A Statistical Operator for Detecting Weak Edges in Low Contrast Images

Ajay Mittal[1], Sanjeev Sofat[1], Edwin Hancock[2], and Stéphane Mousset[3]

[1] Department of Comp. Science & Engg., PEC University of Technology, Chandigarh, India
{ajaymittal,sanjeevsofat}@pec.ac.in
[2] Department of Computer Science, University of York, UK
erh@cs.york.ac.uk
[3] LITIS EA4108 INSA de Rouen/ Université de Rouen
stephane.mousset@insa-rouen.fr

Abstract. Edge detection is an indispensible initial step in many contour-based computer vision applications like edge-based obstacle detection, edge-based target recognition, etc. The performance of these applications is highly dependent on the quality of edges detected in the initial step. Most of the edge detectors used in these applications only detect boundaries separating two regions with high intensity gradient. However, certain computer vision applications require detection of low contrast boundaries. This paper presents a statistical operator for detecting low contrast boundaries. The proposed operator is highly suited for obstacle detection systems for poor visibility conditions. To evaluate its edge detection capability under normal and low contrast conditions, it is tested on a dataset of 40 object images and on MARS/PRESCAN dataset containing foggy virtual images. The quantitative evaluations using Matthew's correlation coefficient and Pratt's figure of merit indicate that the proposed method outperforms other edge detectors.

Keywords: Edge detection, low contrast boundaries, weak edges.

1 Introduction

Edge detection is a fundamental low level image processing operation required in majority of image processing and computer vision applications. The aim of edge detection is to identify and locate sharp intensity discontinuities in an image. The discontinuities are abrupt changes in pixel intensity which characterizes boundaries of objects in a scene. This object boundary localization is an indispensable initial step in many contour-based computer-vision algorithms like curve-based stereo [1, 2], contour-based image compression [3], edge-based target recognition [4], edge-based object detection [5], edge-based face detection [6] and many more. Since, the edge detection has high impact on the overall performance of these contour-based algorithms; it is an important area of research in computer vision.

The most natural way of detecting edges is to take the first or second order derivatives and look for maxima or zero crossings in the output. Classical edge detectors

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like Roberts, Sobel, Prewitt, etc. [7] are based on this observation. Derivative based edge detectors are sensitive to noise and require filtering by a Gaussian or similar masks. Marr and Hildreth [8] filtered the image by Gaussian smoothing filter before applying Laplacian operator to find second order derivatives. The output of derivative based operators is highly dependent on the size of Gaussian filter and the threshold value used. Canny [9] alleviated these problems by using an optimal finite length filter and two thresholds, a high threshold and a low threshold, along with hysteresis.

The 2-D Gaussian filter smears the edge information, while suppressing noise and disturbs the edge localization. Fast edge detectors based on processing 1-D profile of the image are proposed by Kumar et. al [10] and Miché et. al [11]. These edge detectors solve the edge localization problem either by applying 1-D Gaussian smoothing filter and the edge detection filter in orthogonal directions or by eliminating the need for Gaussian smoothing at all. Kumar applied 1-D Gaussian smoothing filter and Discrete Hilbert Transform for edge detection in orthogonal directions to obtain partial edge maps. The horizontal and vertical edge maps are combined and thresholded to obtain the edge map of the input image. A static value is used for thresholding and the method lacks self adaptability. Miché developed a self-adaptive method for edge detection, in which the local extremities of gray level intensities in an image scan line are determined. The set of contiguous pixels limited by two consecutive local extremities is termed as declivity [11]. He modeled an image scan line as sequence of declivities, which are categorized as significant or non-significant depending upon their amplitude. Non-significant declivities, i.e. low amplitude declivities, correspond to noise and non-significant elements in the image. Significant declivities, i.e. high-amplitude declivities, correspond to edges. The value selected for thresholding a declivity into being significant or non-significant is computed from the statistical analysis of an image scan line. Thus, the declivity operator was self-adaptive.

The declivity operator is used in stereo matching [2,12, 13], vehicle detection [14, 15], extraction of 3D edges of obstacle [16], etc. during the recent years. However, declivity operator has a shortcoming. It is unable to detect low contrast boundaries. Miché [11] addressed this problem by devising an extended declivity operator, which extends the basic declivities by apply region growing principle. A n^{th} order extended declivity operator joins n-right and n-left neighboring declivities of same sign to form an extended declivity. The operator lacks adaptability in a sense that the number of declivities to be merged does not vary as per image contrast. During the reduced visibility conditions due to fog, haze, twilight, poor lighting, etc., the acquired images have variably low contrast. Hence, the applications relying on the basic and extended declivity operators to segment road obstacles tend to give poor results.

This paper presents a different approach to enhance the basic declivity operator so as to detect low contrast boundaries or edges in low contrast images. An implementation of modified declivity operator using loop vectorization is done. The proposed operator is quantitatively evaluated on a dataset [17] of 40 object images using Matthew's correlation coefficient and on a set of virtual stereo images [18] using Pratt's figure of merit (FOM). The quantitative evaluation indicates that the proposed method gives good results even in low contrast images. The rest of the paper is structured as follows: Section 2 presents an overview of basic declivity operator. Section 3 presents the proposed modified declivity operator. The experimental results of the modified declivity operator are shown and discussed in Section 4. Section 5 makes the concluding remarks.

2 Basic Declivity Operator

The local extremities of gray level intensities in an image scan line are determined. The set of contiguous pixels limited by two local extremities is termed as a declivity [11]. An image scan line is modeled as sequence of declivities, as shown in Fig. 1.

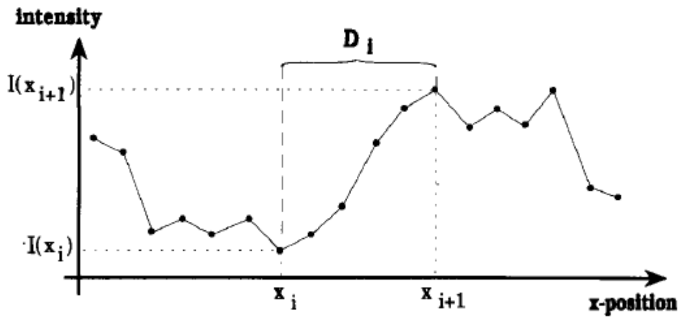


Fig. 1. Image scan line modeled as sequence of declivities, Figure source [11]

A declivity D_i in an image scan line is characterized by the following attributes [14]:

i) its starting position x_i in the image scan line
ii) its end position x_{i+1} in the image scan line
iii) its amplitude, $d_i = I(x_{i+1}) - I(x_i)$
iv) its position, X_i: The position of a declivity is determined by computing the mean position of the declivity points weighted by the gradients squared in the image scan line, as given by equation 1:

$$X_i = \frac{\sum_{x=x_i}^{x_{i+1}-1}[I(x+1)-I(x)]^2(x+0.5)}{\sum_{x=x_i}^{x_{i+1}-1}[I(x+1)-I(x)]^2} \tag{1}$$

A declivity D_i is significant if its amplitude d_i is such that $d_i^2 \geq d_t^2$, where d_t is a threshold value. The value d_t selected for thresholding is computed from the statistical analysis of the image scan line. For this purpose, we assume that the image signal $I(x)$ is composed of a deterministic signal $I'(x)$ on which is superimposed a white Gaussian noise $\eta(x)$ with null mean, i.e.

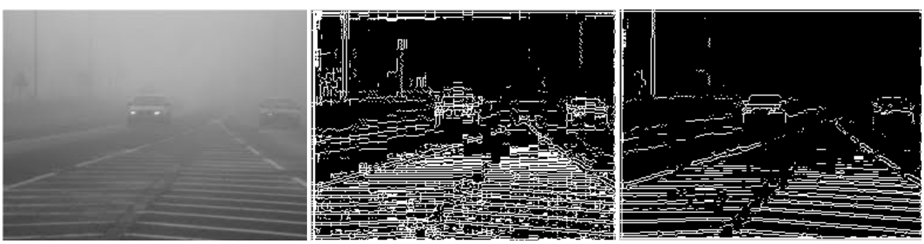
$$I(x) = I'(x) + \eta(x) \tag{2}$$

$$G(x) = I(x+1) - I(x) \tag{3}$$

The gradient $G(x)$, defined by the equation 3, is computed for the image scan line. The most of the $G(x)$ entries are zero or have small absolute value, which corresponds to white Gaussian noise or non-significant elements in an image scan line. It has few high absolute values which correspond to significant elements, i.e. edges, in the image scan line. Therefore, the distribution of $G(x)$ is similar to that of Gaussian noise with null mean. In order to filter the noise and non-significant elements with 99.5% confidence, a threshold value equal to 2.8 times the standard deviation of the noise component is selected. The standard deviation of the noise component is approximated to be same as the standard deviation of gradient $G(x)$ for the image scan line.

3 Modified Declivity Operator

The basic declivity operator classifies high amplitude declivities as edges. The low amplitude declivities are filtered as that of resulting from noise. Thus, in case of low contrast images or low contrast boundaries separating two regions with homogenous gray levels, the declivities with low amplitude, known as weak edges, which actually corresponds to true edges are misled as that of resulting from noise and are filtered out. One of the simplest solutions to this problem is to lower the threshold value used for classifying the declivities. The result of application of basic declivity operator on a foggy road scene with low threshold values is shown in Fig. 2.



(a) (b) (c)

Fig. 2. Application of basic declivity operator on low contrast foggy road scene. (a) Original image. (b) Threshold value 0.5σ. (c) Threshold value 1.5σ.

As seen in Fig. 2, lowering the threshold led to the emergence of many spurious edges. Canny proposed solution to this problem by using two thresholds along with hysteresis [9]. High threshold value is used to detect strong edges. The weak edges can be either due to true edges or due to noise. Weak edges due to noise will be distributed in the entire image and only a small amount will be located adjacent to strong edges. Weak edges corresponding to true edges are more likely to be connected to strong edges. Thus, the weak edges connected to strong edges are also selected by Canny. However, low contrast images have few strong edges. Hence, detecting all the weak edges on the basis of their connectivity to strong edges is difficult and tends to fail.

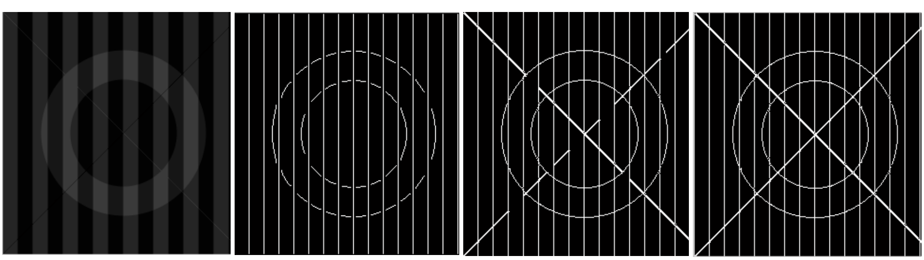
The proposed method detects low contrast boundaries or weak edges in a low contrast image without relying on their connectivity with strong edges. Two threshold values, a high threshold value d_{ht} equal to 2.8σ and a low threshold value d_{lt} equal to α times the high threshold are used, where α is a constant scale factor, and σ is the standard deviation of noise determined in Section 2. The value of α ranges between [0.33, 0.5] as suggested by Canny [9]. Declivities with $d_i^2 \geq d_{ht}^2$ correspond to strong edges and are accepted. Declivities with $d_i^2 < d_{lt}^2$ correspond to weak edges due to noise and are filtered out. Declivities with $d_{ht}^2 \geq d_i^2 \geq d_{lt}^2$ correspond to weak edges, which can be either due to true edges or due to noise, and need further processing. Weak edges which correspond to noise will have smaller edge length as compared to the edge length of weak edges which corresponds to true low contrast edges. The number of weak edges due to noise will be more as compared to the number of weak edges corresponding to the true edges in the image. This hypothesis is corroborated by the probability density function of edge length of weak edges. Weak edges having edge length less than 95th percentile of their edge lengths are removed. The result of modified declivity operator applied on Fig. 2(a) is shown in Fig. 3(b). The detected strong and weak edges in the image are shown in red and green, respectively, in Fig. 3(c).

(a) (b) (c)

Fig. 3. Detection of weak edges in low contrast foggy road scene. (a) Output of basic declivity operator. (b) Output of modified declivity operator, α=0.4. (c) Output of modified declivity operator, strong edges shown in red and weak edges in green color.

4 Experimental Results and Discussions

An efficient MATLAB® implementation of modified declivity operator using loop vectorization is done. The result of modified declivity operator and other operators applied on a synthetic ledge image is shown in Fig. 4.



(a) (b) (c) (d)

Fig. 4. Application of edge detectors on a synthetic ledge image. (a) Original image, contrast = 19.2 (b) Output of Canny operator (c) Output of basic declivity operator. (d) Output of modified declivity operator.

The proposed operator is tested on a dataset [17] of 40 object images with their ground truth known and is evaluated using Matthew's correlation coefficient (MCC) metric. MCC is a balanced measure that takes into account true and false positives and is determined as:

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \tag{4}$$

The value of MCC lies between -1 and +1. A MCC value of +1 represents a perfect classification, 0 represents a random classification and -1 signifies an inverse classification. The MCC values for Canny, basic declivity and modified declivity operators applied on 40 object images is plotted in Fig. 5.

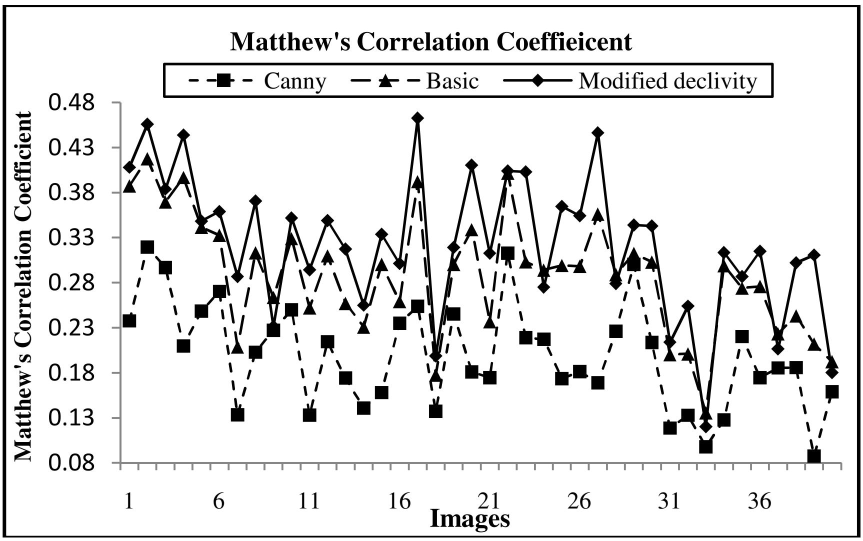


Fig. 5. MCC values for Canny, basic declivity and modified declivity operators for 40 object images

The proposed operator is also evaluated on a set of foggy MARS/PRESCAN virtual stereo images using Pratt's FOM. To compute FOM, the ground truth edge map of an image is approximated with the edge map of its corresponding image without fog. The edge maps of the foggy images are compared with their corresponding approximated ground truth edge maps, to determine the deterioration in the performance of an edge detection operator under low contrast condition. The contrast of an image is calculated as the standard deviation of the histogram of the gray levels, as defined in equation 5.

$$Contrast = \sqrt{\frac{\sum X_i^2 f_i}{n} - \left(\frac{\sum X_i f_i}{n}\right)^2} \tag{5}$$

where, X_i's are the histogram bins, $i \in \{0..255\}$ for a 8-bit grayscale image, f_i represents the frequency of the i^{th} bin, and n is the total frequency. The results of the experiment on an left stereo image of fogless and foggy sequences are shown in Fig. 6 and the average FOM values for Canny, basic declivity and modified declivity operators with respect to contrast of images is plotted in Fig. 7.

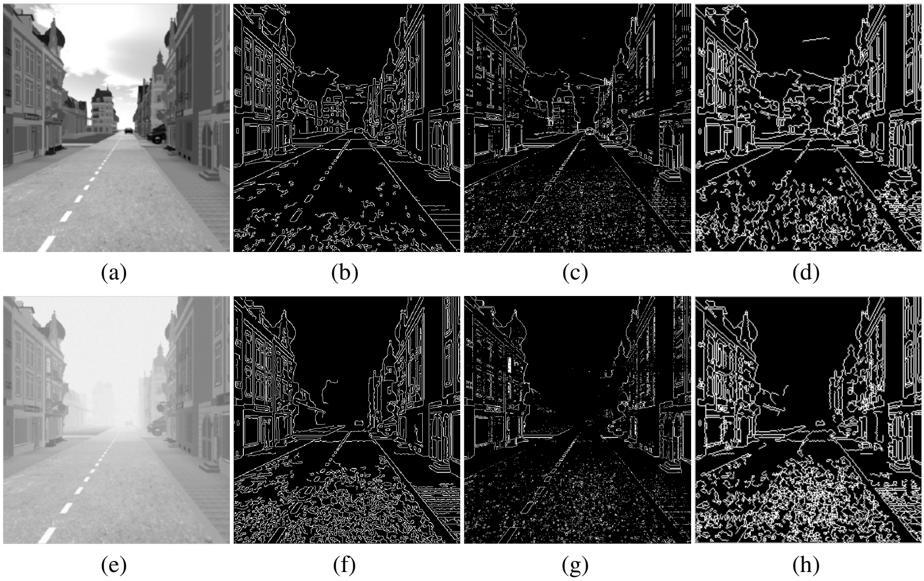


Fig. 6. Comparison of edge detectors. (a) A left stereo image of fogless sequence, contrast = 57.79. (e) Corresponding left stereo image of foggy sequence, contrast = 38. Top row: (b-d) Results of Canny, basic declivity and modified declivity operators on (a). Bottom row: (f-h) Results of Canny (FOM=0.6901), basic declivity (FOM=0.6864) and modified declivity (FOM=0.7420) operators on (e).

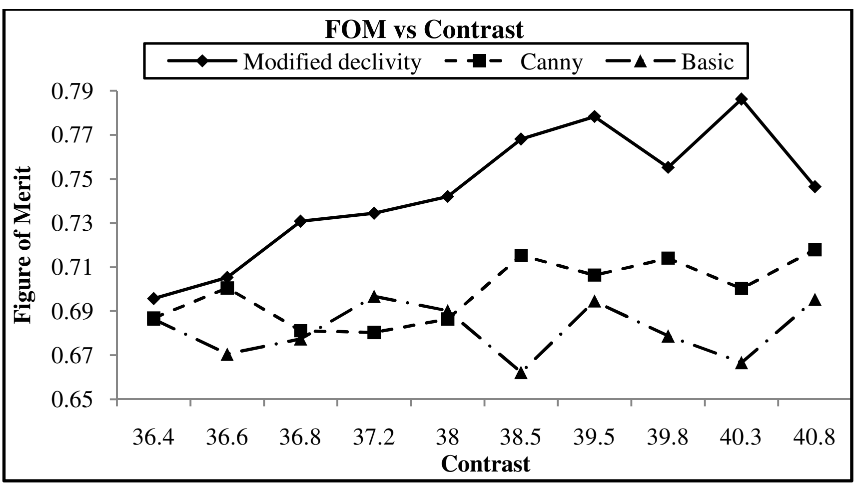


Fig. 7. Average FOM values for Canny operator, basic declivity operator and modified declivity operator with respect to contrast of images

5 Conclusion

The existing edge detection algorithms fail to detect weak edges with tight threshold, and produce lot of false edges due to noise with loose threshold. Moreover, these algorithms preprocess the image with a smoothing filter which smears edge information. The present paper proposes an edge detection operator which removes these flaws while enable the detection of weak edges. The results indicate that the proposed method has better edge detection capability than Canny and basic declivity operators both in normal and low contrast images. The present work can be extended to detect edges in color images.

References

1. Nasrabadi, N.M.: A Stereo-vision technique using curve segments and relaxation matching. IEEE PAMI 14(5), 566–572 (1992)
2. Anasari, M., Mousset, S., Bensrhair, A.: Temporal consistent real-time stereo for Intelligent vehicles. Pattern Reco. Letters (2010)
3. Kurt, B., Gokmen, M.: Image compression based on Centipede Model. Bulletin of the Istanbul Technical University 54(3), 35–43 (2005)
4. Olson, C.F., Huttenlocher, D.P.: Automatic Traget Recognition by matching oriented edge pixels. IEEE Transactions on Image Processing 6(1), 103–112 (1997)
5. Yokoyama, M., Poggio, T.: A contour based moving object detection and Tracking. In: Proc. 2nd IEEE Int. Wkshp on Visual Surv. and Perf. Eval. of Trackg and Survi., pp. 271–276 (2005)
6. Yilmaz, A., Gokmen, M.: Face recognition based on eigenhills. In: Proc. of 7th Conference on Signal Processing and Applications, SIU 1999 (1999)
7. Pratt, W.K.: Digital Image Processing, 4th edn. John Wiley Inc. (2007)
8. Marr, D., Hildreth, E.: Theory of Edge detection. Proc. of Royal Soc., 187–217 (1986)
9. Canny, J.F.: A computational approach to Edge detection. IEEE PAMI, 679–698 (1987)
10. Kumar, P.K., Das, S., Yegnanarayana, B.: One-Dimensional Processing for edge detection using Hilbert Transform. In: Conference on Computer Vision Graphics and Image Processing, December 20-22 (2000)
11. Miche, P., Debrie,R.: Fast and Self adaptive image segmentation using extended declivity. Annals of Telecommnunication (1995)
12. Bensrhair, A., Miche, P., Debrie, R.: Fast and automatic stereo vision matching algorithm based on dynamic programming method. Pattern Recognition Letters, 457–466 (1996)
13. Ansari, M.E, Mousset, S., Bensrhair, A.: Temporal Consistent Real-Time Stereo for Intelligent Vehicles. Pattern Reco. Letters (2010)
14. Cabani, I.,Toulminet, G., Bensrhair, A.: A fast and self-adaptive color setero vision matching: a first step for road obstacle detection. In: Proc. of Intelligent Vehicles Symposium, Japan, June 13-15, pp. 58–63 (2006)
15. Toulminet, G., Bertozzi, M., Mousset, S., Bensrhair, A., Broggi, A.: Vehicle detection by means of stereo vision-based obstacle features extraction and monocular pattern analysis. IEEE Trans. Img. Proc., 2364–2375 (2006)
16. Cabani, I., Toulminet, G., Bensrhair, A.: A color stereo vision system for extraction of 3D edges of obstacle. In: Proc. of IEEE Intell. Trans. Sys. Conf. (2006)
17. `http://marathon.csee.ucf.edu/edge/edgecompare.html`
18. Stereo data for algorithm evaluation, `http://stereodatasets.wvandermark.com/`