

### Abstract

Edges characterize boundaries and are therefore considered for prime importance in image processing. Edge detection filters out useless data, noise and frequencies while preserving the important structural properties in an image. Since edge detection is in the forefront of image processing for object detection, it is crucial to have a good understanding of edge detection methods. In this paper the comparative analysis of various Image Edge Detection methods is presented. The evidence for the best detector type is judged by studying the edge maps relative to each other through statistical evaluation. Upon this evaluation, an edge detection method can be employed to characterize edges to represent the image for further analysis and implementation. It has been shown that the Canny's edge detection algorithm performs better than all these operators under almost all scenarios. eywor

**Keywords:** About four key words or phrases in alphabetical order, separated by commas.

### Introduction

Edges are boundaries between different textures. Edge also can be defined as discontinuities in image intensity from one pixel to another. The edges for an image are always the important characteristics that offer an indication for a higher frequency. Detection of edges for an image may help for image segmentation, data compression, and also help for well matching, such as image reconstruction and so on[3]. Variables involved in the selection of an edge detection operator include Edge orientation, Noise environment and Edge structure[1]. The geometry of the operator determines a characteristic direction in which it is most sensitive to edges. Operators can be optimized to look for horizontal, vertical, or diagonal edges. Edge detection is difficult in noisy images, since both the noise and the edges contain high-frequency content. Attempts to reduce the noise result in blurred and distorted edges[2]. Operators used on noisy images are typically larger in scope, so they can average enough data to discount localized noisy pixels. This results in less accurate localization of the detected edges. Not all edges involve a step change in intensity. Effects such as refraction or poor focus can result in objects with boundaries defined by a gradual change in intensity [4].

The operator needs to be chosen to be responsive to

such a gradual change in those cases. So, there are problems of false edge detection, missing true edges, edge localization, high computational time and problems due to noise etc. Therefore, the objective is to do the comparison of various edge detection techniques and analyze the performance of the various techniques in different conditions

### Experimental analysis

Edges are detected using the Sobel, Prewitt, and Roberts methods, by thresholding the gradient function. For the Laplacian of Gaussian method, thresholding is computed for the slope of the zero crossings after filtering the image with the LoG filter. For the Canny method, a threshold is applied to the gradient using the derivative of a Gaussian filter.



*Figure 1*

**A. Detection using Sobel filter**

As mentioned before, the Sobel method finds edges using the Sobel approximation to the derivative. It returns edges at those points where the gradient of the image is maximum. Figure 2 displays the results of applying the Sobel method to the image of Figure 1.

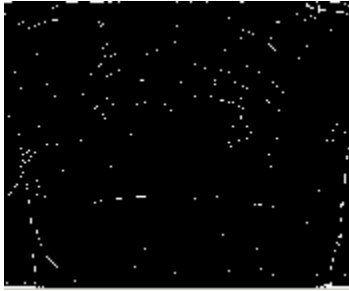


Figure 2: Sobel edge map of Figure 1

**B. Detection using Prewitt filter**

The Prewitt method finds edges using the Prewitt approximation to the derivative. It returns edges at those points where the gradient of the image is maximum. Results of applying this filter to Figure 1 are displayed in Figure 3.



Figure 3: Prewitt edge map of Figure 1.

**C. Detection using Roberts**

The Roberts method finds edges using the Roberts approximation to the derivative. It returns edges at those points where the gradient of the image is maximum. Results of applying this filter to Figure 1 are displayed in Figure 4.



Figure 4: Roberts edge map of Figure 1

**D. Detection using Laplacian of Gaussian**

The Laplacian of Gaussian method finds edges by looking for zero crossings after filtering the image with the Laplacian of Gaussian filter. The edge map is shown in Figure 5.

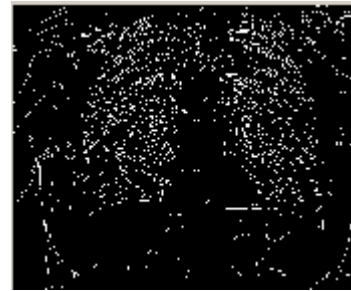


Figure 5: Laplacian of Gaussian edge map of Figure 1

**E. Detection using Canny**

The Canny method finds edges by looking for local maxima of the gradient of the image. The gradient is calculated using the derivative of the Gaussian filter. The method uses two thresholds to detect strong and weak edges, and includes the weak edges in the output only if they are connected to strong edges. This method is therefore less likely than the others to be "fooled" by noise, and more likely to detect true weak edges. Figure 6 illustrates these points which are the result of applying this method to the image of Figure 1.

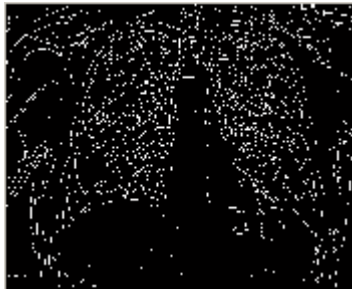


Figure 6: Canny edge map of Figure 1

Evaluation of the images showed that under noisy conditions Canny, Robert, Sobel exhibit better performance, respectively. Canny yielded the best results as shown in Figure 13. This was expected as Canny edge detection accounts for regions in an image. Canny yields thin lines for its edges by using non-maximal suppression. Canny also utilizes hysteresis with thresholding.

**Performance evaluation**

Edge detection methods investigated so far are further assessed by quality measures that give reliable statistical evidence to distinguish among the edge maps obtained[14]-[17]. The absence of the ground truth edge map reveals the search for an alternative approach to assess and compare the quality of the edge maps resulted from the detectors exploited so far. The evidence for the best detector type is judged by studying the edge maps relative to each other through statistical evaluation. Upon this evaluation, an edge detection method can be employed to characterize edges to represent the image for further analysis and implementation.

Table 1 Relative frequencies (R) of the detected edge pixels

Operator	Canny	Lap of gaussian
Canny	1	0.6238
Lap of Gaussian	1.60	1
Prewitt	3.723	2.32
Sobel	3.69	2.30
Robert	4.28	2.673

Operator	Prewitt	Sobel	Robert
Canny	0.268	0.270	0.2333
Lap of Gaussian	0.430	0.433	0.374
Prewitt	1	1.00	0.869
Sobel	0.992	1	0.862
Robert	1.150	1.158	1

Table 2 gives the relative frequencies of the occurrence of edge pixels in the previous filters. For each edge map,  $\max(n_{df})$  where  $n_{df}$  is the frequency  $f$  of occurrence for the filter  $f$  is reported, and the ratio with respect to each other gives comparative statistics for the occurrence of edges. The Canny filter reports the higher detected edge pixels.

Table 2: Significant edge differences at edge

	Can/ap	Can/Pre	Can/Sob	Can/Rob	Lap/Pre
H	1	1	1	1	1
P	0	0	0	0	0
CI	(0.037, 0.064)	(0.077, 0.084)	(0.070, 0.0845)	(0.0811, 0.0886)	(0.036, 0.042)
STA TS	18.74	42.18	42.10	44.63	25.71

	Can/ap	Can/Pre	Can/Sob	Can/Rob	Lap/Pre
H	1	1	0	1	1
P	0	0	0.84	1.28e(-004)	5.00e(-005)
CI	(0.036, 0.042)	(0.040, 0.046)	(-0.0023, 0.0018)	(0.0019, 0.0059)	(0.0021, 0.061)
STA TS	25.61	28.69	-0.20	3.85	4.07

Table 2 summarizes the t-test for every pair combination of the detected edge maps on comparing the average of the pair wise edge maps, the following statistics gives evidence on the judge for the best method in such environment. The only non significant difference exists between the Prewitt and the Sobel at 0.05 level of significance, with P-value

given in the second row of the table. The STATS gives the t-statistics for every pair.

The CI gives the confidence limit. In conclusion, Table 2

gives the evidence that the methods produce different edge maps, only for the Prewitt and Sobel as mentioned previously.

### Discussion

Figures 2 through 6 give edges maps for the different operators highlighted above. The focus in this study is on the detection of edges that produces a map representing the original image. This provides a foundation for selecting an appropriate edge detector for further application. Investigation is aimed at aiding the choice of an appropriate operator that is capable of detecting boundaries based on intensity discontinuities[18]-[20]. From the results above, although the Sobel operator provides both differencing and smoothing, it detects part of the edges in the image. The problem with the Roberts detector is that it relies on finding high spatial frequencies which fail to detect fine edges. This is illustrated in Figure 10. The Laplacian responds to transitions in intensity. As a second order derivative, the Laplacian is sensitive to noise. Moreover, the Laplacian produces double edges and is sometimes unable to detect edge direction. The canny edge detector is capable of reducing noise. The Canny operator works in a multistage process. These can be summarized in a smoothing with a Gaussian filter, followed by gradient computation and use of a double threshold. The analysis in Table 2 illustrates the differences in the methods pair wise, only Prewitt and Sobel have approximately the same edge map. The Canny produces the best edge map as evidenced by the relative frequency analysis in Table 1.

### Conclusion

In this paper, we have analyzed the behavior of zero crossing operators and gradient operator on the capability of edge detection for images. The methods are applied to the whole image. No specific texture or shape is specified. The objective is to investigate the effect of the various methods applied in finding a representation for the image under study. On visual perception, it can be shown clearly that the Sobel, Prewitt, and Roberts provide low quality edge maps

relative to the others. A representation of the image can be obtained through the Canny and Laplacian of Gaussian methods. Among the various methods investigated, the Canny method is able to detect both strong and weak edges, and seems to be more suitable than the Laplacian of Gaussian. A statistical analysis of the performance gives a robust conclusion for this complicated class of images.

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