www.ijecs.in
International Journal Of Engineering And Computer Science ISSN: 2319-7242
Volume 3 Issue 6 June, 2014 Page No. 6311-6318

Analysis and comparison of various edge detection technique

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Abstract: The main problem in image processing is to find out the correct boundaries or edges of any object for clearly identifying it. To characterize the boundaries and edge detection is not an easy task in image processing and it become very difficult when image is noisy. Edges are significant local or sharp change of intensity in an image and it occur on the boundary between two different regions in an image. It means that if the edge of any object can be identified accurately and all of the object can be located then basic properties such as area shape can be measured. Edge detection of an image significantly reduces the amount of irrelevant data and filters out the useless information while preserving the main structural properties of any object. It is very crucial to have a better understanding of edge detection algorithm. Many techniques of have been developed for edge detection. This paper tries to provide a comparison of different edge detection schemes that fall in three main categories of edge detectors: Gradient based edge detectors, Laplacian based edge detectors and Non-derivative based edge detectors. Pratts figure of merit is used to compare quantitatively results of edge maps for a synthetic image at various levels of noise. Results of real life image are analyzed qualitatively. Non-derivative based edge detector SUSAN gives the best results even in presence of noise.

Keywords: Image Processing, Edge Detection, Noise, Canny, Laplacian, Robert, Sobel, Prewitt.

Introduction

Edge can be defined as a sharp discontinuity or geometrical change in an image. The edges carry important information related to the objects present in an image. Edge detection is a process of considering edge pixels of any object in an image, it's a task of huge importance in feature-based image processing. Accurately find the edges of object which separate them from the background and help in calculation of different features of objects like, geometrical shape, perimeter and area. There are many number of image processing and computer vision applications that rely on correctly detected edges of any object within an image. For example, many applications like military applications involving tasks such as object recognition and motion analysis, security applications including coding of data, hiding of data, and watermarking also benefit from improved edge detection capabilities. A lot of research work has been done in this field in last few years. The performance measure for the edge detection is how well edge detector markings match with the visual perception of object boundaries [6]. The detection process is carried out by the examination of local intensity changes at each pixel element of an image. There are many ways to perform edge detection. However, the various edge detection methods may be grouped into three categories:

Gradient Based Edge Detection: Gradient based edge detectors derivative of image is taken and edges of objects are detected by looking for minimum and maximum in that derivative.

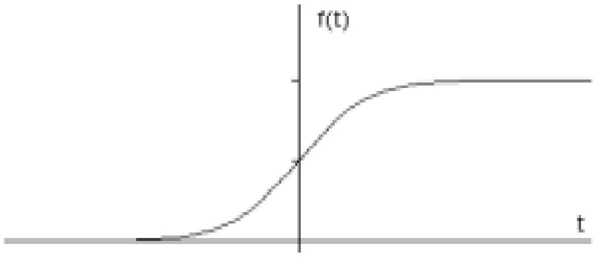


figure1

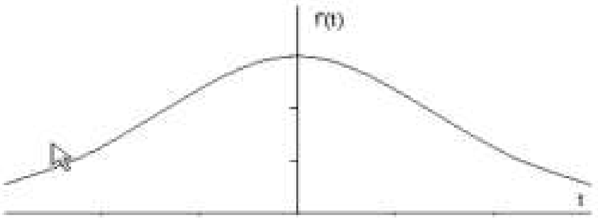


figure2

We consider one dimensional ramp edge shown in figure 1. We take its gradient with respect to t which gives signal as given in figure2.Clearly, In the original signal the derivative shows a maximum located at the center of the edge. This technique of locating an edge is characteristic of the gradient filter family of edge detection filters A pixel location is declared an edge location if the value of the gradient exceeds some threshold. So the pixel intensity values of edges are higher as compared to neighboring pixels. So once a threshold is set, gradient value can be compared to the threshold value and an edge is detected whenever the threshold is exceeded [3].

Laplacian Based Edge Detection: The Laplacian method searches for zero crossings in the second derivative of the image to find edges. If the first derivative is maximum, and the second derivative is zero. As a result, another alternative to understand or detect the location of an edge is to locate the zeros in the second derivative. This technique is known as the Laplacian and the second derivative of the signal of figure1 is shown in below.

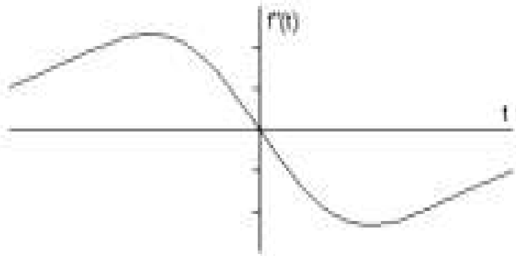


Figure3.

Non-derivative Based Edge Detection: In this category all the edge detectors do not require image derivatives at all. There are many problems associated with edge detection like false edge detection, missing true edges of objects, edge localization, very high computational time and the major problems which generate due to noise. Old research and experience with various edge detectors indicates that the problem of locating edges in real images is extremely difficult. The performance of an edge detector depends on how well localized its response to real and synthetic images is. All real life images contain noise. Usually, to minimize the effect of this noise low pass filtering (using Gaussian kernels) is performed prior to edge detection. But, this smoothing also reduces the effect of sharp discontinuities due to edges [7]. Smoothing performed by filter can be controlled by varying parameters of filter. Increasing strength of filter produce the better result in effective removal of noise but detected edges will have large localization errors and many edges would not be picked. On the other hand decreasing strength of filter would result in ineffective removal of noise but fine details would be preserved [1].The main point is that an edge detecting operator should be a scalable differential operator, which can compute the first or second derivatives at different scales. This can be achieved by using a Laplacian of Gaussian (LoG) operator,which was as:

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

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

figure 4

The magnitude and directions of the gradient can be given

$$|G| = sqrt(Gx^2 + Gy^2) \qquad (1)$$

$$a(x,y) = arctan(Gy/Gx) \qquad (2)$$

In above equations Gx and Gy are the two images of the further approximated by the Difference of Gaussian (DoG). Zero-crossings are needed to detect edges in images which are filtered using these filters. This operator opened new heights in the field of edge detection. Zero-crossings from derivatives of the Gaussian are only reliable if edges are well separated and the signal-to-noise ratio in the image is high. But there is a problem with Gaussian differential algorithm, that it produces false edges i.e. those which do not result from major intensity changes in the image. [5]

Canny [4] presented edge detection as an optimization problem with constraints. His optimization objectives were high signal to noise ratio, well defined edge points, and single response of edges. He produced a mathematical expression for these objectives and then showed that a successful use of the first derivative of a Gaussian approximation achieved optimal results. However, Canny's algorithm is more sensitive to weak edges, making it declare false and unstable boundaries as edges, resulting in a corrupted edge map [2]. In short, most Gaussian based edge detectors have problems like false contours, localization errors and missing information. Much work has been done to overcome the issues related to these detectors but most of the techniques are computationally expensive.

Edge Detection Techniques

In this section a brief description of some famous edge detection algorithms is provided. Comparison of these detectors will be presented in next sections.

Prewitt: The Prewitt operator [11] is a discrete differentiation operator used to compute the gradient of image intensity function. The Prewitt masks are simple to implement but are very sensitive to noise [8]. The operator uses two 3x3 size masks which provide more information regarding the direction of the edges as they consider the nature of data on the other sides of the center point of the mask. Prewitt filter is a fast method of edge detection. These masks are then convolved with the original image to obtain the approximations of derivatives for the horizontal and vertical edge changes, separately. Calculation of the gradients is done with the help of these mask are shown in figure 4.Same size as the original image and these show horizontal and vertical gradient at each point.

Sobel: A way to avoid having the gradient calculated about an interpolated point between the pixels which is used 3 x 3 neighborhoods for the gradient calculations The Sobel operator is a discrete differentiation operator which computes the gradient at each point in an image for the intensity changes at each like Prewitt operator. This operator is much better for noise suppression as compared to Prewitt operator [7]. Masks used are shown in figure 5. Direction and magnitude and of gradient are calculated using equation (1) and (2).

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

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

Figure 5

LoG: This operator related to Laplacian based edge detectors class. Laplacian operator spoted the regions of rapid intensity changes of pixels in an image. As the Laplacian of an image detects the noise along with the edges in an image, the image is smoothened first by convolving by a 2-D Gaussian kernel of standard deviation σ.

$$G(x,y) = e^{(x^2+y^2)/2\sigma^2} \qquad (3)$$

The expression for LOG is given as

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

LoG is then convolved with input image I(x,y) giving resultant edge map.

$$g(x,y) = I(x,y) * \nabla^2 G(x,y) \qquad (5)$$

0	0	1	0	0
0	1	2	1	0
1	2	-16	2	1
0	1	2	1	0
0	0	1	0	0

Figure 6

The kernels of any size can be approximated by using the above expression for LoG. The edge detection in an image using LoG operator can thus be obtained by the following steps:
1.Apply Log to the input image.
2.Detect the zero-crossings of the image.
3.Apply threshold to minimize the weak zero-crossings caused due to noise.

Canny: The Canny edge detection algorithm has the following basic steps:
1. Noise is filtered and image is smoothed using Gaussian filter.
2. Edge strength is found by computing the gradient magnitude and angle of gradient vector for edge direction.
3. Non-maxima suppression is applied to the gradient magnitude to trace move along the edge direction and suppress those pixel values that are not considered edge and thus resulting in thinning of edge.
4. Final step is to use hysteresis and connectivity analysis to detect and connect edges. If threshold value for edge detection is kept too low or too high there can be problem of either false positive or false edges. Canny algorithm provides the solution for this problem by using two thresholds: A low threshold and a high threshold.

Susan*:* SUSAN Edge detector was presented in 1995 and the fact that it uses no image derivatives makes its performance good in noisy image. SUSAN stands for minimum Uni value Segment Assimilating Nucleus. The idea behind this detector is to use a pixel's similarity to its neighbors gray values as the classification criteria (a non linear filter). Figure 7 shows that the area of the USAN carries information about the image structure around a given point. The area of the USAN is at a maximum in a flat region, becomes half when USAN is near a straight edge and becomes further low when mask is used near a corner. Circular masks placed at different locations of an image containing a rectangle can be seen in figure. USAN is marked in dark color for each circular mask.

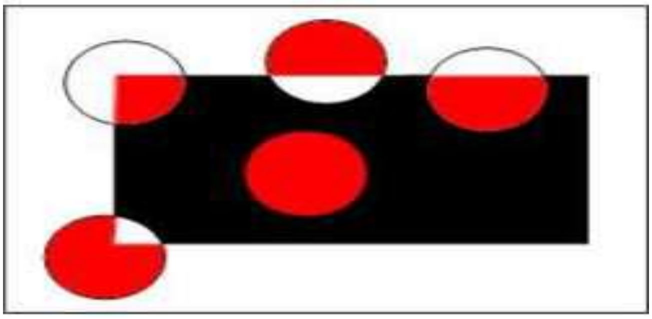


Figure 7

The edge detection algorithm has the following steps:
Circular mask is placed at each pixel and weight calculated of the circular mask. The weight of the USAN is

$$n(r_0) = \sum_r compare(r, r_0) \qquad (6)$$

Where compare(r; r0) is defined as:

$$compare(r,r_0) = \begin{cases} 1 \; if \; |I(r) - I(r_0) \le t \\ 0 \; if \; |I(r) - I(r_0)| > t \end{cases} \qquad (7)$$

Here it is a threshold defining pixel gray level similarity. Edge strength is calculated at each pixel using the formula:

$$response(r_0) = \begin{cases} g - n(r_0) \; if \; n(r_0) < g \\ 0 \; otherwise \end{cases} \qquad (8)$$

Here geometric threshold is g and the value of g is 3/4. After computing the edge response image non maxima suppression is performed for which direction perpendicular to edge is required. The direction is depended on the edge type which is being examined either inter-pixel (edge is between pixels) or intra-pixel (pixel itself is part of the edge).For inter pixel case, if the USAN area is greater than the mask diameter and the center of gravity of the USAN lies more than one pixel from the nucleus. The center of gravity of the USAN is defined as:

$$CG(r_0) = \sum_r r\ compare(r, r_0) / \sum_r compare(r, r_0) \qquad (9)$$

Direction required which is given by r0 − C G(r0). For intra pixel case, if the USAN area is smaller than the mask diameter or the USAN center of gravity lies less than one pixel from the core. And the second order moments of the USAN is computed by
nucleus r0 = (x0 , y0):

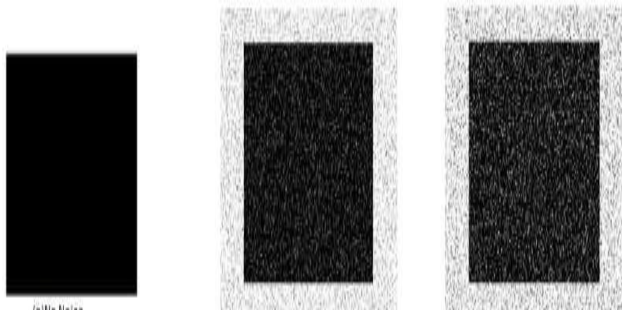
$$\overline{(x - x_0)^2} = \sum_r (x - x_0)^2\, compare(r, r_0) \qquad (10)$$

$$\overline{(y - y_0)^2} = \sum_r (y - y_0)^2\, compare(r, r_0) \qquad (11)$$

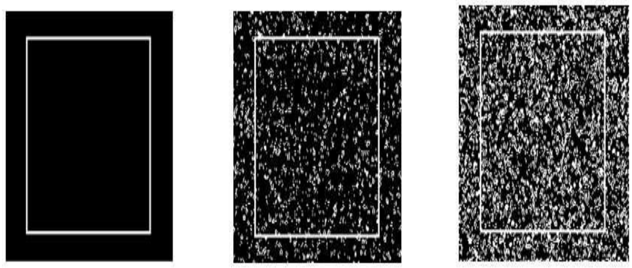
The ratio of equation 10 and equation 11 produced the edge orientation.

Quantitative Comparison

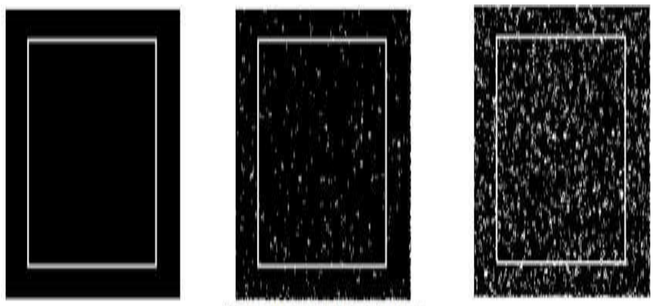
In this section we have tried to compare edge detectors described in the previous section. There are mainly three common problems associated with edge detectors: (1) missing real edge points,(2) failure to localize edge points and (3) classification of noise fluctuations as edge pixels. A figure of merit has been introduced by Pratt that balances these three types of error [10]. Pratt's Figure of Merit is chosen to quantify the results of edge detectors. This quantitative measure is determined as follows.
where, NI represents the number of true edge pixels, NA represent the number of detected edge pixels, and d(k) is the distance from the kth actual edge to the corresponding detected edge. And the scaling constant is α and the value of α is 1/9 as is often done in the literature. We have taken a synthetic image (box shape) as an input, and get its edge map at different levels of independent Gaussian noise. Threshold parameters of every edge detector are chosen to maximize Pratt's FOM. Outputs of all detectors are shown in figure 8 and resulting values of Pratts FOM are given in table 1.



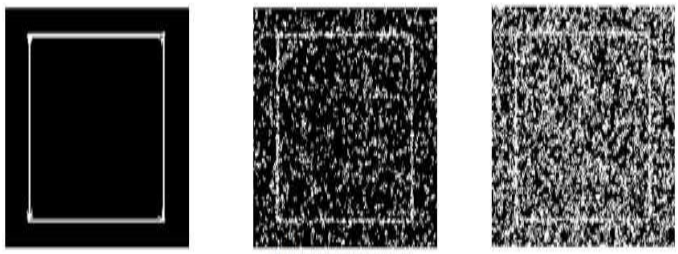
(a)No Noise (b)Gaussian noise of 0.05 var (c)Gaussian noise of 0.1 var



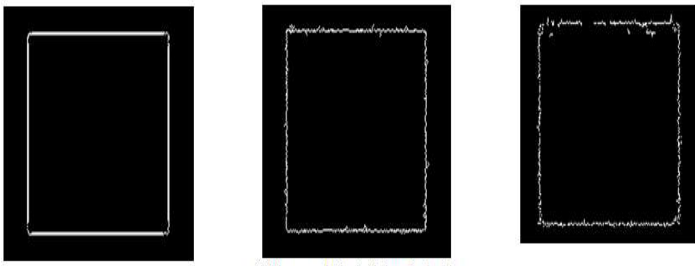
(d) Edge maps obtained with Prewitt Edge detector



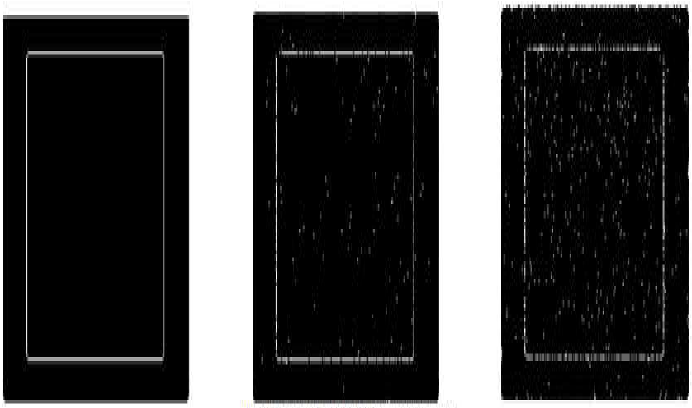
(e) Edge maps obtained with Sobel Edge detector



(f) Edge maps obtained with LoG



(g) Edge maps obtained with Canny's algorithm



(h)Edge maps obtained with Susan Edge detector

Figure 8. Edge maps of different edge detectors at different levels of noise.

PRATT'S FOM FOR VARIOUS EDGE DETECTORS			
Operator	Image without noise	Image with Gaussian noise of 0.05 variance	Image with Gaussian noise of 0.1 variance
Prewitt	0.8743	0.6757	0.3708
Sobel	0.8743	0.3601	0.2528
LoG	0.9095	0.378	0.254
Canny	0.8740	0.8580	0.343
Susan	0.9611	0.86	0.6378

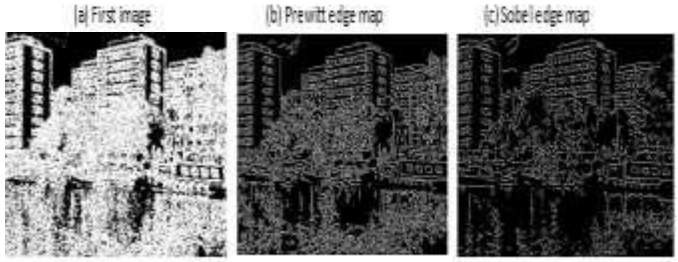
Table 1

Also, it is calculated from figure 8 that the visual appearance of the output isn't always as good as the numerical. This is due to the limitations of the figure of merit measure (for which the output edge maps were optimized).

Comparison For Real Images

As defined in last section quantitative comparison of detected edge maps require ground real images. However, manually constructing ground truth for real intensity images is problematic. Even the definition of an intensity edge is debatable. The difficulties involved in obtaining ground truth for real images are so great that, researchers simply do not conduct quantitative evaluations of edge detectors using real images. In this section we have applied edge detection algorithms to three real life images and tried to observed algorithms qualitatively. Images are taken from Berkeley Segmentation Data set [10]. It has been tried to make sure that images contain necessary features to test abilities of edge detection techniques. Images taken contain areas of fine detail as well as areas of consistent colors. Three images and their results can be seen in figure 9.Results of Sobel and Prewitt are more similar but their edge maps miss many true edges which can be observed in results. LoG produces edges that are much thicker. Canny with low Gaussian smoothing give many false edges but miss many if Gaussian smoothing is increased therefore a tradeoff between the two is required to produce better results. Susan give much better results which can be observed from figures. Consider all parameters of all detectors are selected to give best possible results.

(a) First image (b) Prewitt edge map (c) Sobel edge map



d) LoG edge map e) Canny edge map with high Gaussian smoothing f) Canny edge map with low value of Gaussian smoothing

(g) Susan edge map

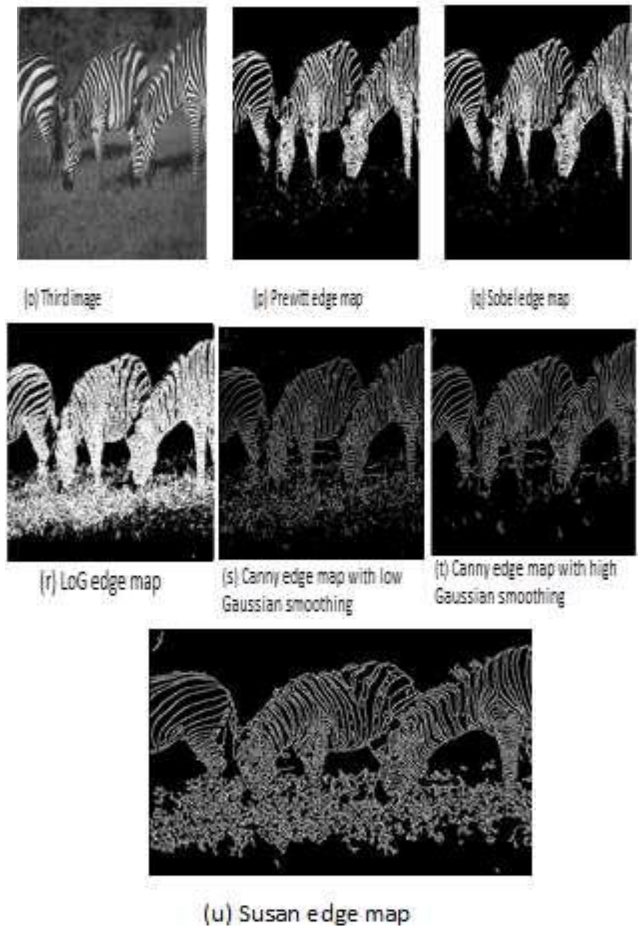


Figure9. Edge maps for real images

CONCLUSIONS

Edge detection is a key tool for image segmentation used for object detection and many other applications. Therefore, it is necessary to use a robust edge detector which gives the best results at all conditions. In this paper we have tried to explain the differences between some famous edge detection algorithms and evaluate them on the basis of their results to different images. Gradient based edge detectors like Prewitt and Sobel are relatively simple and easy to implement,but are very sensitive to noise. LoG tests a wider area close to the pixel and find the correct edges, but malfunctions at corners and curves. It also does not find edge orientation because of using Laplacian filter. Cannys algorithm is provide a solution to problem of edge detection which gives better detection specially in presence of noise, but it takes very time and it require more parameter setting. SUSAN edge detector doesn't use image derivatives which explain why the performance is good in the presence of noise. The integrating effect of the principle, together with its non-linear response, gives strong noise rejection. This can be understood simply if an input signal with identically independently distributed Gaussian noise is considered. As long as the noise is quite enough for the USAN function to contain each same value, the noise is neglected. The integration of individual values in the calculation of areas further reduces the effect of noise. And other strength of the SUSAN edge detector is that the use of controlling parameters is much simpler and less arbitrary (and therefore easier to automate) than with most other edge detection algorithms. Numerical analysis of these algorithms is done for synthetic image (with known edges)at various noise levels using Pratts figure of merit. For real image results are analyzed visually.

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