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# Analysis of Edge Detection Techniques for Identifying an Image Object

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**ABSTRACT**

Edge detection referred to the course of identifying and tracing, locating sharp discontinuities in an image. The discontinuities are abrupt changes in pixel intensity value which distinguish boundaries of objects in a scene. Classical methods of edge detection involve convolving the image object through an operator 2-Dimension filter, which isbuilt to be subtle to large gradients in the image while returning zero values in uniform regions. This is an exceedingly large number of edge detection operators available, each intended to be very sensitive to certain types of edges. Variables involved in the selection of edge detection operators that include Gradient, Laplacian, Laplacian of Gaussian. This paper presents an analysis of edge boundary point detection to improve edge detection techniques.

*Keywords:* Edge Detection, Gradient, Laplacian, Edge Enhancement, Edge Localization.

## 1. INTRODUCTION

Edge Orientation is the geometry of the operator that determines a characteristic to sensitive edges. Operators may be optimized to look for horizontal or vertical or diagonal edges. One of the problems of edge detection is the presence of noise in images. Attempts to reduce the noise result in blurred and distorted edges. The operators used on the noisy images are classicallygreater in scope, so they can average enough data to discount localized noisy pixels. These fallouts in much less precise localization of detected edges. Edge Shape deals with borders nevertheless not all the edges involve a phase change in the intensity. Effects such as refraction or poor focus can result in objects with boundaries defined by a regular change in the intensity. The operator has to be selected to be receptive to such a regularmodification in those cases. Novel wavelet-based methodsreally characterize the nature of the transition for each edge in order to distinguish, for example, edges related with hair from edges related with a face. There are many ways to perform edge detection. Though, the mainstream of various methods can be classified into two categories *Gradient and Laplacian*. The gradient techniquedetects edges by observing for maximum and minimum in the first derivative of the image. The Laplacian method searches for zero crossings [1] in the second derivative of the image to find edges. An edge has the one-dimensional outline of a ramp and manipulating the derivative of image object can highlight its location. Suppose it has the following signal, with an edge shown by the jump in intensity in figure 1.

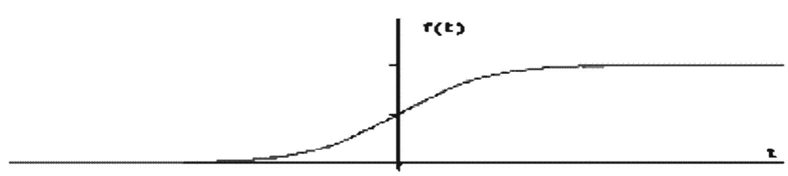


**Figure 1: The Signal Apply to the Edge Detector**

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If it takes the gradient of this signal it gets the intensity shown in figure 2.

Evidently, the derivative displaysaextreme located at center of the edge in the original signal. This technique of locating the edge isthe main characteristic of the gradient filter family of edge detection filters and includes the Sobel method. A pixel positionis declared the edge location suppose the value of the gradient exceeds some threshold. As mentioned before, edges have greater pixel intensity than those adjacenttoit. So once a threshold is set, one can compare the gradient values to that of threshold value and detect the edge each time the threshold is exceeded. Moreover, when the first derivative is at a maximumthe second derivative is at zero. By way ofresult, another alternative to finding the location of an edgeisto find the zero's in the second derivative. In this method is known as the Laplacian and the second derivative of the signal is shown in figure 3.

The purpose of detecting sharp changes in image brightness is to observesignificant events and modifications in the properties of the world. It can be shown that under rather general conventions for the image formation ideal, the discontinuities in image brightness are likely to correspond to discontinuities in complexity. In the perfect case, the result of implementing an edge detector for an image may lead to a set of connected curves that indicate the borders of the objects, the borders of superficial markings as well curves that correspond to discontinuities in superficial orientation. Thus the implementation ofan edge detector can significantly reduce the amount of data to filter the information whichare less relevant, while preserving the important structural characteristics of the image. The edge detection step is fruitful when the subsequent task of interpreting the information contents in the real sample imageissignificantly simplified. Unfortunately, it is not always possible to obtain as such perfect edges from original life images of medium complexity. Edges extracted from non-trivial images are often interfered by the fragmentation, which means that the edge shape curves are not linked which complicates the task of interpreting the image data.

## A Simple Edge Model

Although certain literatures have considered the detection of perfect edges, the edges obtained from natural real imagesarenot optimal. Theyare normally affected by one or several of the subsequent effects:

- The Focal blurisproduced by a determinate depth of field and finite pixel point spread function.
- The Penumbral blur that produced by the shadows created by lightisthecauses of non-zero radius.
- The Shading at a smooth object edge.
- The Local specularities or inter-reflections in the vicinity of object edges.

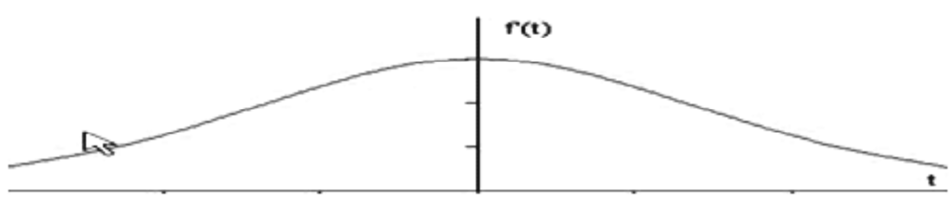

**Figure 2: The Gradient First Derivative Signal**

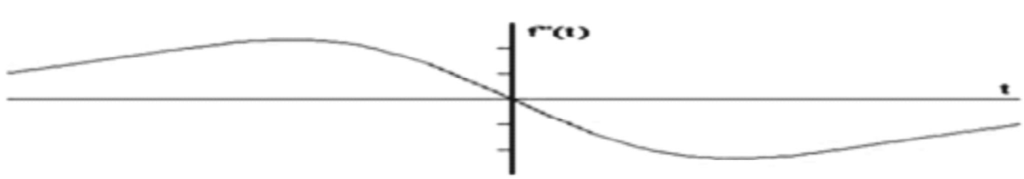

**Figure 3: The Gradient Second Derivative Signal**

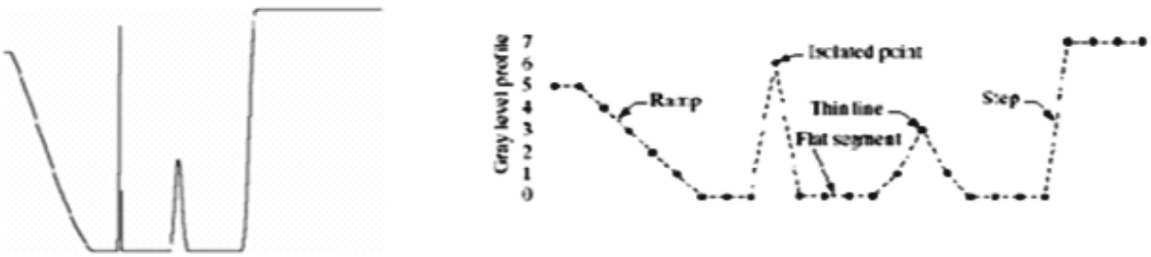


**Figure 4: Gray Scale Profile**

Although the upcoming model does not observe and capture the complete variability of real-life edges, the error function which have been handled by a many researchers as the formal extension of the perfect step edge model for modeling the effects of edge blurring in the practical implementations. Thus, a 1Df which has exactly one edge placed at x = 0 may be modeled as:

$$f(x) = \frac{I_r - I_l}{2}\left( erf\left(\frac{x}{\sqrt{2\sigma}}\right) + 1 \right) + I_l \tag{1}$$

At the left side of the edge shown in figure 4 where intensity is $I_l = \lim_{x\to\infty} f(x)$ and the intensity of theright side edgeis $I_r = \lim_{x\to\infty} f(x)$.

## 2. SURVEY ON EDGE DETECTORS

Some of the earliest works of edge detection employ small convolution masks to approximate either the first derivative or the second derivative of an image. For example, Roberts filter, Sobel filter, Prewitt filter, and Laplacian filter. They focus on the “edge enhancement” part of edge detection, with none or very little “smoothing”. A threshold is then applied to the output of these filters to identify the edge points. These filters, though easy to implement and generally with the advantage of speed over later edge detectors, provide very little control over smoothing and edge localization, by which noise is reduced. Therefore, these filters are very noise-sensitive.

Marr and Hildreth [2, 3] have proposed the use of zero-crossings of the Laplacian of Gaussian. Using the fact that a step edge corresponds to a sharp change in the image, the first derivative of the image should have a maximum at the position corresponding to an edge in the image, and so the second derivative should be zero at the same position. Obviously, it is easier to find a zero-crossing than a local maximum in a two-dimensional function. On the other hand, the higher-order derivatives are also more sensitive to noise. In order to reduce noise, the image has to be smoothed. When choosing a smoothing filter, two criteria should be fulfilled [45]. First, the filter should be smooth and roughly band-limited in the frequency domain to reduce the number of frequencies at which image function changes can take place. Secondly, the constraint of spatial localization required the response of a filter to be from nearby points in the image. These two criteria are conflicting, and the Gaussian filter is a compromise between spatial and frequential criteria.

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

*Note:* $G(x, y)$-Guassian filter at the $x$, $y$

The edge detection operator is the second derivative of a smoothed two-dimensional image function $f(x, y)$, which is

$$\nabla^2((G(x, y; \sigma) \times F(x, y)) \tag{3}$$

*Note:* $F(x, y)$ is the image function

It is usually called LOG as an abbreviation of Laplacian of Gaussian where the Laplacian operator is the second-derivative operator which can be represented numerically as the linear operator

$$\nabla^2 = \frac{\partial^2}{\partial x^2} + \frac{\partial^2}{\partial y^2} \tag{4}$$

$$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$

The order of differentiation and Gaussian smoothing is interchangeable because of the derivative property of convolution1. Therefore, the operator in Equation (3) can be rewritten as

$$\nabla^2 G(x, y; \sigma) \times f(x, y)) \tag{5}$$

The filter now can be written as $r2G$ which is introduced as a cubic spline filter. The image is smoothed by a cubic spline filter before differentiation. It is shown that the result of the cubic spline filter is very similar to Gaussian smoothing. Canny described a widely used edge detecting algorithm [2] which is optimal to step edges corrupted by noise. Three criteria are defined for the optimality edge detection:

For Good Detectionthe detector must minimize the probability of false edges caused by noise, as well as missing real edges. For Good Localization the edges detected must be as close as possible to the true edges. For Single Response the detector must return one point only for each true edge point.These criteria and their variations are also widely used in other research. First two criteria are then developed quantitatively into a set of functions with mini 1Derivative property of convolution. If the signal $x(t)$ has an ordinary first derivative x(t), the convolution x(t) to v(t) has an ordinary first derivative,

$$\frac{d}{dt}[x(t)*v(t)\} = x(t)*v(t) = x(t)*v(t) \tag{6}$$

Normal and maximal constraints. A closed form solution is found using variational calculus. Without the third criterion, the optimal detector for a step edge

$$G(x) = \begin{cases} 0x < 0 \\ Ax \geq 0 \end{cases} \tag{7}$$

$G(x)$: Gaussian filter at point $x$.

$f(x) = -G(x)$ in $[-W, W]$, assuming the filter width is $2W$. Therefore, the optimal, one-dimensional step edge detector is a truncated step. Unfortunately, this filter contains a very high bandwidth and tends to produce many maxima with noisy step edges. If the third criterion is added, the optimal solution may be found by numerical method. The result filter can be approximated with error less than 20% by the first derivative of a Gaussian smoothing filter. This is similar to Marr-Hildreth edge detector [4] which is based on the Laplacian of a Gaussian. The detector is then generalized to two-dimensions. Non-maximum suppression is then applied on the results of the filter to thin wide edges in order to produce 1-pixel wide edges. It is done by finding local maxima in the direction perpendicular to the edges. Finally, weak edges are removed using thresholding. The thresholding is applied with hysteresis. Edges contours are processed as units and two threshold values are defined. Each contour must have at least one point with gradient magnitude above the higher threshold, while all points in the contours must not go below the lower threshold. Canny also proposed feature synthesis which is a multiple-scale approach where the standard deviations of the Gaussian are used as the scaling factor. All significant edges from the operator with the smallest scale are marked first, and the edges for larger scale are synthesized from these marked edges and then compared to the actual detector output. Additional edges are marked only if they have a significantly stronger response than that predicted by the synthetic response. Many researchers are inspired by Canny's work. For example, Deriche [5] extended Canny's initial filter to two-dimensions and implemented it using recursive filtering. Petrou and Kittler [8] derived another optimal detector for a blurred step edge model using criteria similar to those by Canny. Canny's feature synthesis is not the first attempt to detect edges using different scale parameters. Marr and Hildreth [4] have suggested to obtain a description of an image at different scales by applying a feature detector at different scales and combining the edge information. If one creates a series of images $It(x, y, t)$ from original image $I_0(x, y)$ by convolving $I_0(x, y)$ with a Gaussian kernel $G(x, y; t)$ with variance $t$, as pointed out by Koenderink [7] and Hummel [5], this family of images can be viewed as the solution of the isotropic diffusion equation

$$\frac{dI}{dt} = \nabla^2 I = \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2} \tag{8}$$

with the initial condition $I(x, y, 0) = I_0(x, y)$, the original image. One disadvantage

of linear isotropic diffusion is that the diffusion would blur features as well as smooth noise. An isotropic diffusion method is introduced by Perona and Malik [10]. A nonlinear diffusion equation is used.

$$\frac{dI}{dt} = \nabla.\left(c\left(x,y,t\right)\nabla I\right) = c\left(x,y,t\right)\nabla^2 I + \nabla c.\nabla I \tag{9}$$

Canny at point $x$, where $c(x, y, t)$ is chosen as

$$c(x, y, t) = g(\nabla I(s, y, t)) \tag{10}$$

$c$ and $g$ is a nonnegative monotonically decreasing function with $g(0) = 1$. A different function $g$ would generate different scale-spaces, though they turn out to be perceptually similar. This way, the points with strong features, *i.e.*, with high |delta| values, would have less diffusion effect than other points, thus retains most of the features in the image. To make the diffusion anisotropic, the function $c(x, y, t)$ should be directional and is perpendicular to the orientation of the gradient of the image. The nonlinear diffusion methods process an image with different smoothing parameters such that it could blur noise and at the same time keep the edges sharp. Another approach of edge detection is parametric fitting. This involves fitting the image with an edge model with parameters, then finding the parameters that minimize the fitting error. The Hueckel edge detection [2] is an example of the parametric fitting method. A two-dimensional step edge model in a circular window is fitted to each image pixel.

The parameters of the edge model are the gray scale values, the edge orientation, and the distance from the center of the window to the edge. An edge is detected if the fit is accurate enough, while the accuracy of edge fitting is measured in terms of the mean square error. Hueckel introduced a polar Fourier expansion and used the first eight Fourier coefficients in the fitting process in order to reduce the computation. Experimental results indicated that Hueckel operator performs well in noisy and highly textured environments, though no analysis of the operator in the presence of noise isdocumented.Some other detectors that can be categorized as parametric fitting approach are used in the same model to detect line edges. Since this approach used a rich description of the image structure, edge detectors using this approach could provide edge attributes such as position with subpixel accuracy, contrast, blur, and width. In other words, this approach could provide more thorough description of the edges. One problem of this approach is that it is not easy to provide a two dimensional edge model with an arbitrary-shaped curve. Most edge detectors used a straight edge model. For some complex features such as a corner, or more than one edges within the window, the detectors can still pick the accurate parameter set that minimizes the edge fitting error. Therefore the value of the edge fitting error is increased, and the edge might be rejected once the error exceeds the default threshold. Some edge detecting techniques converted the edge detecting problem into energy functions then finds the optimal edges by minimizing the energy functions. Two examples of such techniques are deformable contours [5], and the Mumford-Shah theory [6].

## 3. ANALYSIS OF EDGE POINT PROFILE

An edge point has two principle directions, the edge normal direction, and edge direction. These two directions are introduced. The edge direction indicates the continuity of the edge, while the edge normal direction yields an edge profile. This paper describes the process of localizing an edge point in the vicinity of a given point.The detection of the first edge point is one of the most critical steps, since without any prior knowledge of the edge, choosing an optimal edge profile is difficult, and sometimes impossible. For example, given a point that forms a complicated edge profile, in other words, it is composed of multiple step/ramp profiles. Determining whether this point belongs to an edge with that complicated profile or multiple edges with simple profiles is impossible without the global view of the edge curves. Sometimes multiple interpretations are equally valid. Sometimes, the consistency of the profiles along the edge curve can be used to identify the best interpretation among the different valid ones. If the edge curves with simple profiles are parallel, it may be able to use one edge curve with composite profile to replace all these edges. On the other hand, sometimes the decision cannot be performed without prior knowledge, which is beyond the scope of this work.

One of the key structures of edge detector is profiles. As mentioned in this work, a profile is a one-dimensional image extracted from a two-dimensional image along a line segment. The position of the profile issubpixel-level precision. Since the pixel values in profiles are sampled with subpixel-level precision, the choice of subpixel-level precision of the positions does not increase the complexity of the process of edge detection at all. Moreover, it can reduce the zigzag effect caused by the digitization of the images. Although such effect is not very significant, the choices of subpixel-level precision do not remove it completely. The difference is still visible as shown in Figure 1. As it shows, the curves generated by a subpixel-level edge detector appear smoother, and more natural. While it is possible to perform curvature smoothing on the outputs of pixel-level edge detectors and achieve similar visual results as the subpixel-level detectors, precaution have to be taken in order to keep the smoothed curves remain attached to edges on the image. There is also the fact that smoothing tends to remove some fine detail, in this case, sharp corners might be removed accidentally.To detect edges with profile-based approach, some functions should be provided for different “classes” of edges. They should also produce some abstract edge properties such as the edge width and colors on both sides of the edge. Such properties can then be used in edge linking process, because all the edge points on the same edge share many of these properties. A candidate edge point would be the oriented point whose profile yields a local minimum among its neighborhood according to a specific function. The minimization reduces the necessity of a threshold, but cannot remove it completely. In case where there is no edge point except random noise, a local minimum should not validate a false edge point. Therefore, a threshold is still required for the purpose of validation. If thresholding cannot be avoided, it should at least make the selection of the threshold reasonable.

## 4. RESULTS AND DISCUSSION

The outputs which are represented in figure 5.isthecomparative analysis results of a pixel-level edge detector with a subpixel-level edge detector on three images taken from UCI repositories.

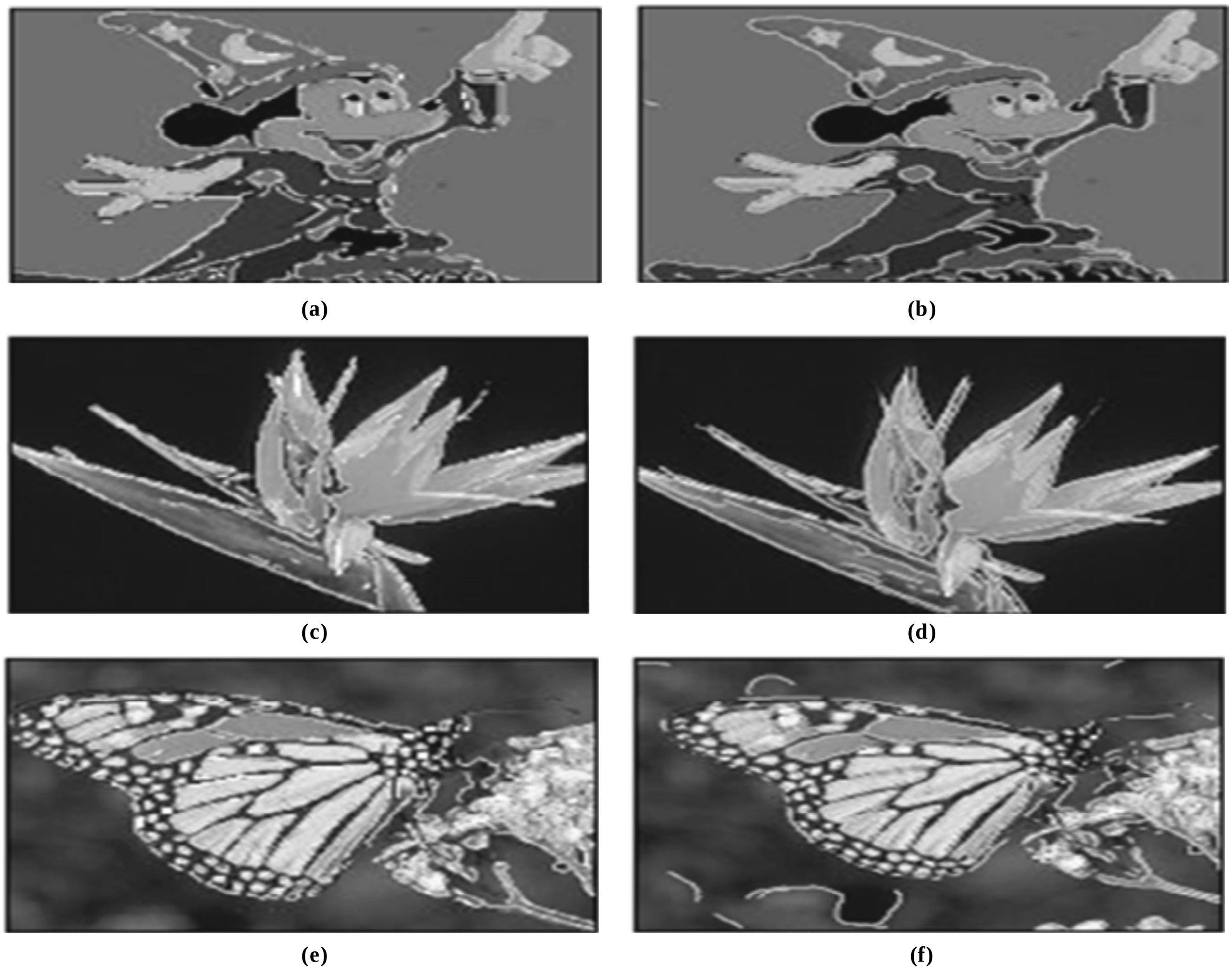

**Figure 5: (A) Canny's Output of The Picture of Mickey Mouse. (b) Profile-based detector's Output of The Picture of Mickey Mouse. (c) Canny's Output of The Picture of a Flower. (d) Profile-based detector's Output of The Picture of a Flower. (e) Canny's Output of The Picture of a Butterfly. (f) Profile-based detector's output of the picture of a butterfly**

As the main objective of thresholdingis to differentiate the noisy edges from real edges, the verification of the profile is done by comparing both the noise and edge magnitudes.The noise magnitude of the image is often measured by calculating the standard deviation over the colors of quasi-constant regions. This is considered as stable regions in general. The edge magnitude should be adequate with the standard deviation of the profile's transient region. The values of both noise and edge magnitudes might not be very accurate as the size of the data is too small for statistic calculation. The possible reason is, if the transient region of a profile is fluctuating than the profile's stable regions then the noise cannot be distinguished from the transient region. The proportion of the signal and noise known as SNR, is the widely used method in signal process. Certain edge detection methods such as Canny's use SNR as the important factors of edge detection. The measure of SN is more likely to be smaller than the real SNR by the effect of additional alignment. However, the alignment effect is considered as a part of noise as the detector is in the suppixel-level. The measured noise magnitude not only contributes to SNR calculation but also used in the edge linking process when the two adjacent points of the profile is compared. In addition, if the profiles of the edges are similar, they are grouped as the same category in the post-processing stage.

The noise magnitude isonce again the main factor of determining the threshold value as the image data information can come from various sources. Forexample, in medical imaging applications the images are digitized from x-rays, ultrasound waves tool and the Magnetic Resonance Response tool. Satellite sensors

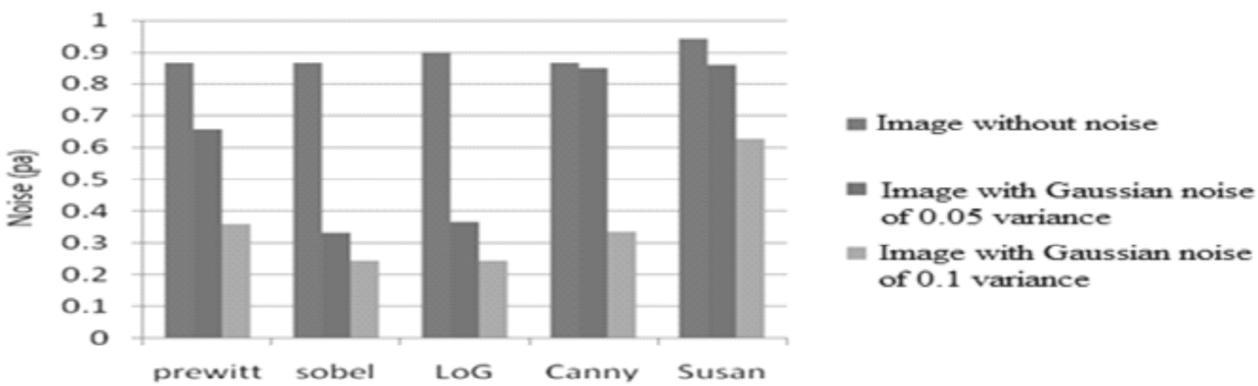


**Figure 6: Performance Analysis of Various Edge Detectors**

produce digital images directly from the measurements of infrared or microwave radiationsusedfor astronomy and military applications.Avisual system uses a combination of active and passive spatial image datafor auto vehicle navigation applications. An image may be degraded by several factors during image digitization in which the most common is the restriction of sampling frequency. In sampling theorem, the image has to be sampled at a rate of twice the highest spatial frequencyaslikeoriginal image. There is no way to control the highest spatial frequency in natural scenes and this theorem does not satisfy this necessity. The blurring effect of apertureisthesecond factor. The third one is the quantization error which employs finite number of values to represent the infinite value range of original images. Finally, the fourthis additive and multiplicative noise produced by quantization devices, such as thermal effects in electronic components, which is often modeled as Gaussian noise.If a color picture or multi-spectrum image is digitized with three channels: red, green and blue (RGB) the image can be represented in three intensity buffers which is called a true color image.The RGB color space is one of the standard color spaces used to physically detect and generate colored light, the other derivative color spaces that are created to aid color image processing. This paperrestrictsthe discussion to the processing of gray scale images. Generally, all operations on gray scale images can be extended to process color images simply by applying them to each color component of the image, such as to intensity, or to hue, or to a single color component respectively. The comparative analysis of the methodsis done and the results are presented in table.1.

**Table 1**
**Performance analysis of Various Edge Detectors**

| *Operator* | *Image without Noise (pa)* | *Image with Gaussian noise of 0.05 variance (pa)* | *Image with Gaussian noise of 0.1 variance (pa)* |
|---|---|---|---|
| Prewitt | 0.8643 | 0.6557 | 0.3608 |
| sobel | 0.8643 | 0.3301 | 0.2428 |
| LoG | 0.8995 | 0.368 | 0.244 |
| Canny | 0.864 | 0.848 | 0.333 |
| Susan | 0.9411 | 0.86 | 0.6278 |

## 5. CONCLUSION

Edges of an image provide the topology and structure information of objects.Theedge detection characterizesthechanges in the intensity of images in terms of the physical processes that have originated the original image. The techniques of edge detection are widely used in feature extraction, region segmentation, and object or boundary description. By using edge detection techniques, image processing systems and machine vision,one can build a variety of applications. But, the detection of the first and optimal edge point is more difficult and sometimes impossible as itrequires a prior knowledge on the edge. To overcome the issue, this paper describes the process of localizing an edge point in the vicinity of a given point through the concept of edge detector profiles. The proposed method is compared with the existing edge techniques and the results are significant in originating the optimal edge profile than the comparative algorithms.

## REFERENCES


[1] Chen, L., "Laplacian Embedded Regression for Scalable Manifold Regularization", *Neural Networks and Learning Systems, IEEE Transactions,* **(23)**, 902-915, 2012.

[2] Giannarou S. and Stathaki T., "Optimal edge detection using multiple operators for image understanding". *EURASIP Journal on Advances in Signal Processing*, 1-19, 2011.

[3] J.W. Buchanan and M.C. Sousa., "The Edge Buffer: A Data Structure for Easy Silhouette Rendering", *In Proceedings of the 1st International Symposium on Non-photorealistic Animation and Rendering,* 39-42, 2000.

[4] Seif, A., *et.al.*, "A hardware architecture of Prewitt edge detection", *Sustainable Utilization and Development in Engineering and Technology (STUDENT), 2010 IEEE Conference, Malaysia*, 99-101, 2010.

[5] T.G. Smith Jr., *et.al.*, "Edge detection in images using Marr-Hildreth filtering techniques*", Journal of Neuroscience Methods,* **26(1)***,* 75-81, 1988.

[6] J. Bartovsky, D. Schneider, E. Dokladalova, P. Dokladal,V. Georgiev, and M. Akil. "Morphological classi_cation of particles recorded by the timepix detector*". In 7th ISPA* 343-348, 2011.

[7] J. Bartovsk_y, P. Dokl_adal, E. Dokl_adalov_a, and M. Bilodeau. "One-scan algorithm for arbitrarily oriented 1-D morphological opening and slope pattern spectrum". *In International Conference on Image Processing*, 133-136, 2012.

[8] Shafarenko, L., Petrou, H. and Kittler, J., 1998. "Histogram-based segmentation in a perceptually uniform color space." *IEEE transactions on image processing*, **7(9)**, 1354-1358, 1998.

[9] N. Senthilkumaran, R. Rajesh, "Edge Detection Techniques for Image Segmentation and A Survey of Soft Computing Approaches"*, International Journal of Recent Trends in Engineering,* **1(2)**, 250-254, 2009.

[10] Black, Michael J., Guillermo Sapiro, David H. Marimont, and David Heeger. "Robust anisotropic diffusion." *IEEE Transactions on image processing* **7**, 421-432, 1998.

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