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# Comparative study of traditional edge detection methods and phase congruency based method

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**ABSTRACT**

Finding relevant and crucial details from images and effectively interpreting what they represent are two of image processing's main goals. An edge is the line that separates an object from its backdrop and shows where two things meet. Mining the picture's borders for extracting useful data remains one of the trickiest steps in understanding of an image. The borders of the objects may be used to build the image's edges, which are its basic characteristics. There are different types of traditional edge retrieval techniques that are conventionally categorized as first order and second gradient based methods such as Roberts, Prwitt, Kirsch, Robinson, canny, Laplacian and Laplacian of gaussian. The majority of research and review work on edge detection algorithms focuses on conventional algorithms and soft computing based methods, neglecting illumination invariant phase congruency based edge detector. This study aims to compare traditional derivative based edge detection algorithms with log Gabor wavelet based edge detector phase congruency. This work does a thorough examination of various edge-detecting approaches, including traditional boundary detection methods and log Gabor wavelet based method. To test effectiveness of edge detection algorithms, experimental results are obtained on images from DRIVE, STARE, and BSDS500 dataset.



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## 1. INTRODUCTION

Finding outlines of objects in a picture was referred to as edge detection. It also implies that each element in a picture can be found and fundamental attributes like region, boundaries, or form may be assessed if the borders can be precisely determined [1], [2]. Detecting edges is a crucial technique as machine vision entails finding and categorization of features in an image. The image computer vision and examination often involve edge detection. A number of multiple kinds of algorithms ate available for identifying edges [3], [4].

Finding those locations or pixels in a picture where the luminous intensity changes noticeably or suddenly is known as detecting edges [5]-[8]. The goal of recognizing edges is to determine discontinuities in images. In order to deal with the selection of a border finding approaches this paper examines edge detection strategies. Boundary detection mechanisms use filters to eliminate noise from a picture and focus on edges.

Among the image-filtering operations that can be initiated by the techniques used to filter include softening, sharpening, and border enhancements. For the purpose of effectively enhancing image, these actions can be utilized alternately. The objective of the filtering is to identify the abrupt, jagged edges. It is possible to discover prominent key locations for object recognition in images more effectively with the use of filters.

The most widely used traditional edge finding methods are gradient based methods i.e first order and second order derivative based methods. Drawback of gradient based methods is its sensitivity to noise. Canny edge detection procedure is less sensitive to noise and shows better performance as compared to other gradient based methods [9]. Recently devised phase congruency based method is computationally complex but it is invariant to illumination variance. There are a lot of reviews and comparisons on edge detection algorithms that don't take phase congruency-based edge detector method into account. This Study focuses on comparison of classical edge detection algorithms with recently developed illumination invariant phase congruency based edge detection method. Section 2 presents detail description of traditional edge detection methods. Section 3 outlines log Gabor wavelet based edge detection method. Section 4 presents a comparative analysis of conventional edge detection techniques and phase congruency based method. Conclusion is given in section 5.

## 2. TRADITIONAL EDGE DETECTION METHODS

The basic stage in image analysis is identifying the edges or boundaries of objects in the images. The process of identifying boundaries and their locations is known as edge detection [9]. Edges are produced by sudden, rapid changes in an image's brightness (intensity). Traditional edge operators are categorized as first order and second order derivative based methods. Gradient operators such as Prewitt and Roberts are examples of first order derivative based methods. Canny, Laplacian of gaussian is examples of second order derivative based methods [9]. Traditional methods of edge detection are described as follows.

### 2.1. Roberts boundary-detection

Roberts [10], [11] is credited with developing the Roberts edge detection (1965). It measures a picture's two-dimensional (2-D) position gradients in an easy-to-compute manner. This technique highlights highly frequent spatial locations, which frequently line up with edges. The primary use of this approach is when an identical grey scale picture is used as both the source and the resultant image. The projected full amplitude of the source picture's location gradient at each place in the output image is represented by values.

The operator, as depicted in Figure 1, is composed of two by two convolution kernels in principle. To put it simply, one mask is the other ninety degree revolved. The Sobel-operator and this are really similar.

| | |
|---|---|
| +1 | 0 |
| 0 | -1 |

$GM_x$

| | |
|---|---|
| 0 | +1 |
| -1 | 0 |

$GM_y$

Figure 1. Roberts masks

With kernels for each of both at right angles positions, these kernels are made to react as much as possible to edges which lie at a 45-degree angle to the pixels matrix [10], [11]. Each gradient component for every direction can be measured independently by applying the kernels individually to the input image. Numbers may then be summed together to determine the gradient's position and overall magnitude at every location. The following gives the gradient magnitude (GM):

$$|GM| = \sqrt{GMx^2 + GMy^2} \quad (1)$$

Typically, however, an estimated quantity is calculated using:

$$|\mathrm{GM}| = |\mathrm{GMx}| + |\mathrm{GMy}| \quad (2)$$

Advantages
a) Easy to compute
b) Points in the perpendicular position are maintained
Disadvantages
a) Subtle to noise
b) It is not detecting boundaries accurately

### 2.2. Prewitt

The Prewitt function [12], [13] uses two masks of filtering to convolutionally locate picture edges, one for each direction - horizontal and vertical. This allows us to extract: i) horizontal edge (boundaries) along the x-axis and ii) vertical edges (boundaries) along the y-axis.

The operator finds an edge whenever there is a sharp shift in pixel intensity. Differentiation may be used to compute the boundary as it is characterized as the shift in pixel intensities. A first- ordered derivation mask is the Prewitt mask. The outer boundary can be expressed by the regional maxima or regional minimums in the graph that depicts Prewitt-mask's finding. There are just eight potential directions; however research indicates that most direct direction predictions aren't all that accurate. This gradient-based edge detection is calculated for 8 directions in the three-by-three neighborhood as depicted in Figure 2. Each one of the 8 kernel masks is computed. Next, one complication mask is chosen, specifically for the biggest module.

| | | |
|---|---|---|
| -1 | -1 | -1 |
| 0 | 0 | 0 |
| +1 | +1 | +1 |

$GM_x$

| | | |
|---|---|---|
| -1 | 0 | +1 |
| -1 | 0 | +1 |
| -1 | 0 | +1 |

$GM_y$

Figure 2. Prewitt operators

To every location in the picture, the resultant gradient estimates can be assembled to provide the GM, employing:

$$GM = \sqrt{GMx^2 + GMy^2} \quad (3)$$

By utilizing this gradients direction can be computed as:

$$\varphi = \mathrm{atan2}(GM_x, GM_y) \quad (4)$$

For instance, when a y-direction boundary is blacker on its right-hand position, ϕ equals zero.
Advantages
a) Simple to implement
Disadvantages
a) Noisier outcomes
b) Produces inaccurate results

### 2.3. Sobel-operator

A well-liked detector of edges approach called the Sobel operators [14], [15] uses a convolution between the picture (called the input) and dual specialized kernels as shown in Figure 3, one for horizontal boundary detection and the other for vertical detection of borders, to estimate the first derivatives of the image. The process of determining edges maps using Sobel operators is depicted in Figure 4. There are 2 kernels in the method.
a) A kernel for approximating x-direction luminance change.
b) Another kernel is designed to mimic a pixel's y-direction luminance shift.
To determine the areas wherein the gradient is greatest in intensity in both directions, every pixel in the input picture have been convolved with both kernels. The two kernels are as follows:

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

$GM_x$ = x-direction kernel

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

$GM_y$ = y-direction kernel

Figure 3. Sobel operators

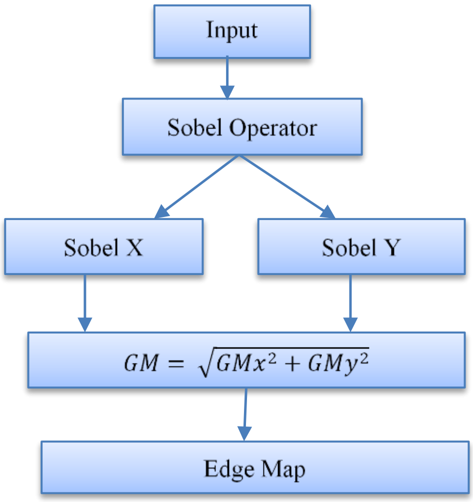



Figure 4. Sobel edge detection process

To determine the gradient's magnitude at pixel (x,y), add the numbers above:

$$GM = \sqrt{GMx^2 + GMy^2} \tag{5}$$

gradient's direction at each location is calculated as,

$$\Theta = atan(GMy \,/\, GMx) \tag{6}$$

where, at an indicates the arc-tangent operator.

In summary, the method traverses each pixel in the picture and creates 3x3 arrays using the corresponding pixel to be the center pixel. The two numbers, gradient estimates in the flat and vertical-directions (GMx, GMy), are obtained by convolving these arrays with the both-direction kernels. To obtain the GM at that pixel, we square both of these values, add them, and then find the square root of the total. Large-magnitude gradient pixels are probably seen around an image's edge.

Advantages
a) Easy to calculate
b) Fast
c) Immune to noise

Disadvantages
a) Produces bushy edges
b) Sensitive to sloping edges
c) Does not consider boundary continuity
d) Does not incorporate smoothness

### 2.4. Kirsch

Kirsch (1971) established the concept of Kirsch detectors for edges [16]. By rotating one mask to each of the eight major magnetic directions, the operator of Kirsch approach is constructed as shown in Figure 5. The masks differ in the following ways. The greatest value achieved through convolution of each masks with the picture is known as the edge-magnitude. The portion of the mask that yields the greatest magnitude defines the direction.

Advantages
a) Simple
b) Fast

Disadvantages
a) Noise sensitivity
b) Inaccurate

$$K1 = \begin{bmatrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & 5 \end{bmatrix} K2 = \begin{bmatrix} -3 & 5 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & -3 \end{bmatrix} K3 = \begin{bmatrix} 5 & 5 & -3 \\ 5 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}$$

$$k4 = \begin{bmatrix} 5 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & -3 & -3 \end{bmatrix} k5 = \begin{bmatrix} -3 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & 5 & -3 \end{bmatrix} K6 = \begin{bmatrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & 5 \end{bmatrix}$$

$$K7 = \begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & -3 \\ 5 & 5 & 5 \end{bmatrix} \mathrm{K8}= \begin{bmatrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & 5 & 5 \end{bmatrix}$$

Figure 5. Kirsch masks

### 2.5. Robinson

Comparable to Kirsch-masks, the Robinson technique [17] is simpler to use because it just requires values of zero, one, and two. Masks as depicted in Figure 6 are uniform in directional axis. It is essential to obtain the results of four masks, results of remaining masks is obtained by reversing values of first four.

$$E = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} NE = \begin{bmatrix} 0 & 1 & 2 \\ -1 & 0 & 1 \\ -2 & -1 & 0 \end{bmatrix} N = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

$$NW = \begin{bmatrix} 2 & 1 & 0 \\ 1 & 0 & -1 \\ 0 & -1 & -2 \end{bmatrix} W = \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix} SW = \begin{bmatrix} 0 & -1 & -2 \\ 1 & 0 & -1 \\ 2 & 1 & 0 \end{bmatrix}$$

$$S = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & -3 \\ 1 & 2 & 1 \end{bmatrix} \mathrm{SE}= \begin{bmatrix} -2 & -1 & 0 \\ -1 & 0 & 1 \\ 0 & 1 & 2 \end{bmatrix}$$

Figure 6. Robinson masks

The gradient's angle may be roughly represented simply the position of the path of zeros in the mask that yields the largest respond. The gradient's magnitude is the highest value obtained by using a total of 8 masks to the pixels neighbors.

Merits
a) Simple
b) Fast

Demerits
a) Noise sensitivity
b) Inaccurate

### 2.6. Canny-operator

The Canny's boundary-detector can identify a range of real edges in image [18], [19]. The detecting method smooth's the image's lines to eliminate the unwanted pixels that are noisy since they provide deceptive edges. This specific edge discovery provides a higher signal-to-noise ratio (SNR) than earlier methods. This demonstrates the widespread use of Canny's boundary-detection in image visualization.

The picture is initially normalized using a suitable filter to reduce the effect of noise. The regional gradients and edge directions of every single point are then found. Figure 7 shows canny masks.

| | | |
|---|---|---|
| -1 | 0 | +1 |
| -2 | 0 | +2 |
| -1 | 0 | +1 |

$GR_x$ = x-direction kernel

| | | |
|---|---|---|
| -1 | -2 | -1 |
| 0 | 0 | 0 |
| +1 | +2 | +1 |

$GR_y$ = y-direction kernel

Figure 7. Canny masks

The following is how the gradient-magnitudes may be found using an approach akin to the Sobel operation:

$$|GR| = \sqrt{GRx^2 + GRy^2} \tag{7}$$

$$|\mathrm{GM}| = |\mathrm{GRx}| + |\mathrm{GRy}| \tag{8}$$

the edges' directions has to be recorded according to:

$$\theta = \mathrm{atan}\left(\frac{|\mathrm{GRy}|}{|\mathrm{GRx}|}\right) \tag{9}$$

Peaks in the gradient's measure originate from these edge spots. The slope's course is at its most intense here. When the boundary-detector moves laterally the peaks of this outlines, it arrays the values of the pixels that is not on the edge's peak to zero. The result is a thin line in the output.

These contour pixels are thresholded using the higher cutoff (C2) and lower cutoff (C1) values. Depending on whether their values fall between the lower threshold (C1) and the upper threshold (C2) or exceed the upper cutoff (C2), ridge pixels are classified as either stronger edge pixels or solid edge pixels. The image's borders are then connected by identifying the weaker picture components that are connected to the solid pixels.

Advantages

a) Enhances signal to noise ratio

b) Good retrieval of edges

Disadvantages

a) Consumes more time

b) Difficult computations

c) Incorrect zero-crossings

### 2.7. Laplacian

Another derivative-based operator for locating boundaries in a picture is the Laplacian operator [20]-[22]. Laplacian known as second-order derivative procedure, in contrast to Prewitt-operator, Sobel-operator, Robinson-operator, and Kirsch, which are all considered as first order methods. This is main distinction from Laplacian and the others. Two other classes are available for this mask: +ve Laplacian and -ve Laplacian operator. Positive and negative Laplacian are depicted in Figure 8.

| | | |
|---|---|---|
| 0 | 1 | 0 |
| 1 | -4 | 1 |
| 0 | 1 | 0 |

Positive Mask

| | | |
|---|---|---|
| 0 | -1 | 0 |
| -1 | 4 | -1 |
| 0 | -1 | 0 |

Negative Mask

Figure 8. Laplacian mask

The Laplacian equation is a differentiation method that is employed to draw attention to regions of a picture where the grey value changes slowly and to minimize those that do not. These pictures with grey intensity edges and other break on a black backdrop are the outcome of this process. This causes an image's edges to be toward the inside and outside.

One filter needs to be applied on image. Both masks cannot be applied on source image. The sharper picture is achieved by subtraction of the resulting picture from the source picture after applying the positive Laplacian mask to the image. In a similar vein, to obtain a sharper image, we must add the generated image to the original image after using the negative Laplacian operator. Figure 9 demonstrates results of negative and positive Laplacian operator applied on input image. Figure 9(a) is the original image, while Figure 9(b) and 9(c) show results using the positive and negative Laplacian operators, respectively.

### 2.8. Laplacian of gaussian

It comes from the fusion of gaussian and Laplacian-edge detector [23]-[25]. There is further smoothing of the picture. An image's Laplacian indicates areas of abrupt changes in pixel value. Another name for this technique is the Marr-Hildreth edge retrieval. To minimize a image's exposure to noise, the method known as Laplacian is frequently employed once the picture was first smoothed using an approximation of a gaussian leveling filter. Characteristically, the log receives single grey level picture as source and yields an additional grey-level image. An image's Laplacian, which is frequently employed for edge identification, indicates areas of abrupt intensity shift. Before the differentiation stage, pre-processing procedure lowers the higher frequency noise constituents.

$$LoG(x, y) = -\frac{1}{\pi\sigma^2}\left[1 - \frac{x^2+y^2}{2\sigma^2}\right] e^{-\frac{x2+y2}{2\sigma^2}} \tag{10}$$

The parallel axis' distance to the origin is represented by x, while the perpendicular axis' distance to the source is represented by y. Two commonly employed kernels are presented in Figure 10.

(a) (b) (c)

Figure 9. Laplacian negative and positive operator example: (a) original image, (b) positive operator, and (c) negative operator

| | | |
|---|---|---|
| 1 | 1 | 1 |
| 1 | 8 | 1 |
| 1 | 1 | 1 |

| | | |
|---|---|---|
| -1 | -2 | -1 |
| -2 | -4 | -2 |
| -1 | 2 | -1 |

Figure 10. Two commonly used Laplacian kernels

## 3. IMAGE EDGE USING PHASE CONGRUENCY

This work advocates use of logarithmic Gabor based phase congruency feature detector for edge detection as traditional gradient-based methods intended for edge detection are insufficient to catch edges composed of mixtures of steps, heights and tops. Phase congruency is a dimensionless measure that is immune to changes in image illumination or contrast [26]. Edges are first detected in term of the high phase congruency in the gray-level image. Edges are obtained by performing non maximal suppression and hysteresis thresholding.

A newly developed detector, phase congruency (PhaseCong), built on the logarithmic Gabor wavelet (LoG), is used to extract edges in the picture [27]. Outcomes for both the edge and step are acquired. The properties of the method include resistance to amplification and stability in the face of variations in light inside pictures. Based on the local energy model, features in a picture are located [28], [29]. PhaseCong scores are high at the border and edge regions of the object. Peter Kovesi proposed use of logarithmic Gabor wavelets for the purpose of calculating phase congruency, and log Gabor wavelets are used because they have the ability to cover a large range of frequencies while keeping a zero bias voltage in the symmetrically oriented filters. Filters in Fourier space are constructed based on polar coordinates. The two components of the log Gabor Wavelet consist of an angled section and a radial direction element. The full filter is obtained by multiplying two portions together. The computation of phase congruency at various scales and angles involves convolving the picture with an array of logarithmic Gabor wavelets. The specific localization of phase congruency is defined as [29], [30].

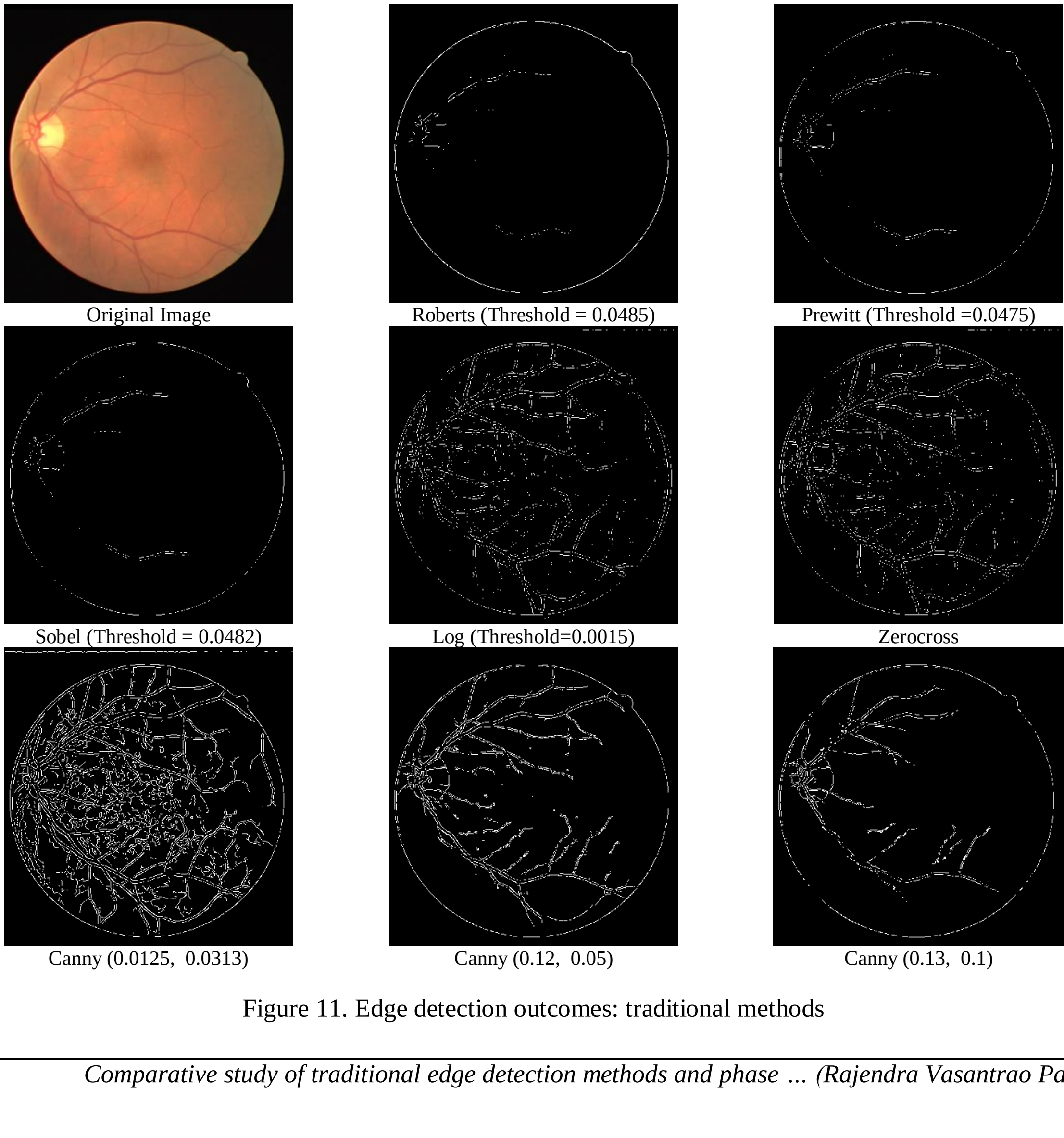
$$\begin{aligned} \mathrm{PhaseCong1}^{\mathrm{or}}(\mathrm{i},\mathrm{j}) = \\ \textstyle\sum_{\mathrm{n}} \mathrm{WG}^{\mathrm{or}} \Big[\mathrm{AMP}_{\mathrm{n}}^{\mathrm{or}}(\mathrm{i},\mathrm{j}) \left(\cos\left(\mathrm{ph}_{\mathrm{n}}^{\mathrm{or}}(\mathrm{i},\mathrm{j})\right) - \mathrm{ph}_{\mathrm{n}}^{-\mathrm{or}}(\mathrm{i},\mathrm{j})\right) \\ - \left|\sin(\mathrm{ph}_{\mathrm{n}}^{\mathrm{or}}(\mathrm{i},\mathrm{j}) - \mathrm{ph}_{\mathrm{n}}^{-\mathrm{or}}(\mathrm{i},\mathrm{j})\right| - \mathrm{NC}\Big] \\ \times \left(\textstyle\sum_{\mathrm{n}} \mathrm{AMP}_{\mathrm{n}}^{\mathrm{or}}(\mathrm{i},\mathrm{j}) + \varepsilon\right)^{-1} \end{aligned} \tag{11}$$

where the revolution slant value is or, the frequency spread-based weightiness component is $WG^{or}(i,j)$, and $AMP_n^{or}(i,j)$ and $ph_n^{-or}(i,j)$ stand the largeness and phase correspondingly, $Ph_n^{or}(i,j)$ stands the weighted average, $NC$ remains noise component, sigma stands for negligible quantity. MATLAB code to calculate phase congruency is made available by Peter Kovesi on his home page. For details refer [26].

## 4. EXPERIMENTAL RESULTS AND DISCUSSION

Different border detection approaches have been made available by investigators for employing in a wide range of use cases, including machine vision, medical imaging, image segmentation, earth observations, and remote sensing [31]. This section focuses on comparison of traditional edge detectors with phase congruence based edge detector. Three decades before, derivative based algorithms including gradient (which include the Prewitt, Sobel, Roberts) and Laplacian and LoG were presented. These were the earliest and most widely used edge detectors. The masks of these operators are set to a three by three size array. Whereas the Laplacian is referred to as the zero-crossing operator, the gradient's operators are also referred to as the local maxima operators.

To assess performance of different edge operator's subjective approach and objective approach is used. The identification of genuine boundaries, time taken to process, errors proportion, levels of noise, and other factors are commonly used to assess the effectiveness of edge detection algorithms. This study presents an mean square error (MSE) and peak signal-to-noise ratio (PSNR) comparison of different well-known edge detectors. MATLAB software is used to determine edges in test images. PSNR value in every edge retrieved image and ground truth image is calculated to compare performance. Edge detection methods are tested on publicly available databases such as DRIVE, STARE, and BSDS500. Figure 11 presents edge detection results obtained using traditional edge detection algorithms.



Original Image | Roberts (Threshold = 0.0485) | Prewitt (Threshold =0.0475)

Sobel (Threshold = 0.0482) | Log (Threshold=0.0015) | Zerocross

Canny (0.0125, 0.0313) | Canny (0.12, 0.05) | Canny (0.13, 0.1)

Figure 11. Edge detection outcomes: traditional methods

The traditional derivative based methods main benefits are straightforwardness. The GM may be approximated simply using the Roberts cross operator. The ability to identify boundaries and their positions is the conventional operator's primary strength. These cross operator’s susceptibility to noise in identifying edges and position is one of its drawbacks. An image's noise level will gradually cause the edges magnitude to decrease. As the GM of the edges reduces, the primary drawback is the inaccuracy. It's likely that accuracy declines as well. LoG is effective in detecting sharp edges with images having smooth intensity changes. But it is sensitive to noise if smoothing not performed sufficiently. Robinson's compass mask and Kirsch are very identical. It features an eight-direction compass, too. The ability to modify the mask to meet requirements is the primary distinction between Kirsch and Robinson compass masks.

Every edge finding algorithm requires threshold values as a parameter. All of the methods need upper and lower cutoff value. Roberts, Robinson and Sobel requires output threshold that needs to be adjusted [32]. The canny don’t require threshold values but it involves sigma value and filter value that needs to be adjusted to get desired outcomes. The computational outcomes demonstrate that the Sobel and Prewitt edge detection exhibits a superior overall PSNR. However, out of the examined methods, the most efficient operator exhibits the lowest mean PSNR. It's crucial to remember that the edge finding method with the lowest PSNR has the best edge identification skills, and Canny seems to be the one with the lowest average PSNR and lowest maximum average MSE. It is evident that the canny method exhibits good PSNR in simpler pictures. This is a result of the canny operator's increased likelihood of identifying fake edges due to its ability to identify weak edges. Edge detection outcomes using phase congruency based edge detector are shown in Figure 12.

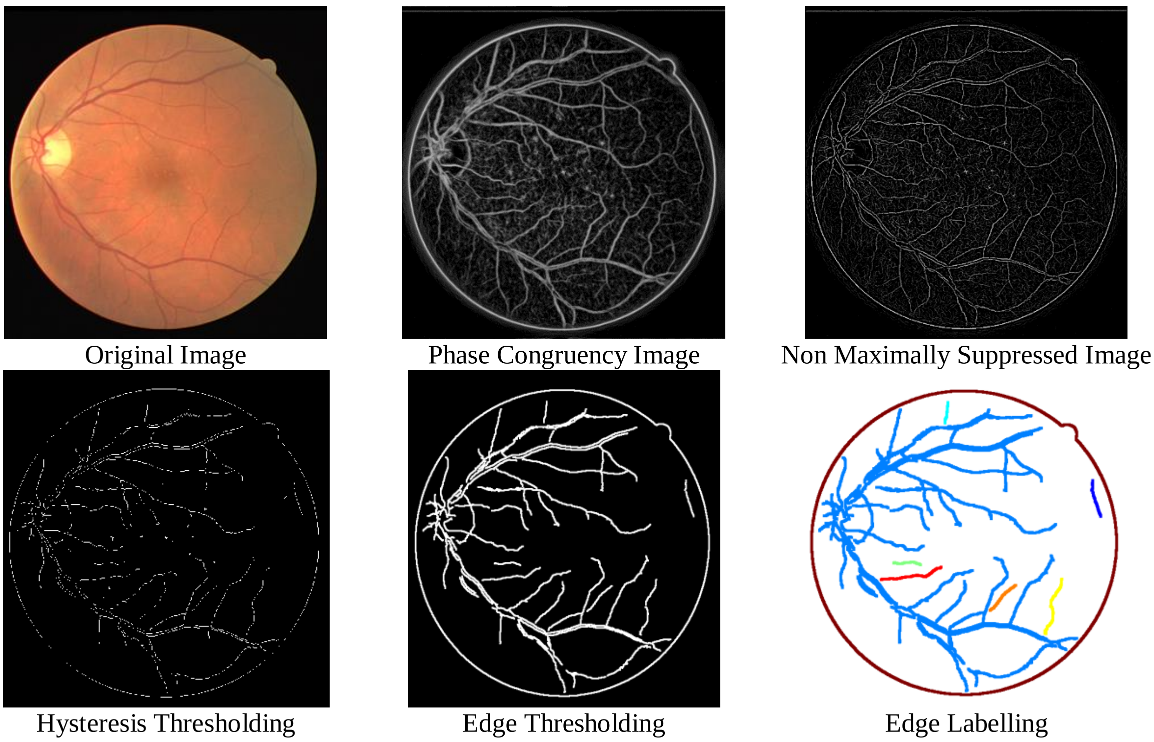



Figure 12. Edge detection outcomes: traditional methods

Phase congruency based edge detector method is more suitable to obtain edges in images acquired in different lighting conditions. Illumination invariant Log wavelet based phase congruency method is more efficient for images having complex structures whereas canny works well with sharp edges. Canny first uses gaussian to smooth image then calculates GM and position to detect edges. Non maximal suppression is used to thin edges in canny and phase congruency based method also. Phase congruency technique calculates phase information at different scales and different orientation in the Fourier domain to locations where Fourier components are aligned indicating an edge feature.

It was additionally noted that every algorithms have intrinsic advantages and disadvantages. The Roberts method, for instance, was quick but often only identifies edges on the zero and ninety degree axes.

Although the Sobel method took longer to execute than the Roberts method, it was still able to identify edges on the zero and ninety degree axes as well as the forty-five and 135 degree axis. The Robinson was able to identify an increased amount of variable angle borders for an extra processing speed. Although it had the worst execution time, the canny method seems to be the greatest fit for identification of edges. Phase Congruency is more robust to illumination changes with additional complexity and computation cost. Table 1 summarizes advantages and disadvantages of traditional edge detection approaches and phase congruency based edge detection technique.

Table 1. Comparison of edge detection methods

| Method | Technique | Advantages | Disadvantages |
|---|---|---|---|
| Roberts | Gradient based | ✓ Easy to compute<br>✓ Points in the perpendicular position are maintained | ✓ Subtle to noise.<br>✓ It is not detecting boundaries accurately<br>✓ Thick edges |
| Prewitt | Gradient based | ✓ Simple to implement<br>✓ Fast | ✓ Noisier outcomes.<br>✓ Produces inaccurate results<br>✓ Thick edges |
| Sobel | Gradient based | ✓ Simple<br>✓ Detects edges and orientations | ✓ Noise sensitive<br>✓ Inaccuracy<br>✓ Thick edges |
| Kirsch | Gradient based | ✓ Simple<br>✓ Fast | ✓ Noise sensitivity<br>✓ Inaccurate |
| Robinson | First derivative | ✓ Simple<br>✓ Fast | ✓ Noise sensitivity<br>✓ Inaccurate |
| Laplacian | Second derivative | ✓ Thin and correct edges.<br>✓ Detects both edges and corners. | ✓ Requires large kernel size<br>✓ False edges<br>✓ Noise sensitive |
| LoG | Gaussian | ✓ Observing more neighborhood pixels<br>✓ Identifies correct positions of edges. | ✓ Malfunctions around corners and curves<br>✓ Not detecting direction of edges |
| Canny | Second derivative | ✓ Improves SNR<br>✓ Better detection<br>✓ Thin and continuous edges<br>✓ Less false edges | ✓ Time consuming<br>✓ Complex calculations<br>✓ False zero crossing<br>✓ Manual thresholds |
| Phase congruency | Wavelet based | ✓ Illumination invariant<br>✓ Accurate | ✓ Complex<br>✓ Noise sensitive<br>✓ Time consuming |

## 5. CONCLUSION

This study compares and studies many traditional edge detection methods. It is discovered from the research study that, in contrast to first order gradient based methods such as Sobel, Prewitt, and Roberts, second order derivatives (Canny and LoG) function well. Visual perception and picture quality are both improved by the LoG and Canny edge detection technique. Considering that noise might affect the Laplacian of gaussian edge detection approach. Thus, when noise is present, it does not yield better outcomes than the canny edge detection approach. Therefore, the canny edge detector is a superior edge detection approach for creating the edges for both the object's inner and outside lines, as demonstrated by experimental evidence. Compared to first order derivative based methods and Log edge detection, it has a stronger tolerance against noise. Log Gabor wavelet based phase congruency found effective in detecting edges in images acquired under different light conditions. But illumination invariant phase congruency found computationally expensive as compared to first and second order derivative based methods. According to this study, the selection of the input parameters has a significant impact on the performance of classical edge detectors. Finding techniques to automatically establish threshold levels should be the main goal of research in future. Because of its adaptable behavior, a variety of soft computing-based methods for edge detection that make use of deep learning and fuzzy logic have been developed in the literature as a result of AI breakthroughs. This work only considers traditional edge detectors; it has also become essential to do comparative study of classical methods with soft computing based approaches.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

## CONFLICT OF INTEREST STATEMENT
Authors state no conflict of interest.

## INFORMED CONSENT
We have obtained informed consent from all individuals included in this study.

## ETHICAL APPROVAL
This study does not involve human participants and therefore did not require ethical approval.

## DATA AVAILABILITY
Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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