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WAVELET BASED EDGE DETECTION TECHNIQUE

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ABSTRACT: *Edge detection is one of the important preprocessing steps in many of the image processing applications. Wavelet based edge detection is found to be a better technique for various applications. Edge detection significantly reduces the amount of data and filters out useless information, while preserving the important structural properties in an image. In this paper, wavelet based edge detection technique is presented. Wavelet transform plays a very important role in the image processing analysis, for its fine result when it is used in multi-resolution, multi scale modeling. Wavelet analysis is a local analysis; it is especially suitable for time frequency analysis, which is essential for singularity detection, the fact motivated us to develop a technique to find an edge from an image. The edge detected using wavelet is quite poor, but using image fusion and thresholding algorithms improve the result up to the mark.*

Keywords: *Wavelet Transform, Edge Detection, Image Fusion.*

1. Introduction

The concept of wavelet analysis has been developed since the late 1980's. However, its idea can be traced back to the Littlewood-Paley technique and Calder'on-Zygmund theory [1] in harmonic analysis. Fourier analysis is also a good tool for frequency analysis, but it can only provide global frequency information, which is independent of time. Hence, with Fourier analysis, it is impossible to describe the local properties of functions in terms of their spectral properties, which can be viewed as an expression of the Heisenberg uncertainty principle [2]. In many applied areas like digital signal processing, time-frequency analysis is critical. That is, to know the frequency properties of a function in a local time interval. Engineers and mathematicians developed analytic methods that were adapted to these problems, therefore avoiding the inherent difficulties in classical Fourier analysis. For this purpose, Dennis Gabor [3] introduced a “sliding-window” technique, and used a Gaussian function ‘g’ as window function, and then calculated the Fourier transform of a function in the sliding window. The Gabor transform is useful for time-frequency analysis. The Gabor transform was later generalized to the windowed Fourier transform in which ‘g’ is replaced by a “time local “function called the “window” function. However, this analyzing function has the disadvantage that the spatial resolution is limited by the fixed size of the Gaussian envelope [4].The most preeminent books on wavelets are those of Meyer [5], [6] and Daubechies [7]. Meyer focuses on mathematical applications of wavelet theory in harmonic analysis. Daubechies gives a thorough presentation of techniques for constructing wavelet bases with desired properties; along with particular example of an orthonormal wavelet system was introduced by Alfred Haar [8]. However, the Haar wavelets are discontinuous and therefore poorly localized in frequency. Stephan Mallat [9] made a decisive step in the theory of wavelets in 1987 when he proposed a fast algorithm for the computation of wavelet coefficient. Stphan Mallat proposed the pyramidal schemes that decompose signals into sub bands. These techniques can be traced back to the 1970s when they were developed to reduce quantization noise [10].The framework that unifies these algorithms and the theory of wavelets is the concept of a multi-resolution analysis (MRA). In 1997, Chui and Wang [11] further discussed the asymptotically optimal time frequency localization by scaling functions and wavelets. In their paper they proved the convergence of the time-frequency window sizes of cardinal polynomial B-wavelets, which are used in Mallat's algorithm and are important in many other wavelet applications.

An edge in an image is a contour across which the brightness of the image changes abruptly. In image processing, an edge is often interpreted as one class of singularities. In a function, singularities can be characterized easily as discontinuities where the gradient approaches infinity. However, image data is discrete, so edges in an image often are defined as the local maxima of the gradient. Edge detection is a basic of pattern recognition, image segmentation, and scene analysis. An edge detector is basically a high pass filter that can be applied to extract the edge points in an image. This topic has attracted many researchers and many achievements have been made. In this paper, the mechanisms of edge detectors from the point of view of wavelets is explained and develop a way to construct edge detector using wavelet transforms.

2. Traditional Edge detector:

A significant change, usually the intensity, local to the image results in edges in the images. Edge detection is a necessary step in image processing, because the edges in images are the resultant of the boundary established between two objects or between an object and background. By detecting these edges, it is possible to divide the image into segment of meaningful objects. Edges in the image are detected by the first derivative and second derivative of the image intensity function. The fundamental steps in edge detection are:

1. Image smoothing for noise reduction: Noise in the image will affect considerably the first and second derivatives of the intensity. Hence noise must be filtered.
2. Detection of edges: A local operation that selects all the 'possible' edges in the image.
3. Edge localization: Selecting the true edges from the list of the 'possible' edges.

Gradient: The gradient is a measure of change in a function.

$$\nabla f = G\,[f(x,y)] = \begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \frac{\delta f}{\delta x} \\ \frac{\delta f}{\delta y} \end{bmatrix} \qquad (2\text{-}1)$$

The gradient, points in the direction of the maximum rate of increase of the function. The magnitude of it is given as

$$G[f(x,y)] = mag\,(\nabla f) \qquad (2\text{-}2)$$

This is the maximum rate of increase of f(x, y) per unit distance in the direction of G.

$$G[f(x,y)] \approx |G_x| + |G_y|$$
$$G[f(x,y)] = \max(|G_x|, |G_y|) \qquad (2\text{-}3)$$

Direction of gradient is given by

$$\propto = \tan^{-1}\left[\frac{g_y}{g_x}\right] \qquad (2\text{-}4)$$

α is measured with respected to x axis.
Fog digital images, the simplex gradient approximation is

$$g_x = -\frac{\delta f(x,y)}{\delta x} = f(x+1,y) - f(x,y)$$
$$g_y = -\frac{\delta f(x,y)}{\delta x} = f(x,y+1) - f(x,y) \qquad (2.5)$$

These two equations are implemented using following one- dimensional mask

-1	1

-1
1

To detect diagonal edges in images a two-dimensional mask is required. The general form a mask is as follows.

Z_1	Z_2	Z_3
Z_4	Z_5	Z_6
Z_7	Z_8	Z_9

2.1 Types of Edge Detectors

Edge detectors can be classified into two broad categories and are given below along with the list of some important approaches followed in that category.

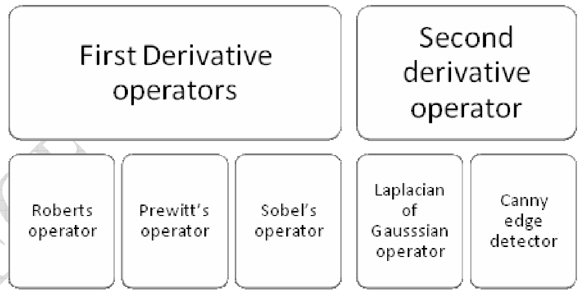

Figure 1: Type of Edge Detector

2.1.1 First Derivative Operators

The method of finding the edge using first derivative operators is called as Gradient method of edge detection. This technique uses the maximum and minimum in the gradient of the first derivative of the image.

1. Roberts Operator:

This operator is used to detect the diagonal edges and then are put together to find resultant edge. This operator highlights regions of high spatial frequency which often correspond to edges. It takes grayscale image as input to the operator and gives grayscale image as the output. This is the simple approximation to find gradient magnitude and is given by

$$G[f(x,y)] = |f(x,y) - f(x+1,y+1)| + |f(x+1,y) - f(x,y+1)| \qquad (2\text{-}6)$$

$$G[f(x,y)] = |G_x| + |G_y| \qquad (2\text{-}7)$$

where Gx and Gy can be calculated as by

G_x

-1	0
0	1

G_y

0	-1
1	0

2. Prewitt Operator:

This operator uses masks of size 3X3 to approximate to the partial derivatives. This operator is quite accurate when compared with the Roberts operator. The Prewitt operator is given by

G_x

-1	-1	-1
0	0	0
1	1	1

G_y

-1	0	1
-1	0	1
-1	0	1

The derivative in x-direction is calculated by the difference between third and first rows of 3x3 regions. Similarly for y direction third and first columns difference is considered i.e.

$$g_x = \frac{\delta f}{\delta x} = (Z_7 + Z_8 + Z_9) - (Z_1 + Z_2 + Z_3)$$

$$g_y = \frac{\delta f}{\delta y} = (Z_3 + Z_6 + Z_9) - (Z_1 + Z_4 + Z_7) \quad (2\text{-}8)$$

3. Sobel Operator:

This is a 3 X 3 mask and is the modified version of Prewitt operator. In Prewitt operator, the center coefficient used is '1'. If this coefficient is changed to '2' the resultant mask is Sobel operator to find edges. The kernels can be applied separately to the input image, to produce separate measurements of the gradient component in each orientation, g_x and g_y. These can then be combined together to find the absolute magnitude of the gradient at each point and the orientation of that gradient . The masks used to convolute Sobel operator are

-1	-2	-1
0	0	0
1	2	1

-1	0	1
-2	0	2
-1	0	1

The Sobel operator is the magnitude of the gradient and can be calculated as,

$$M = \sqrt{g_x^2 + g_x^2} \quad (2\text{-}9)$$

Where

$$g_x = \frac{\delta f}{\delta x} = (Z_7 + 2Z_8 + Z_9) - (Z_1 + 2Z_2 + Z_3)$$

$$g_y = \frac{\delta f}{\delta y} = (Z_3 + 2Z_6 + Z_9) - (Z_1 + 2Z_4 + Z_7)$$

(2-10)

The edge detection can be made selective by thresholding the gradient image. In order to highlight the principal edges as well as gaining high connectivity smoothing can be included along with threshold.

2.1.2 Second Derivative Operators:

The second order derivative finds local maxima in gradient values and considers them as edges. There will be a zero crossing in second derivative of the gradient at the detected edges. For better edge performance, the operator should be capable of computing first or second derivative for every pixel in the image and it should be compatible for any image scale. Compatibility with varying image scales results in sharper edge detection.

Laplacian Operator:

This is the basic operator used with the second derivative technique. The Laplacian operator for a function f(x, y) is given by

$$\nabla^2 = \frac{\delta^2 f}{\delta x^2} + \frac{\delta^2 f}{\delta y^2} \quad (2\text{-}11)$$

Where

$$\frac{\delta^2 f}{\delta x^2} = f(x, y+1) - 2f(x, y) + f(x, y-1)$$

$$\frac{\delta^2 f}{\delta y^2} = f(x+1, y) - 2f(x, y) + f(x-1, y) \quad (2\text{-}12)$$

The above equations are used to obtain the following mask,

$$\nabla^2 = \begin{matrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{matrix}$$

The Laplacian operator detects an edge when it takes transition through zero. This operator ignores uniform zero region, since to detect the edge, 'transition across zero' is the only indication but not the zero value itself. This operator will give the point at which edge is present but the actual edge location should be determined by the interpolation method.

1. **Laplacian of Gaussian (LoG) Operator:**

LoG operator uses zero crossing technique for the edge detection and edge location is estimated using sub-pixel resolution by linear interpolation. LoG filter used for this purpose is $\nabla^2 G$ where

$$\nabla^2 \text{ is } \frac{\delta^2}{\delta x^2} + \frac{\delta^2}{\delta y^2} \quad (2\text{-}13)$$

$$G \text{ is } G(x, y) = e^{-\frac{x^2+y^2}{2\sigma^2}}$$

Where σ is space constant

$$\nabla^2 G = \frac{\delta^2 G(x,y)}{\delta x^2} + \frac{\delta^2 G(x,y)}{\delta y^2} \quad (2\text{-}14)$$

Solving this equation yields

$$\nabla^2 G(x, y) = \left[\frac{x^2 + y^2 - 2\sigma^2}{\sigma^4}\right] e^{-\frac{x^4+y^4}{2\sigma^2}} \quad (2\text{-}15)$$

In this approach, an image is to be convolved with Gaussian filter to get better noise performance. The insignificant edges are ignored because the pixel is treated as edge if and only if it has peak value greater than some thresholds. The final output of LoG is obtained by convolution operation

$h(x,y) = [\nabla^2 G(x,y)] * f(x,y)$ (2-16)

where f(x,y) is an image intensity function.

Masks of any size can be generated using the LoG operator by sampling it and scaling the coefficients to get their sum as zero.

2. **Canny Edge Detector Operator:**

The canny edge operator is superior to the operator covered till now in the discussion. This operator is characterized by low error rate, better localization of edge points and importantly single edge point response. For 2-dimensional edges, image is first smoothed by using circular two- dimension Gaussian function, computing the gradient of the result and then using the gradient magnitude and direction to approximate edge strength and direction at every point.

The convolution of the image with the Gaussian filter gives an array of smoothed data f_s,

$f_s = [G(x,y) * f(x,y)]$ (2-17)

Where, f(x,y) is the input image and

$G(x,y) = e^{-\frac{x^2+y^2}{2\sigma^2}}$

The next step is to compute the gradient magnitude and angle,

$M(x,y) = \sqrt{g_x^2 + g_y^2}$ and

$\alpha(x,y) = \tan^{-1}\left[\frac{g_y}{g_x}\right]$ (2-18)

Where,

$g_x = \frac{\delta f_s}{\delta x}$ and $g_y = \frac{\delta f_s}{\delta y}$ (2-19)

Then the filter masks are used to obtain g_x and g_y. The magnitude array M(x,y) will have large ridges around the local maxima. These are not desirable and hence are minimized using the technique called non-maxima suppression. The intension of including this step is to specify the number of discrete orientations of the edge normal. The false edge fragments that reside after non-maxima suppression are reduced by using double thresholding algorithm that uses 2 thresholds T1 and T2 with T2 ≈2T1. The inclusion these two steps reduces the edge to one pixel size.

3. **Wavelet Transform for an image**

The Wavelet representation for an image corresponds to a decomposition of the vertical image into a set of independent frequency bands; approximation and three spatial: horizontal, vertical and diagonal (oblique) orientations. Grannock founds discrete wavelet transform very useful in edge detection [12]. The basic of wavelet decomposition can be represented as shown in figure 1 and 2.

The 3 X 3 masks are constructed symmetrically about the center point. The masks with symmetry around the centre point are much helpful to consider nature of data on either sides of the centre point to detect edges [1]. The coefficients of masks used must be sum to zero, because this gives a response of zero in areas of constant intensity which is a characteristic of derivative operator.

The method, by which the decomposition components are fetched from the original data, is shown in figure 3. The filters used after down-sampling decide the output characteristics. These filters are used in the pair by different scientist and these are well known as the wavelet families.

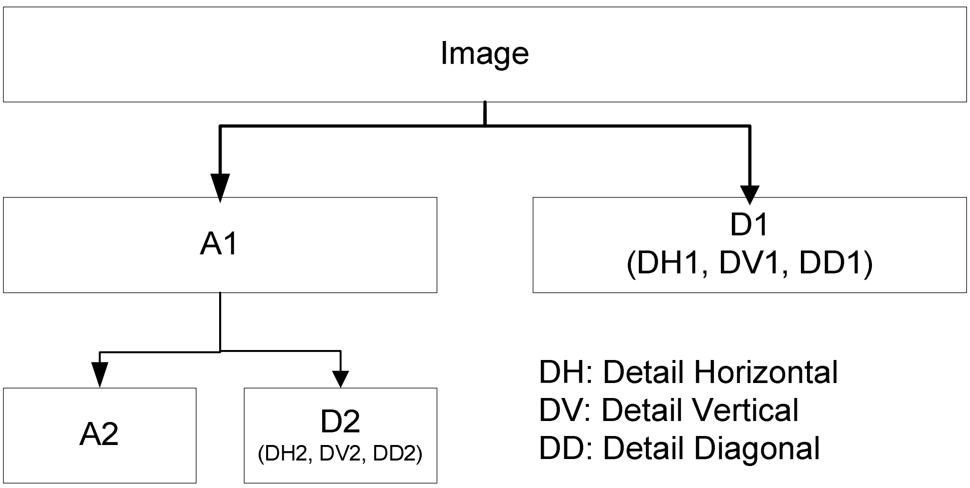

Figure 2: Wavelet Decomposition

<table>
<tr><td>LL2
(A2)</td><td>HL2
(DH2)</td><td rowspan="2" colspan="2">HL1
(DH1)</td></tr>
<tr><td>LH2
(DV2)</td><td>HH2
(DD2)</td></tr>
<tr><td colspan="2">LH1
(DV1)</td><td colspan="2">HH1
(DD1)</td></tr>
</table>

Figure 3: Wave Decomposition Representation for Image

There are different types of wavelet families whose qualities vary according to several criteria. The different Wavelet families are HAAR, Daubechies, Symlets, Coiflets, Biorthogonal, Reverse Biorthogonal, Meyer, Discrete Approximation of Meyer, Gaussian, Mexican Hat, Morlet, Complex Gaussian, Shannon, Frequency B-Spline, Complex Morlet etc.

The different wavelet family performs different filtering applications, and based on that output may differ, for the application of wavelet for edge detection, Daubechies-2 performs better.

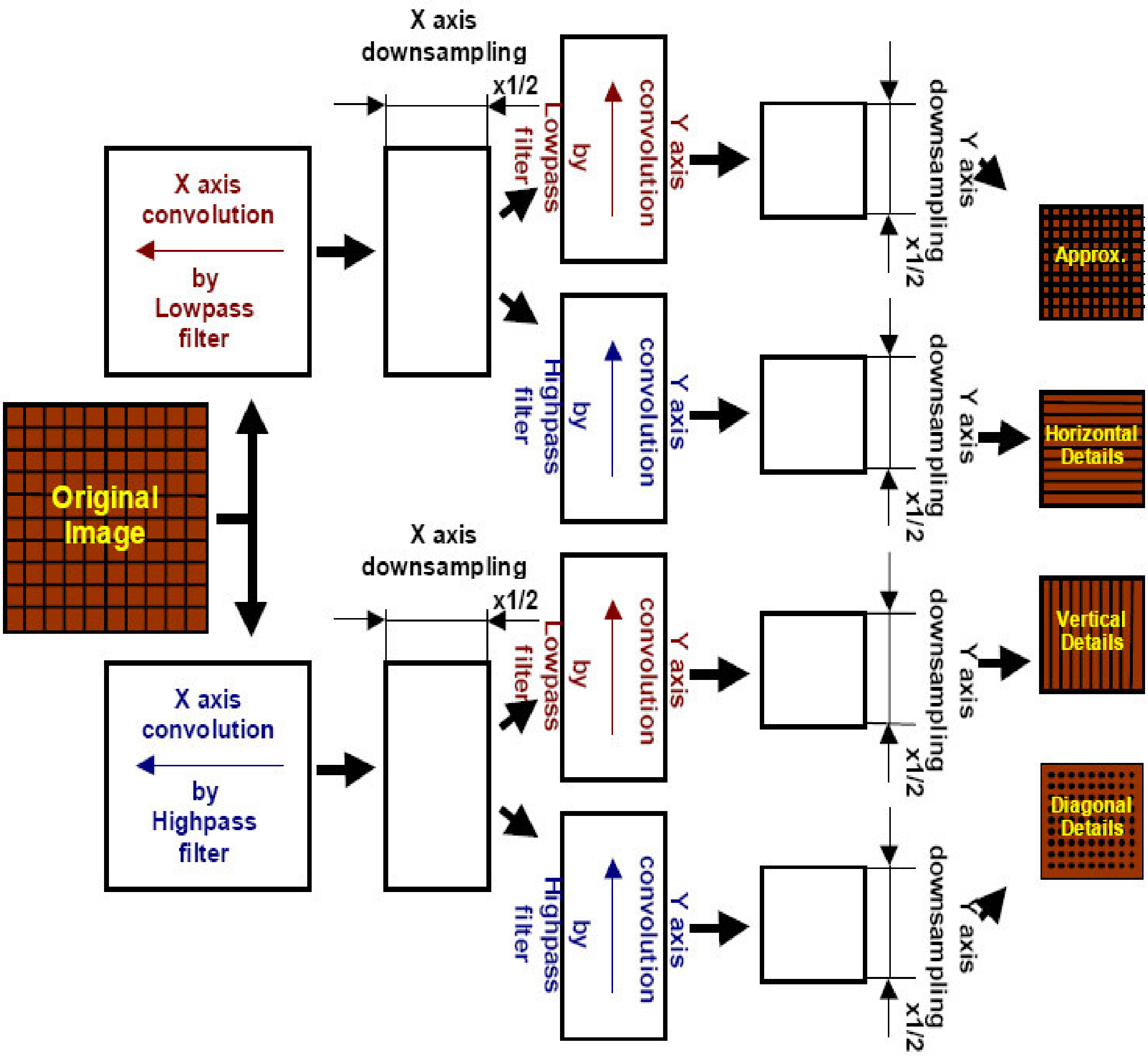

Figure 4: Wavelet Decomposition Generator

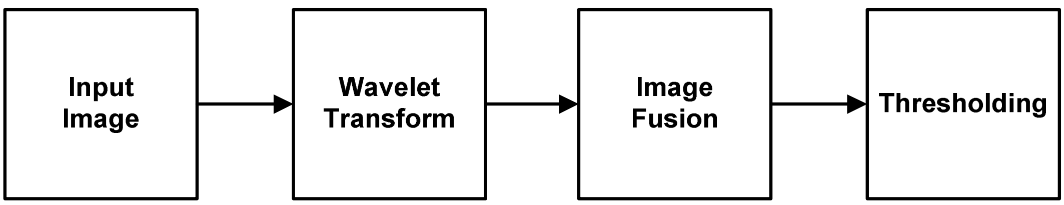

Figure 5: Proposed wavelet based edge detection techniques

The proposed technique has composed with four different blocks as shown in figure 4, each of them are described as under.

A. Input Image
The images are used in this paper are gray scaled image, where each pixel contains different intensity values of grey from 0 to 255.

B. Wavelet Transform
The image which is come from the previous block is used here for the wavelet transform. The wavelets are applied on processed image which creates different sub-bands like LL, LH, HH and HL. The wavelet transform is basically a convolution operation, which is equivalent to passing an image through low-pass and high-pass filters. Let the original image be I(w, h), then the LH sub-band represents the vertical edges, HL sub-band represents the horizontal edges and HH sub-band represents the diagonal edges of I(w, h).using these properties of the LH,HH and HL sub-bands, construct an edge image.

C. Image fusion for edge detection
The LH sub-band represents the vertical edges, HL sub-band represents the horizontal edges are connected with the help of image fusion, and hence this adds the vertical and horizontal edges to get all the edges of the image.

D. Thresholding
The edge that is generated with the help of the image fusion is a bit not clear and thresholding will improve the edges.

The proposed technique can be observed from the figure 5. The Original Image is first converted into the four decomposition levels by wavelet transformation using Daubechies-2 wavelet family. The Horizontal Component and Vertical components are fused together using wavelet fusion techniques to fetch out the edges of the image. This edges are not clear in visualization, and is improves after thresholding.

5. Experimental result using MATLAB

The proposed technique has found the edges from the gray scale images which are very evident and clear by the visualization. The Daubechies-2 wavelet based response is shown in the figure 6 and 7. The basic grid image and Chakra image are used respectively in figure 6 and figure 7. Image is first wavelet transformation and four decomposition levels are fetched. The approximation component, and three details spatial domain, vertical, horizontal and diagonal component are fetched out. The vertical and horizontal components are fused together using wavelet fusion techniques. The resulting image is the edge of the image, thought visualization is not much clear. In order to improve the edges, this resultant image is passed thought the threshold algorithm and resultant image is good in visualization.

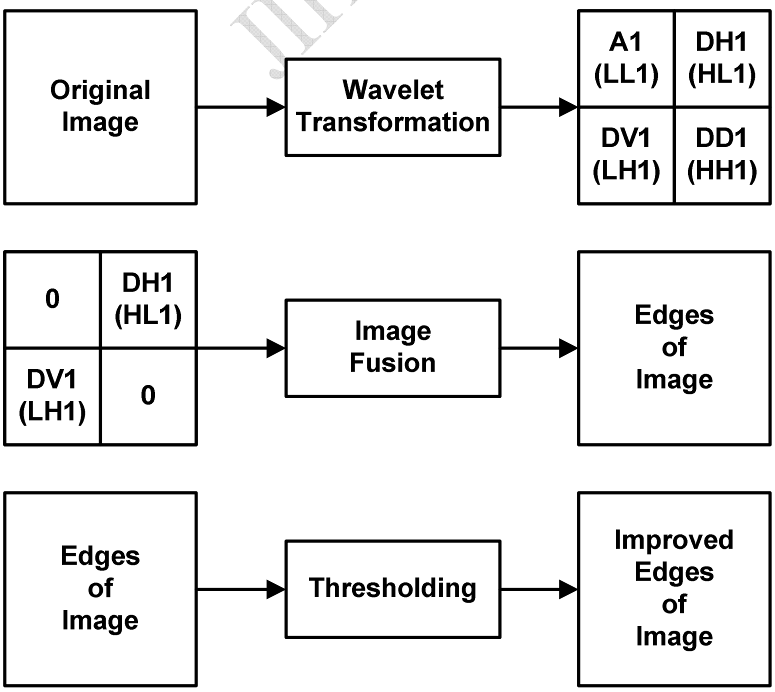

Figure 6: Proposed System detail architecture

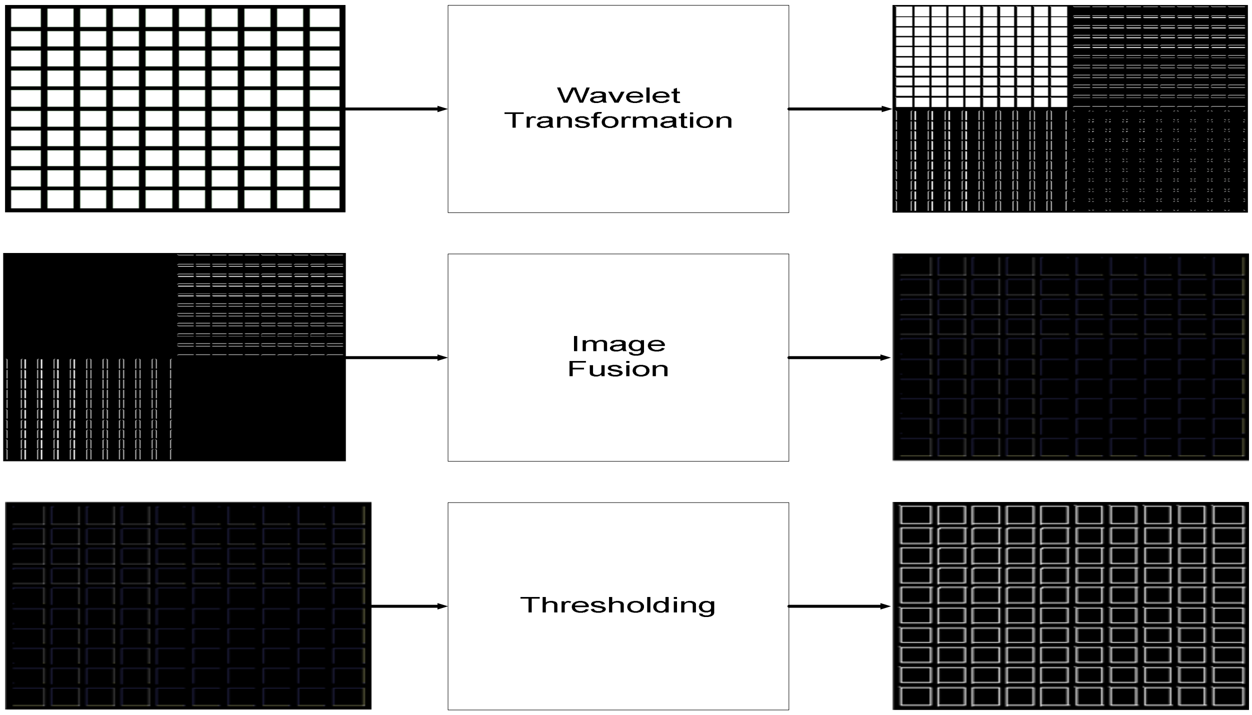

Figure 7: Wavelet Edge Detection over Grid

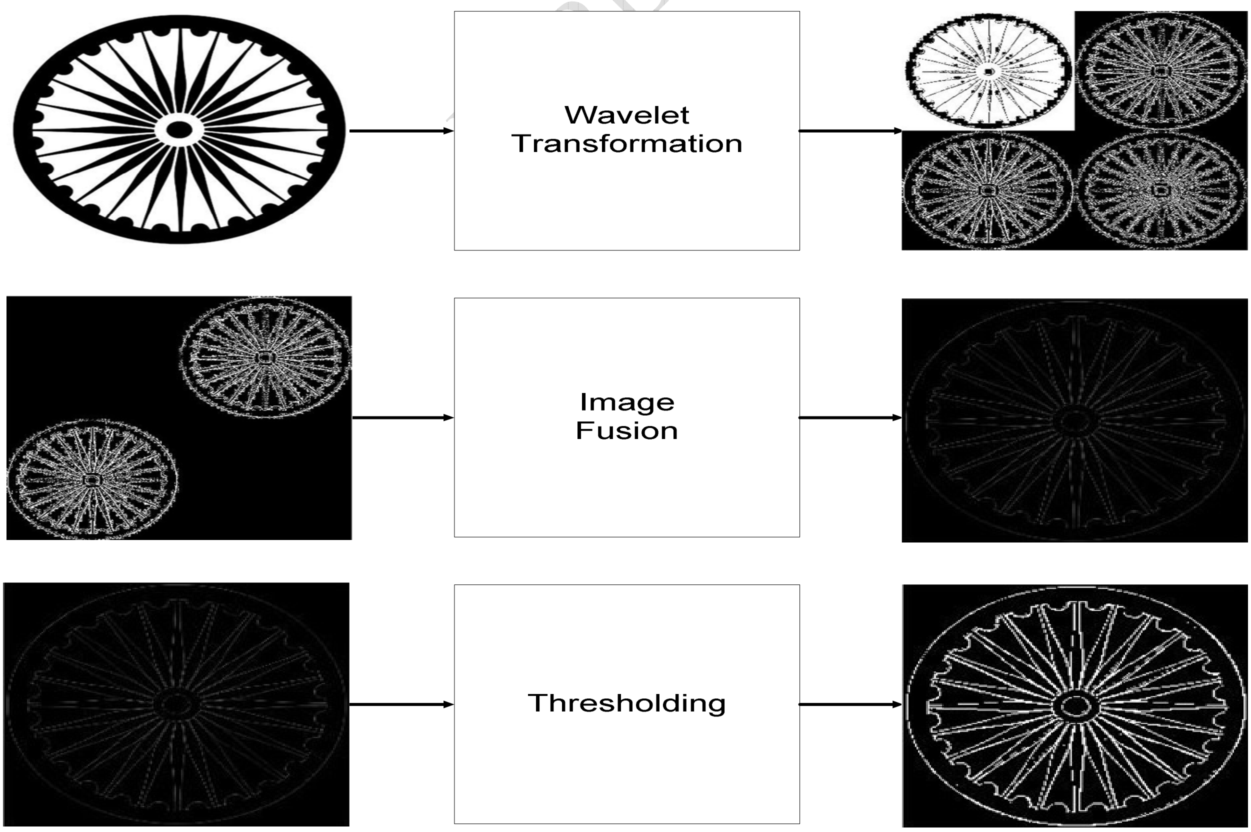

Figure 8: Wavelet Edge Detection over Grid

6. Conclusion

In this paper, edge detection technique using wavelet has been developed. The developed technique has performed over gray scale imagery and produces very promising result. Haar wavelet transform analysis is essential for singularity detection which results as an edge of the original image. Good performance of this technique for such imagery shows that it may be motivating to use this algorithm in other imagery application also. As a scope of further research this technique can also be extended for clustering, indexing and retrieval of image.

7. References

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