Detection of edges in digital images using edge detection operators

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Abstract—Edges structure the framework of an object and furthermore it is the limit between an object and the background. In image handling and image examination edge location and detection is one of the most widely recognized activities. Recognizing exact edges are significant for breaking down the essential properties related with an image. An examination on image edge recognition utilizing deferent edge detection approaches likeGradient and Laplacian model are exhibited in this paper.

Keywords-image, edge, edge detection operators.

I. INTRODUCTION

Edge discovery [1-3] is a significant field in image handling and image vision and image segmentation [4-11]. Edges in computerized images are regions with solid force contrasts and a hop in power starting with one pixel then onto the next can make significant variety in the image quality. Therefore an edge structures[12-18] the layout of an item and furthermore shows the limit between covering objects. Distinguishing proof of precise edges of picture objects dissects and measure some essential properties related with an items or objects of a picture, for example, area, border, and shape. As discontinuities in power estimations of a picture structure the edges of items, so it is fundamental to distinguish exact discontinuities in force levels for precise edge discovery. There are several edge detection operators available for image segmentation and object boundary extraction of digital images. Each operator is designed to be sensitive to certain types of edges like Sobel, Roberts, Prewitt, LoG, and canny, Roberts cross and Laplacian, Lapsian of Gaussian, etc. In this paper a comparative investigation between Roberts cross (which comes under gradient model) and Laplacian of Gaussian operators (which comes under Laplacian model) has been taken in to account.

In this research study the section II introduces comprehensive theoretical and mathematical background for edge detection and computing approaches to edge detection with Roberts cross and Laplacian of Gaussian operators. Section III presents the flowchart and execution of proposed approach. Section IV provides the experimental results and discussion and section V contains a quick discussion about the conclusion.

II. MATEMATICAL MODEL OF EDGE DETECTION

Edge detection is the process of identifying and locating sharp discontinuities in an image. Classical methods of edge detection involve convolving the image with an operator (a 2-D filter). Variables involved in the selection of an edge detection operator include Edge orientation, Noise environment and Edge structure. The geometry of the operator can be optimized by horizontal, vertical, or diagonal edges. The operators will be chosen in such a way that, it can optimize false edge detection, missing true edges and edge localization.

There are many ways to perform edge detection, which can be categorized in two ways:

A. Gradient based Edge Detection

The gradient method detects the edges by finding the maximum and minimum in the first derivative of the image. Several gradient based approaches are already there in existing and online literature like Sobel, Prewitt, Robert, Robert Cross, etc. Among them Robert Cross produces better results than others. In our study the Robert Cross model has been taken into account.

1) Roberts cross Edge Detector: A gradient based approach

Roberts cross Edge detector is a gradient based edge detector was initially proposed by Lawrence Roberts in 1963.Roberts cross operator approximate the gradient of an image through discrete differentiation which is achieved by computing the sum of the squares of the differences between diagonally adjacent pixels.

With these criteria Roberts proposed the mathematical equations as:

$$y_{i,j} = \sqrt{x_{i,j}} \tag{1}$$

$$z_{i,j} = \sqrt{\left(y_{i,j} - y_{i+1,j+1}\right)^2 + \left(y_{i+1,j} - y_{i,j+1}\right)^2} \tag{2}$$

(2)

Where, x is the initial intensity value in the image, z is the computed derivative and i, j represent the location in the image. The results of this operation will highlight changes in intensity in a diagonal direction.

In order to perform edge detection with the Roberts operator we first convolve the original image, with the following two kernels:

$$M_x = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \text{ and } M_y = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} \tag{3}$$

Let $I(x, y)$ be a point in the original image and $G_x(x, y)$ be a point in an image formed by convolving with the first kernel M_x and $G_y(x, y)$ be a point in an image formed by convolving with the second kernel M_y. The gradient can then be defined as:

$$\nabla I(x, y) = G(x, y) = \sqrt{G_x^2 + G_y^2} \tag{4}$$

The direction of the gradient can also be defined as follows:

$$\theta(x, y) = arctan\left(\frac{G_y(x,y)}{G_x(x,y)}\right) - \frac{3\pi}{4} \tag{5}$$

B. Laplacian based Edge Detection

By this method, we find the edge of image by finding zero crossings in the second derivative of the image. Zero crossings always lie on closed contours, and so the output from the zero crossing detector is usually a binary image with single pixel thickness lines showing the positions of the zero crossing points. The Laplacian of an image highlights regions of rapid intensity change and is therefore often used for edge detection. Before using the Laplacian, generally we use a Gaussian smoothing filter in order to reduce its sensitivity to noise, and hence the two variants will be described together here. The operator normally takes a single graylevel image as input and produces another graylevel image as output.

So generally Laplacian approach is well known as Laplacian of Gaussian (LoG) model.

2) Laplacian of Gaussian: A Laplacian based approach

The Laplacian $L(x, y)$ of an image with pixel intensity values $I(x, y)$ is given by:

$$\mathrm{L(x,y)} = \frac{\partial^2 \mathrm{I}}{\partial \mathrm{x}^2} + \frac{\partial^2 \mathrm{I}}{\partial \mathrm{y}^2} \tag{6}$$

This can be calculated using a convolution filter.

Since the input image is represented as a set of discrete pixels, we have to find a discrete convolution kernel that can approximate the second derivatives in the definition of the Laplacian. Two commonly used small kernels are given below.

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

-1	-1	-1
-1	8	-1
-1	-1	-1

Using one of these kernels, the Laplacian can be calculated using standard convolution methods. As these kernels are approximating a second derivative measurement on the image, they are very sensitive to noise. To counter this, the image is often Gaussian smoothed before applying the Laplacian filter. This pre-processing step reduces the high frequency noise components prior to the differentiation step. In fact, since the convolution operation is associative, we can convolve the Gaussian smoothing filter with the Laplacian filter first of all, and then convolve this hybrid filter with the image to achieve the required result. Doing things this way has two advantages:

- Since both the Gaussian and the Laplacian kernels are usually much smaller than the image, this method usually requires far fewer arithmetic operations.
- The LoG (`Laplacian of Gaussian') kernel can be precalculated in advance so only one convolution needs to be performed at run-time on the image.

The 2-D LoG function centered on zero and with Gaussian standard deviation σ has the form:

$$\mathrm{LoG}(x,y) = -\frac{1}{\pi\sigma^4}\left[1-\frac{x^2+y^2}{2\sigma^2}\right]e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{7}$$

III. FLOWCHART AND EXECUTION

The flowchart of the proposed plan is given in underneath in figure 1. In introductory stage colour images are changed over into gray scale images [18-27]. The edges of the images are gathered from the gray scale images with the assistance of Roberts cross and Laplacian of Gaussian edge detection operators.

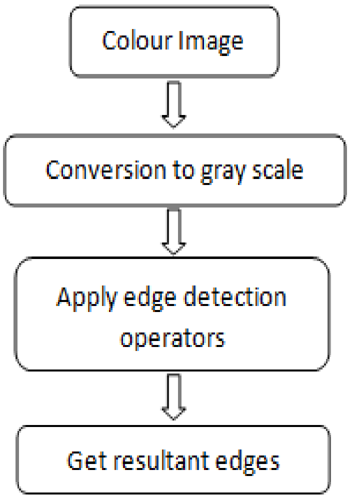

Figure 1. Flowchart of methodology

The methodology is applied on two real life images as appeared in from figure 2 to figure 4 respectively. The resultant images comprise of all edge data and regions about the objects of original image with Roberts cross and Laplacian of Gaussian operators. The resultant images are shown in bellow from figure 5 to figure 10.

Figure 2. Test image: 1

Figure 3. Test image: 2

Figure 4. Test image: 3

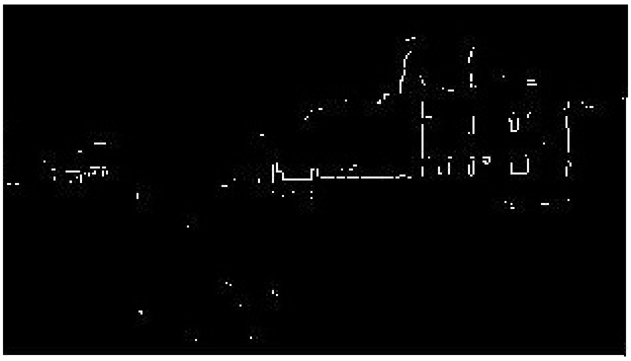

Figure 5. Resultant image of test image: 1 using Roberts cross

Figure 6. Resultant image of test image: 2 using Roberts cross

Figure 7. Resultant image of test image: 3 using Roberts cross

Figure 8. Resultant image of test image:1 using LoG

Figure 9. Resultant image of test image: 2 using LoG

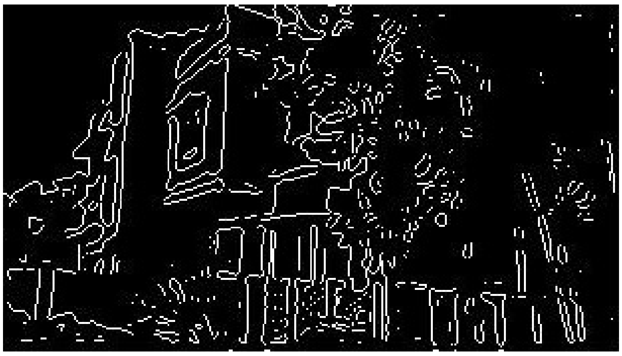

Figure 10. Resultant image of test image: 1 using LoG

The Entropy, Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR)[28-30]of the final segmented images using Roberts cross and Laplacian of Gaussian edge detection operators have been calculated.

Image entropy is a quantity which is used to describe the `business' of an image, i.e. the amount of information which must be coded for by a compression algorithm. Image entropy is calculated with equation:

$$\mathrm{Entropy} = \sum_{i} P_j \log_2 P_j \tag{8}$$

The Peak Signal to Noise Ratio (PSNR) is the value of the noisy image with respect to that of the original image. The value of PSNR and MSE (Mean square Error) for the proposed method is found out experimentally. The PSNR and the Mean Square Error of the retrieved image can be calculated by using the following equations respectively:

$$\mathrm{PSNR}(\mathrm{Img}, \mathrm{Org}) = 10\log10_{10} \frac{S^2}{\mathrm{MSE}(\mathrm{Img},\mathrm{Org})} \tag{9}$$

$$\mathrm{MSE}(\mathrm{Img}, \mathrm{Org}) = \frac{(\Sigma c{=}1 \Sigma i{=}1\ \Sigma j{=}1\ [\mathrm{Org}(i,j,c) - \mathrm{Img}(i,j,c)]}{3NM} \tag{10}$$

Where Org is the original image, Img is the filtered color image of size M. S is the maximum possible intensity value (with m-bit integer values, S will be 2m-1).

The results of the calculations of Entropy, PSNR and MSE for the resultant images are given in Table I.

TABLE I. STATISTICAL ANALYSIS

Image/Operator used	Image	Entropy	PSNR	MSE
Roberts cross	Figure 4	1.4767	27.7048	111.17
	Figure 5	1.5990	27.7330	110.45
	Figure 6	1.7114	28.5826	90.83
LoG	Figure 7	2.1017	28.0480	102.73
	Figure 8	2.1878	28.0087	103.66
	Figure 9	2.1372	28.9245	83.95

Figure 10, 11 and 12 illustrates the Comparative analysis of resultant images obtained using Roberts cross and Laplacian of Gaussian (LoG) edge detection operators based on Entropy, PSNR and MSE. Each Data have various levels to specify their range.

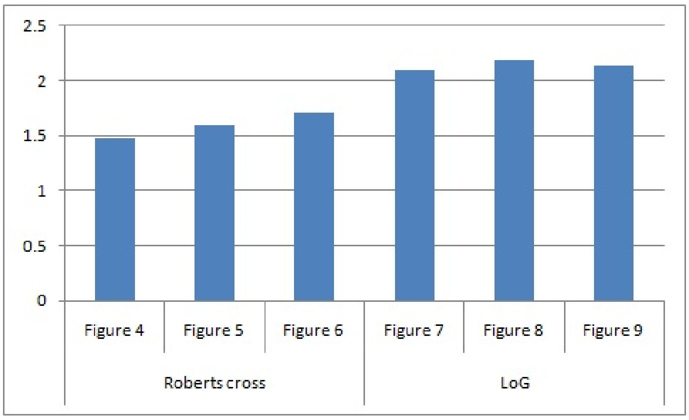

Figure 11. Comparative analysis of Entopy

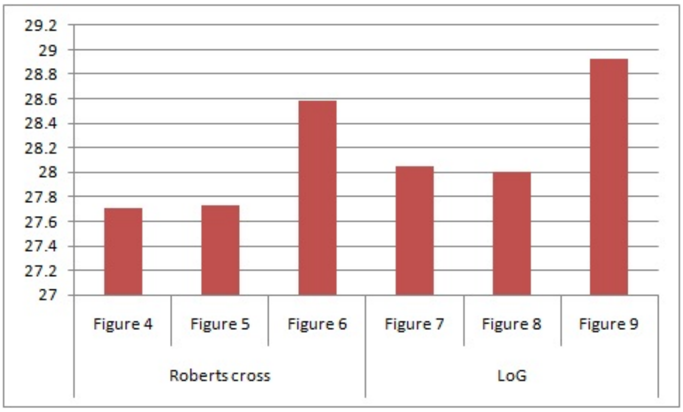

Figure 12. Comparative analysis of PSNR

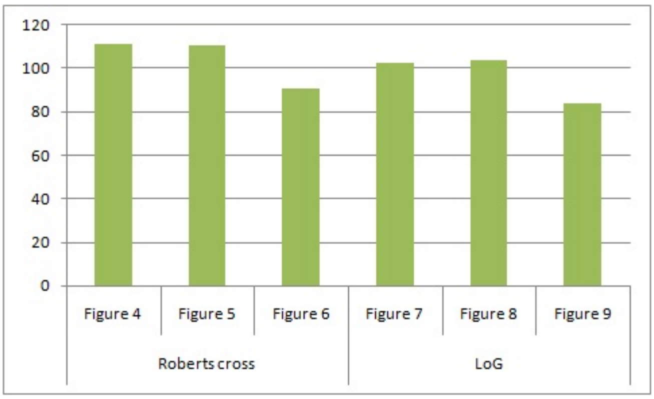

Figure 13. Comparative analysis of MSE

IV. CONCLUSION

In the present work the investigation and comparative examination of Gradient based model and Laplacian based model with Roberts cross and Laplacian of Gaussian edge detectors has been carried out. It has been indicated that the Laplacian based model performs superior to Gradient based model under practically most situations.

REFERENCES

[1] D. Ziou and S. Tabbone, "Edge detection techniques: An overview", International Journal of Pattern Recognition and Image Analysis, 8(4):537–559, 1998.
[2] W. Zhang and F. Bergholm, "Multi-scale blur estimation and edge type classification for scene analysis", International Journal of Computer Vision, vol 24, issue 3, Pages: 219 – 250, 1997.
[3] T. Pajdla and V. Hlavac, "Surface discontinuities in range images," in Proc IEEE 4th Int. Conf. Comput. Vision, pp. 524-528, 1993.
[4] K. Haris,"Hybrid image segmentation using watersheds and fast region merging," IEEE Trans Image Processing, 7(12), pp. 1684-1699, 1998.
[5] Pinaki Pratim Acharjya, Dibyendu Ghoshal, "An Image Matching Method for Digital Images Using Morphological Approach", International Journal of Computer, Information, Systems and Control Engineering, Vol. 8 Issue. 5, 2014.
[6] Dibyendu Ghoshal, Pinaki Pratim Acharjya, "Effect of Various Spatial Sharpening Filters on the Performance of the Segmented Images Using Watershed Approach Based on Image Gradient Magnitude and Direction", International Journal of Computer Applications, Vol. 82, Issue. 6, pp. 10-26, 2013.
[7] Pinaki Pratim Acharjya, Sagnik Dutta, "An Aspect of Biometric Image Segmentation And Authentication For Digital Images", In the proceedings of the 2016 International Conference on Computational Intelligence and Computing Research, pp. 216-223, 2017.
[8] Pinaki Pratim Acharjya, Soumya Mukherjee, Dibyendu Ghoshal, "Digital image segmentation using median filtering and morphological approach", International Journal of Advanced Research in Computer Science and Software Engineering, Vol. 4, Issue. 1, pp. 552-557, 2014.
[9] Vicent L. Solille P, Watershed in digital spaces, "An efficient algorithm based immersion simulations", IEEE Transections PAMI, pp. 538-598, 1991.
[10] S.Beucher, F.Meyer,—The morphological approach to segmentation: The watershed transform‖, in Mathematical Morphology Image Processing, E. R. Dougherty, Ed. New York Marcel Dekker, vol. 12, pp. 433–481, 1993.
[11] Pinaki Pratim Acharjya, Dibyendu Ghoshal, "A Modified Watershed segmentation Algorithm using Distances Transform for image Segmentation", International Journal of Computer Applications, vol. 52, pp. 46-50, 2012.
[12] Sheng Liu ; Zhejiang Univ., Hangzhou, China ; Rui Cao ; Shengyong Chen ; Zichen Chen, "Novel Quality Evaluating Method for Over-Segmentation Approaches Using Real-Time Boundary Information", Workshop on Digital Media and Digital Content Management (DMDCM), pp. 252 – 256, 15-16 May 2011.
[13] Luis Patino, "Fuzzy relations applied to minimize over segmentation in watershed algorithms", Pattern Recognition Letters, Volume 26, Issue 6, Pages 819-828, 1 May 2005.
[14] Mariela Azul Gonzalez, Gustavo Javier Meschino, Virginia Laura Ballarin, "Solving the over segmentation problem in applications of Watershed Transform", ournal of Biomedical Graphics and Computing, , Vol. 3, No. 3, pp.29-40 , 2013.
[15] Pinaki Pratim Acharjya, Dibyendu Ghoshal, "A Modified Watershed Segmentation Algorithm using Distances Transform for Image Segmentation", International Journal of Computer Applications, Volume 52– No.12, pp. 47-50, August 2012.
[16] S. Thilagamani, N.Shanthi, "A Novel Recursive Clustering Algorithm for Image Oversegmentation", European Journal of Scientific Research, Vol.52, No.3, pp.430-436, 2011.
[17] Peter Eggleston, "Understanding Oversegmentation and Region Merging", Vision Systems Design, December 1, 1998.
[18] Alasdair Mcandrew., "Introduction to digital image processing with MATLAB", Course Technology a part of cengage learing.
[19] Tom M´elange, Mike Nachtegael, Etienne E. Kerre., "A Fuzzy Filter for the Removal of Gaussian Noise in Colour Image Sequences", 1474-1479, 2009.
[20] Thangavel, K., Manavalan, R., & Laurence Aroquiaraj, I.,"Removal of Speckle Noise from Ultrasound Medical Image based on Special Filters: Comparative Study", ICGST-GVIP Journal, vol. 9, Issue 3, pp. 25-32, 2009.
[21] Pandey, R.,"An Improved Switching Median nfilter for Uniformly Distributed Impulse Noise Removal", WASET, vol.28, pp. 349-351, 2008.
[22] Lakshmiprabha, S., "A New Method of Image Denoising Based on Fuzzy Logic", International Journal of Software Computing vol. 3, no. 1, pp. 74-77, 2008.
[23] S. Beucher and C. Lantuejoul, "Use of watersheds in contour detection", 1979.
[24] F. Meyer and S. Beucher, "Morphological segmentation," Journal of visual communication and image representation, vol. 1, pp. 21-46, 1990.
[25] F. Meyer, "Topographic distance and watershed lines", Signal Processing, vol. 38, pp. 113-125, 1994.
[26] A. N. Moga and M. Gabbouj, "Parallel image component labeling with watershed transformation," IEEE transactions on pattern analysis and machine intelligence, vol. 19, pp. 441-450, 1997.
[27] J. Roerdink and A. Meijster, "The watershed transform: Definitions, algorithms and parallelization strategies", Mathematical Morphology, vol. 41, pp. 187-S28, 2000.
[28] P. Soille, "Morphological image analysis: principles and applications", Springer-Verlag New York, Inc. Secaucus, NJ, USA, 1999.
[29] J. Serra, "Image analysis and mathematical morphology", Academic Press, Inc. Orlando, FL, USA, 1983.
[30] J. Serra and L. Vincent, "An overview of morphological filtering," Circuits, Systems, and Signal Processing, vol. 11, pp. 47-108, 1992.