\ 0 & 0 & h_0 & h_1 & \cdots \\ 0 & 0 & g_0 & g_1 & \cdots \\ \vdots & \vdots & \vdots & \vdots & \ddots \end{matrix}$$

The first step of the forward Haar transform for an eight element signal is shown below. Here signal is multiplied by the forward transform matrix.

$$\begin{bmatrix} a_0 \\ a_1 \\ a_2 \\ a_3 \\ c_0 \\ c_1 \\ c_2 \\ c_3 \end{bmatrix} \Leftarrow \begin{bmatrix} a_0 \\ c_0 \\ a_1 \\ c_1 \\ a_2 \\ c_2 \\ a_3 \\ c_3 \end{bmatrix} = \begin{bmatrix} \frac{1}{2} & \frac{1}{2} & 0 & 0 & 0 & 0 & 0 & 0 \\ \frac{1}{2} & -\frac{1}{2} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{1}{2} & \frac{1}{2} & 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{1}{2} & -\frac{1}{2} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \frac{1}{2} & \frac{1}{2} & 0 & 0 \\ 0 & 0 & 0 & 0 & \frac{1}{2} & -\frac{1}{2} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \frac{1}{2} & \frac{1}{2} \\ 0 & 0 & 0 & 0 & 0 & 0 & \frac{1}{2} & -\frac{1}{2} \end{bmatrix} \bullet \begin{bmatrix} s_0 \\ s_1 \\ s_2 \\ s_3 \\ s_4 \\ s_5 \\ s_6 \\ s_7 \end{bmatrix}$$

The arrow represents a split operation that reorders the result so that the average values are in the first half of the vector and the coefficients are in the second half. To complete the forward Haar transform there are two more steps. The next step would multiple the ai values by a 4x4 transform matrix, generating two new averages and two new coefficients which would replace the averages in the first step. The last step would multiply these new averages by a 2x2 matrix generating the final avarage and the final coefficient.

The Daubechies D4 Wavelet Tranform :As noted above, the Haar scaling and wavelet functions are calculated using two coefficients, h0, h1 and g0, g1, respectively. As the name suggests, the scaling and wavelet functions of the Daubechies D4 wavelet transform are calculated using four coefficients, h0, h1, h2, h3 and g0, g1, g2, g3.
The scaling function coefficient values are:

$$h_0=\frac{1+\sqrt{3}}{4\sqrt{2}} \qquad (14)$$

$$h_1=\frac{3+\sqrt{3}}{4\sqrt{2}} \qquad (15)$$

$$h_2=\frac{3-\sqrt{3}}{4\sqrt{2}} \qquad (16)$$

$$h_3=\frac{1-\sqrt{3}}{4\sqrt{2}} \qquad (17)$$

The wavelet function coefficient values are:
g0 = h3   g1 = -h2
g2 = h1 (18)
g3 = -h0

As with the Haar transform[4,5] discussed above, the Daubechies scaling and wavelet function coefficients shift from right to left by two places in each iteration of a wavelet transform step. The Daubechies transform has no special cases when applied to an infinite signal. In the finite world outside of mathematics there would be a signal with N elements (ranging from s[0] to s[N-1]). When the scaling and wavelet functions are shifted so that the value of i in the equations above is N-3, two coefficients will stick out beyond the end of the signal (e.g., the inner product will be calculated with s[N] and s[N+1]). Although in practice we don't have infinite signals (or transform matrices) ignoring the special cases allows us to look at the Daubechies transform as a matrix, showing the structure of the coefficients. Daubechies forward transform matrix

$$\begin{bmatrix} \vdots \\ a_i \\ c_i \\ a_{i+1} \\ c_{i+1} \\ a_{i+2} \\ c_{i+2} \\ \vdots \end{bmatrix} = \begin{bmatrix} \ddots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \iddots \\ \cdots & h_0 & h_1 & h_2 & h_3 & 0 & 0 & 0 & 0 & \cdots \\ \cdots & g_0 & g_1 & g_2 & g_3 & 0 & 0 & 0 & 0 & \cdots \\ \cdots & 0 & 0 & h_0 & h_1 & h_2 & h_3 & 0 & 0 & \cdots \\ \cdots & 0 & 0 & g_0 & g_1 & g_2 & g_3 & 0 & 0 & \cdots \\ \cdots & 0 & 0 & 0 & 0 & h_0 & h_1 & h_2 & h_3 & \cdots \\ \cdots & 0 & 0 & 0 & 0 & g_0 & g_1 & g_2 & g_3 & \cdots \\ \iddots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots \end{bmatrix} \bullet \begin{bmatrix} \vdots \\ s_{2i} \\ s_{2i+1} \\ s_{2i+2} \\ s_{2i+3} \\ s_{2i+4} \\ s_{2i+5} \\ \vdots \end{bmatrix}$$

The inverse Daubechies D4 transform matrix is the transpose of the forward transform matrix: Daubechies inverse transform matrix.

$$\begin{bmatrix} \vdots \\ s_{2i} \\ s_{2i+1} \\ s_{2i+2} \\ s_{2i+3} \\ s_{2i+4} \\ s_{2i+5} \\ \vdots \end{bmatrix} = \begin{bmatrix} \ddots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \iddots \\ \cdots & h_2 & g_2 & h_0 & g_0 & 0 & 0 & 0 & 0 & \cdots \\ \cdots & h_3 & g_3 & h_1 & g_1 & 0 & 0 & 0 & 0 & \cdots \\ \cdots & 0 & 0 & h_2 & g_2 & h_0 & g_0 & 0 & 0 & \cdots \\ \cdots & 0 & 0 & h_3 & g_3 & h_1 & g_1 & 0 & 0 & \cdots \\ \cdots & 0 & 0 & 0 & 0 & h_2 & g_2 & h_0 & g_0 & \cdots \\ \cdots & 0 & 0 & 0 & 0 & h_3 & g_3 & h_1 & g_1 & \cdots \\ \iddots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots \end{bmatrix} \bullet \begin{bmatrix} \vdots \\ a_i \\ c_i \\ a_{i+1} \\ c_{i+1} \\ a_{i+2} \\ c_{i+2} \\ \vdots \end{bmatrix} \Leftarrow \begin{matrix} \vdots \\ a_i \\ a_{i+1} \\ a_{i+2} \\ c_i \\ c_{i+1} \\ c_{i+2} \\ \vdots \end{matrix}$$

4. SIMULATION RESULTS

The result that are reported below states that the Haar wavelet transform produces the better result over the Daubechies D4 wavelet transform. Edge founded using Haar wavelet transform is clearer than by the D4 wavelet transform. The Developed algorithms is implemented and tested with the newer version of Interactive data language.

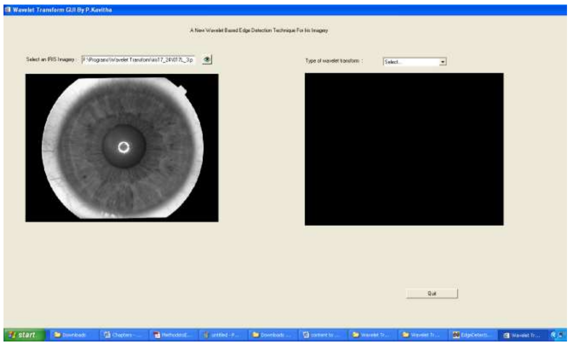

Figure 3. Iris Image Input

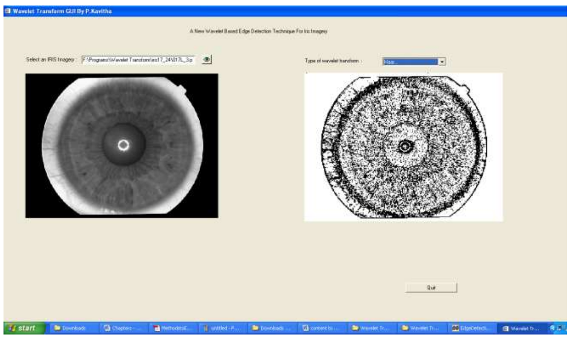

Figure 4. Edge image using Haar wavelet transform

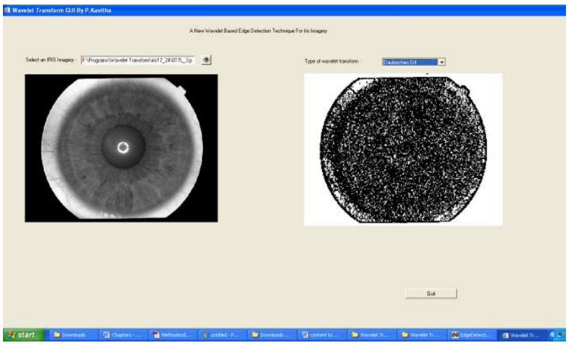

Figure 5. Edge image using Daubechies D4 wavelets

5. CONCLUSION

This reserach has been formulated to detect edges in the iris imagnery. Edge is a main tool in pattern recognition , image segmentation, and scene analysis .Thus this implementation can be used to compare the iris image in case of security. Haar wavelet transform produces better result than Daubechies D4. Thus Haar wavelet transform analysis is essential for singularity detection which results as an edge of the original image.

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