# Analysis of Edge Detection Operators on Fiber Optic Inspection Microscope Connector end face Image Profiles

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## Abstract.

This research was aimed at determining the most suitable image detection operator to be used on a fiber optic connector endface profile from a fiberscope. The contemporary edge detection techniques analyzed are the Canny, Sobel, Prewitt, Laplacian of the Gaussian (LoG), Roberts and Frei-Chen operators using the Matlab® 2013 script. Histogram equalization was implemented on the connector profiles at the onset to improve the performances of the operators. By using the "task-based" empirical evaluation whose figure of merit is the sum total of edges detected, the Canny operator emerged the best candidate technique after yielding the maximum value of 139.1 average detections per section (adps) closely followed by the Laplacian of the Gaussian (LoG) with 103.2 average detections per section. The Sobel, Prewitt, Roberts and Frei-chen operators yielded 49.3, 49.57, 45.19 and 50.98 average detections per profile section respectively.

**Keywords:** *histogram equalization, edge detection, image processing, Matlab* 

## I. INTRODUCTION

Image processing refers to those operations that can be applied to digital images to transform an input image a [m,n] into an output image b[m,n]. Where "m" and "n" are integer coordinates with  $\{m=0,1,2,...,M-1\}$  columns and  $\{n=0,1,2,...,N-1\}$  rows, the intersection of a row and column is termed a pixel. These operations are classified into three categories namely [3]:

Point Operation: This is an operation in which the value b[m,n] at a specific coordinate in the output image is dependent only on the input value at that same corresponding coordinate a[m,n] in the input image.

Local Operation: An operation is local when the output value at a specific coordinate b[m,n] is dependent on the input values in the neighborhood of that same coordinate a[m,n] in the input image.

Global operation: A global image processing operation is one in which the output value at a specific coordinate b[m,n] is dependent on all the values in the input image.

## A. Edge Detection

Edge detection in image processing basically involves the identification of points at which the image brightness experiences discontinuities; these discontinuities are a consequence of geometric or non-geometric events [9].

Detecting these edges and gleaning pertinent information from the image profile requires the use of an appropriate operator, the ideal operator will depend on a set of criterion which include edge orientation, noise environment and edge structure

Edge detection operators are classified into two broad categories [8]

i. Gradient based methods

ii. Laplacian based methods

## Gradient based Methods

The gradient method detects the edges by looking for the maximum and minimum in the first derivative of the image. For a one (1)-dimensional function f(x) the derivative takes on values with a large magnitude at the points where the function has a high rate of change. It is reasonable to expect that these points will correspond to edges in the function as shown in equation (1) [1].

$$f'(x) = \frac{df}{dx}$$
(1)

The generalization of f(x) to a 2-D function f(x, y) is the gradient expressed mathematically in equation (2) [1]:

$$\nabla f(x,y) = \left(\frac{\partial f(x,y)}{\partial x}i_x + \frac{\partial f(x,y)}{\partial x}i_y\right) \quad (2)$$

Where  $i_x$  and  $i_y$  are unit vectors in the x and y directions respectively.

The implementation in the digital domain is by the use of difference equations resolved t into 1-D convolution filter as represented by equations (3) and (4):

first difference:  

$$h(n) = \delta(n) - \delta(n-1) = [1-1] \quad (3)$$

Central difference:

$$h(n) = \delta(n+1) - \delta(n-1) = \frac{1}{2} [1 \ 0 - 1] \quad (4)$$

Thus the difference operations described can be viewed as the convolution of f(n1; n2) with the impulse response of a filter  $h(n_1; n_2)$ . Each impulse response has  $h_1$  corresponding to a filter for detecting horizontal edges, and  $h_2$  for detecting vertical edges [1].

## Second derivative Edge Detection

This method searches for zero crossings in the second derivative of the image profile to find edges. It is applied to an image that has first been smoothed with an operator approximating a Gaussian Smoothing filter in order to reduce its sensitivity to noise [1]. In effect, the Gaussian operator reduces the noise and operator detects the sharp edges [8].

The Gaussian function is expressed mathematically by equation (5) [8]:

$$G(i,j) = \frac{1}{\sqrt{2 \times \pi \sigma^2}} \exp^{-\left(\frac{i^2 + j^2}{2 \times \sigma^2}\right)}$$
(5)

where

 $\sigma$  is the standard deviation.

## II. METHODOLOGY

There exists a number of edge detection operators which are based on first derivative, second derivatives, the contemporary variants to be evaluated are the Canny, Sobel, prewitt, Laplacian of the Gaussian, Rberts and Frei-chen edge detection operators. The performance of these operators when applied to connector endface profile captured from a fiber inspection microscope is evaluated.

However, to ensure the test image is optimized for processing by these edge detection operators histogram equalization is first applied so as to make the edges more evident to the operators. Fig. 1 shows the flowchart of this process while the Matlab implementation of this process is plotted in Fig. 2.



Fig. 1: Flow chart of the image histogram equalization process.



Fig. 2 Histogram outputs

#### **Roberts operator**

Roberts operator's component filters employ first difference equations and are tuned for diagonal edges rather than vertical and horizontal ones. Due to its reliance on first difference equation Roberts operators have high sensitivity to noise which can be minimized by incorporating smoothing into each filter in the direction normal to that of the difference. The Matlab implementation of this operator is shown in Fig. 3



Fig. 3: Connector endface profile of Roberts's operator output

## Prewitt

The Prewitt edge gradient operator simultaneously accomplishes differentiation in one direction using the central difference and noise reduction in the orthogonal direction by means of local averaging. Its use of central difference accounts for its lesser edge-location bias. Implementation is shown in fig. 4.



Fig. 4: Output of Prewitt Operator on connector endface profile.

#### Sobel

This operator is one of the most widely used gradient edge detectors and often a better option than Prewitt However, it is more sensitive to diagonal edges than to vertical or horizontal ones. Fig. 5 shows the Matlab implementation of the Sobel operator.



Fig. 5: Output of Sobel Operator on connector endface profile.

#### **Frei-Chen Operator**

The need for a gradient based operator with an equal gradient magnitude response to diagonal and vertical edges birthed the Frei-chen operator. The matlab implementation of this operator on the connector image profile is as shown in Fig. 6



Fig. 6: Output of Frei-Chen Operator on connector endface profile.

## Lapalacian of Gaussian Edge Detection (LoG)

This non-directional method (devised to tackle both vertical and horizontal edges [5]searches for zero crossings in the second derivative of the image profile to find edges. The image is first smoothed with an operator approximating a Gaussian Smoothing filter before applying the Laplacian derivative operation due to its sensitivity to noise [1], the implementation is as shown in Fig. 7.



Fig. 7: Output of Laplacian of Gaussian Operator on connector endface profile.

## **Canny operator**

This operator was developed in the early 80's for optimal detection of edge images containing white noise[7].It is implemented in three phases which are [4]: Smoothening and differentiation, Non-maximal suppression and Thresholding. Fig. 8 shows the implementation of canny operator.



Fig. 8: Output of Canny Operator on connector endface profile.

#### **B.** Image Profile segmentation

In this section, in order to analyze the performance of these operators across the core, cladding and ferrule region of the connector endface due to their varied composition the edge detected images are split into segments of 5 x 263 pixels each in order to visualize all the segments in a single row and count the total number of edges in each segment using Matlab 2013 image processing toolbox as shown in Fig. 9



Fig. 9: Display of a typical image profile segmentation

#### III. Results and Discussion.

The performance of the edge detection operatos across the segment of each image is plotted as shown in figure 5.1. The total number of edges is random in across all the operators they all have significantly high number of edges between segments 15 and 28 the canny operator has the highest number of total detectd edges closely followed by the LoG operator. Furthermore, the numerical value of the average edges detected per section is computed so as to avoid making subjective analysis therefore table 5.1 confirms the trend observed graphically in fig. 10

Table 5.1AverageConnectorEndfaceedgedetection for the operators under consideration

Edge Detection Operators	Average No. of Edge Detections
Canny	139.1
Sobel	49.43
Prewitt	49.57
Laplacian of Gaussian (LoG)	103.2
Roberts	45.19
Frei-Chen	50.98

#### IV. Conclusion

The Canny operator and the Laplacian of Gaussian (LoG) operator outputs respectively were able to identify the outline of the core of fiber optic connector. However, the Canny operator yielded the best result based on the application specific "task-based" empirical

evaluation whose figure of merit is the total number of detected edges in an image [2].



Fig. 10: Plot of the sum of detected edges along each section of the connector endface.

The highest value of 139.1 edge detections per profile section of the Canny operator makes it the best candidate edge detection method in the modeling & simulation of optical return loss in fiber optic connector end-face using an inspection microscope.

#### V. References.

- Baghai, W. (2013). 'Basic image processing: edge detection'. Retrieved from http://www.dip.ee.uct.ac.za/~nicolls/lectures/eee401f/03 \_edgedet\_notes\_2up.pdf 26/06/ 2013
- [2] Barghavi, G. (2008). A progressive approach to Feedback-Controlled edge Detection using Boolean Derivatives (pp. 56-60). Denmark: Proquest Inc.
- [3] Ian, T. Y. (1998). Fundamentals Of Image Processing. Retrieved from http://www.tnw.tudelft.nl/en/aboutfaculty/departments/imagingphysics/research/researchgroups/quantitativeimaging/courses/ on 26/04/2014, pp. 1-3
- [4] Jayaraman, S., Esakkirajan, S. & Veerakumar, T. (2011). Digital Image Processing (pp. 2-70). India, New Delhi: Tata McGraw-Hill Education.
- [5] Li, T. & Jean, J. (2013). Digital Signal Processing: Fundamentals and Application (pp. 706-720). Massachusetts, USA: Academic Press,.
- [6] Maria, P. & Panagiota, B. (1999). Image Processing: The Fundamentals (pp. 125-127). New Jersey, USA: John Wiley & Sons.
- [7] Paul, W. & Derek, M. (2001). Machine vision Algorithms in Java: Techniques and Implementation (pp.224-300). London: Springer-Verlage
- [8] Rashmi, Mukesh, K., &Rohini, S. (2013). Algorithm and Technique on various edge detection: A survey. *Signal & Image Processing International Journal*, Vol.4 (3), pp 65-75.
- [9] Trucco, E. & Verri, A. (1998). Introductory techniques for 3D computer Vision (pp 16-26, 68-91, 248-275). New Jersey, USA: Prentice Hall.