Combined Edge Detection using Wavelet Transform and Signal Readjustment: A Survey

Abstract

In this work, a method based on Haar wavelet evaluation and Signal Readjustment is used for border detection. Earlier, several border detection techniques as those developed by Sobel, Roberts, Prewitt, Robinson, and Canny were employed. Despite being one of them, Canny Boundary Detector's precision falls short of expectations. To improve the accuracy of Canny Boundary Detector it had been hold-forth to Time-Scale plane. The suggested algorithm will be performed in two stages: first, a line model will be defined as an instance of a signal, and its identification will be carried out using the Haar wavelet filter; second, signal readjustment techniques will be used to examine how the boundary related into an outline is handled. The technique will be examined using various images at various signal-to-noise ratios (SNRs). It will be examined for reliability, accuracy, and sturdiness. The signal Registration approach is used for the construction of edge linkage using readjustment variables.

Key words: Edge identification, Signal Registration, Wavelet Transform, Haar Wavelet Transform.

Introduction

The main purpose of this report is to perform a wavelet transform on an image to detect its boundaries. The relevant (ROI) regions are distinguished by different degrees of the pixel's magnitude significance, according to the boundary identification theory, and a boundary is defined as a location where image level or brightness suddenly changes. A wide range of topics such as image acquisition, enhancement and processing in [1] are helpful in providing an insight for this study. The foundation for the practice of this study was laid by Rosenfeld *et al.* in [2]. After then many researchers worked in the field of image processing [3-6]. Numerous border detection [7] methods now in use depend on pixel intensity, which is determined by the convolution of biased matrices known as the local gradient mask. Another method for detecting boundaries is approximation of circular masks and linking each image point with a local domain of homogeneous intensity. Their major drawbacks of preexisting methods are:

a.) high sensitivity to noise ratio,

b.) and inability to discriminate between edges and textures.

Due to these shortcomings, several sophisticated boundary trackers have been proposed that not only identify boundaries but also improve their quality by joining nearby boundary points into a contour.

To overcome these drawbacks research has been carried out on different boundary detectors based on the scaling, contours, morphological functions and gradient values. Among all the applied methods, the Canny boundary detector [8] is swift, powerful and authentic but the precision is not acceptable, because of the parameter s. To improve the accuracy of Canny boundary detector, it was performed in the time-scale plane [9]. Analyzing signals at different scales tends to increase the authenticity and accuracy of boundary detection. By defining local signal formation, it is possible to simultaneously examine shapes from coarse to precise [10]. The distinction between boundaries and textures can be easily seen when switching among various levels [11]. Due to this potential of wavelets [12], it has special use in detection of boundaries and image segmentation, especially if images are noisy, and of heterogeneous intensities.

Research problems & Motivation

The boundary detection gives an outline with lack of coherence. Computational prototypes which are much more advanced than local boundary detectors are required to remove these disjoints. A hardback boundary linkage model based on image readjustment [13] is suggested to overcome the above problem. The algorithm has two levels. Level 1 is a timescale build detection of contours of an image which results in an edge image. Level 2 removes the disjoints in this boundary image using a readjustment procedure. This method [13] calculates an index value which specifies the level of credence in the subordination of two close by elements in the outline design for the detected outline points.

The report is arranged in different parts:

Element 1: explains the theoretical aspects of boundary identification, signal-based edge modelling, and wavelet-based edge identification.

Element 2: focuses on a contour's boundary interconnection. The signal readjustment approach is used for formulation of boundary linkage using readjustment parameters.

Definition and theoretical aspect of the transform

What is Edge detection?

Edge detection is an image processing [4] technique for finding the boundaries of objects within images. It works by detecting discontinuities in brightness. Boundary detection is used for image segmentation and data extraction in areas such as image processing, computer vision, and machine vision. This boundary detection problem can be remodeled into a problem of unexpected magnitude variations in 1-D signal constituting pixel intensities in matrix form in a signal. Since pixels are usually called as the discrete components in 1D signal samples/images but in our report, we address them as units, instead of pixels or samples. The boundary model is represented in the form of signal and then its boundary detector is developed.

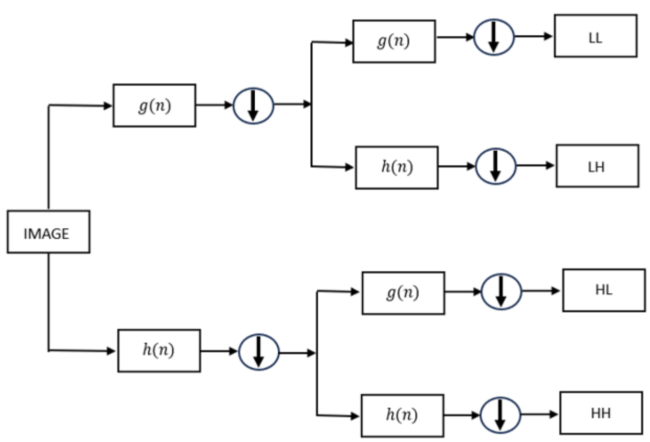

Fig 1: Block Diagram of Haar transform for boundary detection.

What is the Edge model?

Representation of boundary through trained set of data or mathematical equation is a boundary model. An ideal case of boundary model is given in equation1 that has a row signal or a column point which orthogonally cuts a boundary in an image.

$$s(n) = h_0 + h_1 u(n - n_0) \ldots\ldots\ldots (1)$$

where h0 and h1 are different levels of signal prior to and post boundary detection.

Since the boundaries are noisy the belief on boundaries taking shape as step function is expected to malfunction with several real test cases. Hence, a slope function describing a boundary neighborhood, 'f_{slope}' is defined which substitutes the 2nd term in Eq. (1). The 'f_{slope}' function is given as:

$$f_{slope}(n, h_1, \varphi) = \begin{cases} 0, & n < 0 \\ n \cdot tg(\varphi), & n \in [0, k], k = \left\lceil \left\| \frac{h_1}{tg(\varphi)} \right\| \right\rceil \\ h_1, & n > k \end{cases} \ldots\ldots\ldots (2)$$

where 'φ' denotes the slope of boundary, 'h_1' denotes change in signal level while intersecting the component of the boundary. Equation (2) remains justifiable only when the width of boundary is to be modified.

The attributes of boundaries in substantial images are modified depending on the measure of amount of noise and the degree of slope in equation (1) and is described in Eq. (3).

$$s(n) = h_0 + \sum_{i=1}^{N_e} f_{slope}(n - n_i, h_i, \varphi_i) + v(n) \ldots\ldots\ldots (3)$$

where Ne denotes edge number and ν(n) stands for White Gaussian Noise.

Equation (3) gives the position of i_{th} boundary segment but does not describe anything about the substantial boundary position. Hence, the position of the i_{th}boundary e_i is given by:

$$e_i = \left\lceil \frac{k}{2} \right\rceil + n_i \ldots\ldots\ldots (4)$$

Model (3) is more mathematically accurate, clear to grasp, and simpler to use than the standard boundary models. It also describes the restrictions of preexisting boundary detectors based on the amplitude changes, slant and amount of disruption present in signals. The computation of a boundary detector precision, authenticity and sturdiness is easily done through Eq. (4).

Adaptive boundary detection using wavelet transforms.

At various levels, coarse and refined signal components are examined. A time expression is portrayed by the wavelet transformation as a two-dimensional function with the variables 'α' and 's '. Variable 'α'' is used for scaling the function by compressing or stretching it. Variable 's' translates the wavelet function along the time axis. 'α'. Wavelet transform is defined by:

$$W_s(\alpha,\tau) = \sum_{n=0}^{N=1} \frac{1}{\sqrt{\alpha}} s(n)\psi\left(\frac{n-\tau}{\alpha}\right) \dots \dots \dots (5)$$

where N is the length of signal $s(n)$ and $W(t)$ is called mother wavelet. *A mother wavelet is a prototype wavelet from which all other wavelets are generated.* Eq. (6) is a Haar wavelet equation. Haar Wavelet Transform has an ability to represent the amplitude variation in the signal. Haar wavelet is defined as:

$$\psi(n) = 2^{\frac{-\alpha}{2}} \begin{cases} 1, & 0 \le n < 2^{\alpha-1} \\ -1, & 2^{\alpha-1} < n \le 2^{\alpha} \\ 0, & otherwise \end{cases} \dots \dots \dots (6)$$

Henceforth, Haar wavelet transformation of any signal can be described as a summation of the two regions inside the range of wavelet transform. Within the boundary location, the Haar wavelet transformation is given by:

$$W_s(\alpha,\tau) = 2^{\frac{-\alpha}{2}} \left(\sum_{n=\tau-2^{\alpha-1}}^{\tau} n \cdot tg(\varphi) - \sum_{n=\tau}^{\tau+2^{\alpha-1}} n \cdot tg(\varphi) \right) \dots \dots \dots (7)$$

It does not exhibit a lateral shift in the transformation dimension, is orthogonal, and is densely packed. Eq. 7 defines the wavelet transform for inside regions and it depends entirely on the slant of the boundary and scope parameter 'α'. However, we must also consider the circumstances in which the wavelet is in the outside boundary region. Then Eq. (5) and (6) can be combined and given as:

$$W_s(\alpha,\tau) = -2^{\frac{-\alpha}{2}}\left(\sum_{n=n_0+1}^{\tau+2^{\alpha-1}} n \cdot tg(\varphi)\right) \ldots\ldots\ldots (8)$$

If the wavelet is relocated further, such that the condition 's > n0', the transform is stated as:

$$W_s(\alpha,\tau) = 2^{\frac{-\alpha}{2}}\left(\sum_{n=n_0+1}^{\tau} n \cdot tg(\varphi) - \sum_{n=\tau}^{\tau+2^{\alpha-1}} n \cdot tg(\varphi)\right) \ldots\ldots\ldots (9)$$

A max entropy thresholding approach is utilized in the proposed boundary detector. It is a quantity of data based on the crucial value of the threshold 'T' in the time-scale axis that amplifies $H = H_n + H_e$, where H_n and H_e are given by Eq. (10):

$$\begin{aligned} H_n(s(n)) &= -\sum_{i=1}^{T} p_i \cdot \log(p_i) \\ H_n(s(n)) &= -\sum_{i=T+1}^{L} p_i \cdot \log(p_i) \end{aligned} \qquad (10)$$

where p_i is the probability of the specimen value $s(n)$ at i. The threshold T conditioned on the signal and is calculated for each scale individually.

The program of the Haar wavelet transform deployed boundary detector is implemented in 6 paces:

(1) Haar wavelet transform, reduces the time complexity, maintaining the peculiarity of boundary detection and resulting in time-scale plane P. The timescale plane P is then performed with modulus maxima detection resulting in a level, MM.

(2) Connecting each MM maxima point to the P period level P maxima chords. A set S of modal max chords is produced.

(3) On level P, the threshold value T is determined for each level. If the threshold T is surpassed the boundary maxima are detected and this process is called Adaptive boundary maxima selection.

(4) Set S having units of boundary maxima are marked as boundary max chords.

(5) The location of modulus maxima at rock bottom discovered scale is the boundary location.

The suggested boundary detector's fundamental components are the wavelet transformation and changing border modal maxima identification. Boundary detection exclusively is dependent on the data in the dimensions (row or column) of the image. Insertion of a wider region must usher supplementary statistics concerning the standard level of the detected boundary. It has been proved that a few faulty edge detections may also be a part of the result from the image. To remove the liable boundaries out, a boundary linkage activity is set in motion between adjacent dimensions of image signals.

Multi Resolution in Signal Readjustment using Wavelet Theory

With a focus on wavelet theory and multiresolution signal readjustment [14], this study provides a foundational contribution to the discipline of signal processing and classification [15]. The notion of multiresolution analysis utilizing wavelet transformations, which has had a significant impact on different fields of image readjustment [16, 17], image analysis [18], processing [19], detection [20] and data compression, is introduced in [21] and formalized. It involves representing a signal at different levels of resolution and decomposition at different scales using wavelet transform.

Orthogonality in Wavelet Transformation for multi resolution analysis

Even though the original Haar wavelet has drawbacks, its essential concepts have influenced the creation of more sophisticated wavelet families that have enhanced features. The theory of orthogonal function systems [22], which are collections of functions that are orthogonal to one another about a particular inner product. In many mathematical and technical fields, including signal processing, the Haar wavelet is an orthogonal function system that was developed by

Haar. A foundation for representing signals at many sizes and places is the Haar wavelet, which is a piecewise constant function. It is the most basic type of wavelet and provides the basis for wavelet analysis.

Key Concept of Wavelet Analysis

[23] demonstrates how to grasp wavelet transformations by using the ideas of Fourier analysis, convolution, and multiresolution analysis.

Continuous Wavelet Transformations

Using the continuous wavelet transform, signals can be examined at various scales and locations. As a result of its ability to identify localized features in signals, continuous wavelet transformations are an effective method for identifying sudden changes and rhythmic patterns.

Discrete Wavelet Transformations

DWTs are suitable for digital signals. The idea of wavelet coefficients, down sampling, and filter banks, emphasizing the effectiveness of DWT in separating signals into various frequency components. DWT wavelet bases are useful for applications like data compression, denoising, and feature extraction since they are created to satisfy certain criteria.

Image Readjustment

According to their guiding principles, characteristics, and applications, image readjustment [14] techniques are classed, and challenges arise from variances in image scale, rotation, translation, and distortion. The many categories of mage registration techniques are based on the underlying methodologies and strategies [24].

Area Based Methods

The main objective of area-based approaches is to match relevant image sections based on statistical or intensity similarity measurements. These techniques are effective and perform well when pixel values can be compared directly, although they could be sensitive to noise and changes in lighting.

Feature Based Methods

Using feature-based approaches, distinguishing features like points, bends, borders or locations are identified and compared between images. These techniques are suited for situations with considerable topological changes since they are resistant to dimensional and spin alterations.

Hybrid Methods

In order to take advantage, hybrid methods combine aspects of both area-based and feature-based approaches. These techniques are adaptable for a variety of registration jobs since they strive to strike a compromise between accuracy and durability.

Optimization Based Methods

The goal of optimization-based approaches for image readjustment is to identify the transformation parameters that will minimize a specified cost function. These techniques offer an adaptable framework for dealing with varied deformations.

These methods offer helpful insights into the difficulties of aligning images and creating meaningful correspondence by giving a thorough overview of image registration techniques and their applications.

Edge Correlation with wavelet features for image signal readjustment

For automating picture registration utilizing wavelet features and correlation techniques. Below mentioned stages from [25] produce precise and effective image alignment even when there are changes and transformations.

Wavelet-Based Feature Extraction

Wavelet transforms capture both low-frequency and high-frequency components to produce a multiscale representation of the image. These characteristics are more resistant to changes like scaling, rotation, and translation.

Correlation for alignment

Strategies rely on correlation to compare the wavelet properties of the reference and target images. A common technique for determining how similar two signals or images are correlated.

Automated Readjustment workflow

There are various steps in the automated picture registration workflow:

- The reference and target images should be used to extract wavelet features.
- Calculate the correlation between the two images' wavelet features.

- Find the transformation's scale, rotation, and translation parameters to maximum correlation.
- Align the target image with the reference image using the transformation.

In areas where exact image alignment is necessary, automated image registration is crucial. It employs wavelet features and correlation along with parallel processing to address issues in image readjustment. In remote sensing, where matching satellite images obtained at diverse periods or angles is essential for correct analysis and comparison, the automated parallel image registration technique has been used.

Implemented method.

Linkage of Boundaries

Edge linkage is defined as the procedure of linking boundary points of an input image into adjacent rows or columns of contour line. It is a filtering process which aims at determining the relation between two boundaries of adjacent signals. A signal readjustment approach is used for filtering.

Signal Registration

The process of finding spatial alterations from an original signal to a prey signal for finding the best match between the two signals is known as Registration. Regionally or globally the more the degree of resemblance between origin & prey signals, the better is chance of success of alignment. The category of resemblance estimate is based on the properties of matched signals. While picking the resemblance amount it must follow to count only key particulars in both signals and rejects unavailing data. The standard of analogy evaluation among the signals contemplates the quality of the alignment. It means if a boundary influence one of the adjacent signals, then it influences the same in the other one as well. Sometimes registering two signals requires little adjustments. If the requirement is not fulfilled, the registered signals may show unlike components, like as, it cannot be anticipated that it consists of associated parts of the same boundary. The signals on which readjustment has been performed are monistic because they are taken from the same image.

For the sake of similarity measure it is foremost to find the kind of signals that should be inspected in readjustment. From all the suggested measures for monistic signals the summation of squared differences (SSD) [14] has been chosen. SSD relies on a hypothesis that additive white Gaussian noise is the only source of variation in signal amplitudes.

Assume there are two signals from adjoining dimensions in an image. Consider '$s_s(n)$' denotes a source and '$s_t(n)$' denotes a target. A high co-relation among the signal strength of both can be anticipated. Eq (11) shows how to switch from the origin to the destination signal:

$$c \cdot s_t(n) + b = s_s(n + m) \dots \dots \dots (11)$$

where c is the contrast, b is brightness and m is spatial shift. To evaluate the parameters 'c','b','m', the quadratic error function is defined as:

$$E(c, m, b) = \sum_{n \in \Omega} [(c \cdot s_t(n) + b) - s_s(n + m)]^2 \dots \dots \dots (12)$$

Unfortunately, because it is stochastic in parameter m, equation (12) cannot be directly minimized. Therefore, it is approximated by Taylor series expansion.

The signal $s_s(n)$ must be steady and unique. After Taylor conjecture, we get:

$$E(c, m, b) \approx \sum_{n \in \Omega} \left[(c \cdot s_t(n) + b) - s_s(n) + m \frac{\partial s_s(n)}{\partial n}\right]^2 \dots \dots \dots (13)$$

Now the parameter m becomes linear in this quadratic error function and so it can be systematically reduced by converting unspecified variables c, m and b [11]. The acquired structure can also constitute the form of matrix. After metamorphosing Eq. (13), yields:

$$A \cdot u = y \dots \dots \dots (14)$$

Where $k = \left[s_t(\Omega) \frac{\partial s_s}{\partial n} 1\right]$, $A = k \cdot k^T$, and $y = k. s_s(\Omega)$

$$u = \begin{bmatrix} c \\ m \\ b \end{bmatrix} \dots \dots \dots (15)$$

The answer for the specifications for regional positioning calculated from Equation (14) is:

$$u = (k \cdot k^T)^{-1} y \dots \dots \dots (16)$$

The variables in Eq. (16) don't pick their values computed until the present interim. So, it is possible to have completely different alignment parameters for close by regions. To reduce these deviations the alteration between the close by parameters must be even. After extending the equation (12) along with evenness restraint [20] over all the parameters we get.

$$E(c, m, b) = E_r(c, m, b) + E_s(c, m, b) \dots \dots \dots (17)$$

E_s is defined as follows:

$$E_s\ (c, m, b) = \lambda_1 \left(\frac{\partial c}{\partial n}\right)^2 + \lambda_2 \left(\frac{\partial m}{\partial n}\right)^2 + \lambda_3 \left(\frac{\partial b}{\partial n}\right)^2 \dots \dots \dots (18)$$

The uniformity of the unidentified variables is affected by readjustment process parameters λ_i. Equation (17)'s error function is once more minimized. The first portion of it is solved as in Eq. (16), while the latter portion is solved as in Eq. (18) and considers derivatives of unidentified variables that are approximately represented by variations among consecutive values:

$$E_s\ (c, m, b) = \lambda_1 (c_i - c_{i-1})^2 + \lambda_2 (m_i - m_{i-1})^2 + \lambda_3 (b_i - c_{i-1})^2 \dots \dots \dots (19)$$

Equation (19) is now metamorphosed on the unspecified parameters and its value is marked as zero. This structure of equations can also be represented in matrix form. Assuming that the unidentified alignment variables are denoted by the vector u_i and that the uniformity variables λ_i form the diagonal matrix L:

$$\frac{\partial E_s(u_i)}{\partial u_i} = 2L \cdot (u_{i-1} - u_i) \dots \dots \dots (20)$$

Where $$L = \begin{bmatrix} \lambda_1 & 0 & 0 \\ 0 & \lambda_2 & 0 \\ 0 & 0 & \lambda_1 \end{bmatrix} \text{ and } u_i = \begin{bmatrix} c_i \\ m_i \\ b_i \end{bmatrix}$$

On combining equations (16) & (20). The resulting Eq. (21) depicts a repetitive readjustment of unspecified regional parameters, although all in all their earlier values up to the present interim:

$$u_i = \left((k \cdot k^T - L)^{-1} \cdot (y + L \cdot u_i)\right) \dots \dots \dots (21)$$

Eq. (16) defines the initial parameter value u_i. The repetitive signal readjustment technique, depicted by Eq. (21), has the subsequent advantages:

(a) small computational complexity.
(b) Arithmetic intransigency,
(c) regional and global relatedness of readjustment parameters.

Linking readjustment variables is important so a new algorithm method dependent on signal readjustment is proposed to link the boundaries of abutting image and to evaluate the authenticity of the linkage. Based on readjustment variables b, m, and c, boundary calculation accuracy and categorization are determined. Therefore, it is preferable that the above variables serve as examples.

Edge correlation with readjustment variables.

In 1-D signals, edge detection algorithm determines boundaries only on the modulus maxima estimate. In boundary linkage using readjustment parameters a method of boundaries linkage into a shape line is suggested, which generates a linked contour considering the modulus maxima along with readjustment parameters. Morphological operations such as erosion and dilation logic were used in pre-existing boundary linkage models to join boundaries with contour lines. Such an outlined image is an upgrade as compared to the boundary image since they have outlying boundaries and because outlying boundaries could be marked as faulty edges. But these models did not look for similarity between neighborhood boundary areas. And due to it many different boundaries get linked together.

To tame this difficulty, a method has been proposed. Spatial criterion is dominant characteristics for connecting boundaries and because of it the given indirect boundary linkage has a good lead and so the linkage is positive when the coincidence among the boundaries is large, and they are packed adequately near. It leads us to the conclusion that the distance along with shape between two boundaries is meaningful. Based on the readjustment parameters, the boundary linkage joins the boundary pixels whose emergence in the close by dimensions of signal shows the highest similitude. Least spatial move and radiance variation is required for the boundaries to appear very similar. So, if high similitude is gained, the connected pieces are certain to emerge from a similar boundary. A union of outlines connected by dimensions creates the ultimate outlined representation. We obtain a useful outline representation by removing the small and unfamiliar boundary strips.

Simulation & Discussions

A set of real images was used for testing the proposed boundary detection algorithm. Mean absolute distance (MAD) was utilized to evaluate the performance of the boundary detector and was contrasted with multi-scale canny, boundary with constant credence, and COIFLET border detection [20]. Information on the border positions is provided by the MAD. Not only experimental but visual assessment was also done.

Because additive zero mean Gaussian noise (AWGN), which distorts imagery, was present, the obtained SNR was 9 dB. Most of the modulus maxima contour lines were completely detected and the boundary points seem to be chiefly linked. Considering the specimen where the contrast between the boundary positions was 4 units distant the boundary linkage was successful. Under different levels of noise, the execution of our suggested method was compared to Canny multiscale edge detector [19], boundary detection having implanted reliance [20] and COIFLET contour detection. The default threshold T from Eq. (10) was reliant on the altered image adaptively. For the confidence level estimation, the weight value w = 4 throughout our experiments.

In all noiseless images the perfection of the suggested detector was near 0.68 units. From the data recorded we can conclude that the boundary detector worked very accurately.

- The minimum and maximum distances were calculated as 0.65 units and 1.34 units.
- The MAD was 0.80 units,
- The standard deviation 0.12 units

This shows that boundary points were detected perfectly and were very compatible.

If we compare the existing boundary detection model with the proposed method, we observe that the pre-existing model gave good results but not as good as the preferred procedure. The multi-scale canny detection, however, is the most efficient border detector now in use.

- Minimum maximum distances 0.79 units and 1.19 units,
- MAD equaled 1.03 unit,
- 0.11-unit standard deviation.

Also, the boundary detector with inserted conviction with:

- MAD equals 1.37 units,
- 0.09 units of the standard deviation,
- Minimal and maximal separations are 1.15 units and 1.43 units, respectively.

The COIFLET boundary detector is found to be least accurate with:

- In imagery simulations, the typical MAD was 1.68 units,
- The average variation is 0.87 units,
- The minimal and maximal distances are 1.15 and 4.20 units, respectively.

Length is a very important contour feature. The mean lengths of boundaries in images were measured. The exact boundary lengths were 90 units. It gives an inverse proportionality relation i.e., if image noise increases the boundary lengths decreases.

The least lengths were found to be 75 units, which is sufficient for correct image content explanation. The first model had a larger contour length as compared to the second model. The variation in length is since the first model has higher deviations between adjacent rows. The subsequent framework was found to be finer for this reason, which is why the boundary correlation performance was superior. The time complexity grows quadratically because the success of the technique is significantly impacted by the image's size.

Experimentally, it was observed that the execution time of boundary detection on average is less than 2% and the rest of 98% is consumed in boundary linkage process, i.e., it is the signal readjustment,

Fig2: Results for Carriage Image with Haar and COIFLET Filters

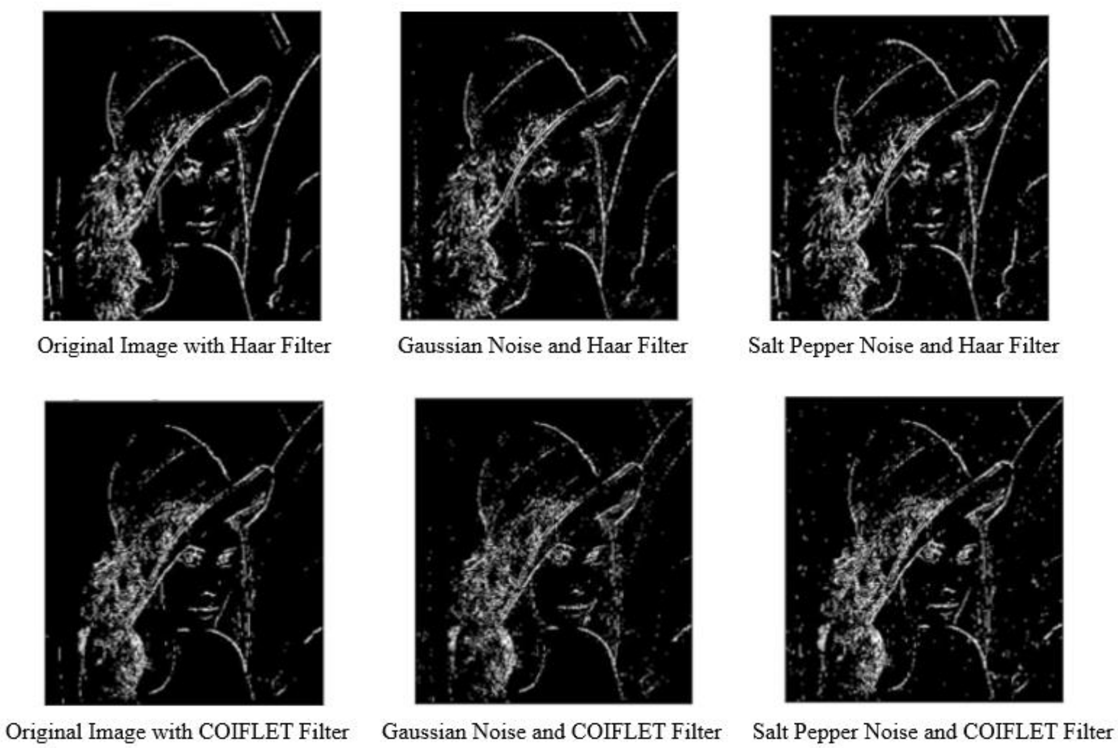

Fig3: Results for Lena Image with Haar and COIFLET Filters

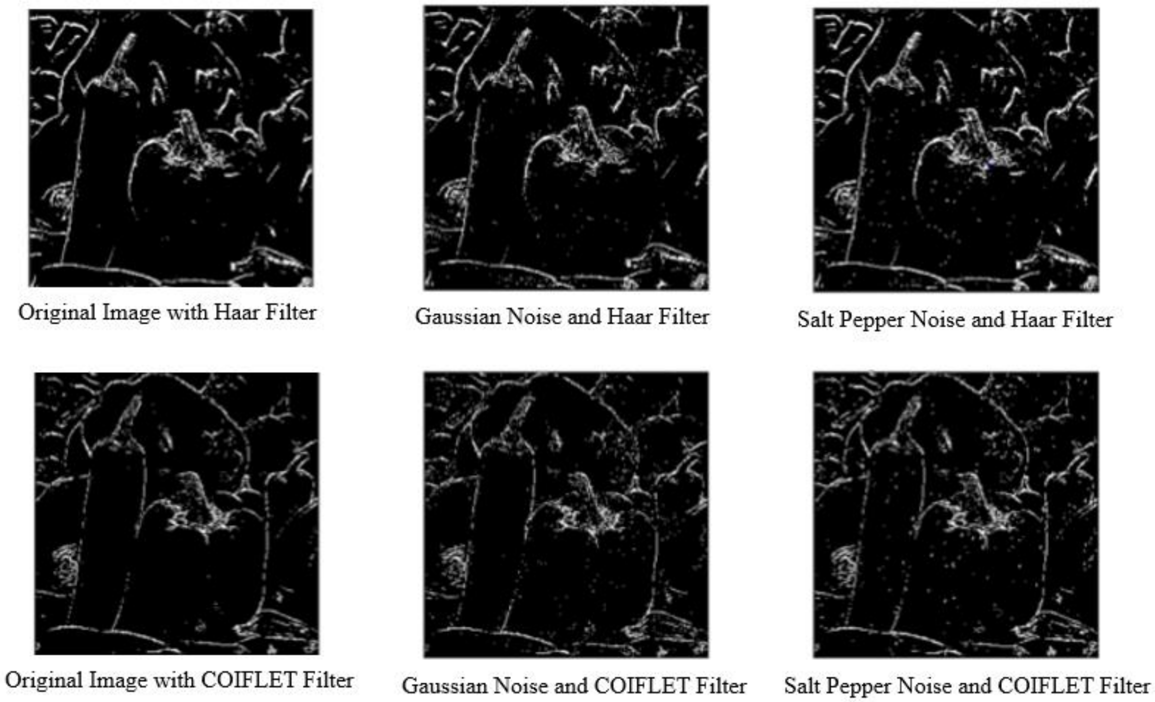

Fig4: Results for Pepper Image with Haar and COIFLET Filters

Conclusion

A very robust and accurate novel boundary detection method is introduced in this report. In this wavelet transform and signal readjustment are combined and performed in two stages. Haar Wavelet transform having max entropy is used to detect boundary points in which positions are described in the form of maximum lines. Then, the image row or column signals are subjected to signal readjustment. At the end, the readjustment parameters and the corresponding boundaries are linked to the contour lines. This results in a outlined image having a credence index specifying the quality and sturdiness of the outline linkages. Hence from the results we can see that the proposed detector is sturdy, precise and functional even with images having considerable amount of distortion.

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