I.J. Image, Graphics and Signal Processing, **2023, 2, 35-46**
Published Online on April 8, 2023 by MECS Press (http://www.mecs-press.org/)
DOI: 10.5815/ijigsp.2023.02.04

Polynomial Differentiation Threshold based Edge Detection of Contrast Enhanced Images

Kuldip Acharya*
Department of Computer Science and Engineering, National Institute of Technology, Agartala, Barjala, Jirania, Tripura (W), Pin: 799046, India.
Email: kuldip.acharjee@gmail.com
ORCID iD: https://orcid.org/0000-0002-1974-5710
*Corresponding Author

Dibyendu Ghoshal
Department of Electronics and Communication Engineering, National Institute of Technology, Agartala, Barjala, Jirania, Tripura (W), Pin: 799046, India
E-mail: tukumw@gmail.com
ORCID iD: https://orcid.org/0000-0002-7548-376X

Received: 19 March, 2022; Revised: 30 April, 2022; Accepted: 18 June, 2022; Published: 08 April, 2023

Abstract: This paper uses a two-step method for edge detection using a polynomial differentiation threshold on contrast-enhanced images. In the first step, to enhance the image contrast, the mean absolute deviation and harmonic mean brightness values of the images are calculated. Mean absolute deviation is used to perform the histogram clipping to restrict over-enhancement. First, the clipped histogram is divided in half, and then two sub-images are created and equalized, and combined into a final image that keeps image quality. The second phase involves edge detection using a polynomial differentiation-based threshold on contrast-improved visuals. The polynomial differentiation curve-fitting method was used to smooth the histogram data. The nearest index value to zero is utilized to calculate the threshold value to detect the edges. The significance of the proposed work is to contrast enhancement of low-light images to extract the edge lines. Its value or merit is to achieve improved edge results in terms of various image quality metrics. The findings of the proposed research work are to detect the edges of low-contrast images. Image quality metrics are computed and it is observed that the suggested algorithm surpasses former methods in respect of Edge-based contrast measure (EBCM), Performance Ratio, F-Measure, and Edge-strength similarity-based image quality metric (ESSIM).

Index Terms: Histogram equalization, Harmonic mean, Mean Absolute Deviation, Polynomial differentiation, Thresholding; Edge Detection, Image enhancement.

1. Introduction

The image segmentation method for finding the edges of objects in images is known as edge detection [1]. The detecting procedure is carried out by observing how an image brightness changes. Image enhancement and edge tracking of digital images were the subjects of numerous research. Edge detection of low-contrast images is accomplished using the suggested method, which involves image improvement via histogram division and thresholding-based clipping. The edge quality was evaluated using a variety of quantitative factors, demonstrating the current method's efficiency. Object edges are useful features for analyzing images, partitioning image regions, and detecting changes in object color. The three primary steps in edge detection are image processing to reduce noise, contrast enhancement to improve the image visual quality, and image sharpening [1]. Peli, T. et al. explore different types of edge detection and their techniques [2].

The goal of the present research paper is contrast enhancement of low light images and to find out proper edge information of desired objects of interest. Low contrast image enhancement and searching of edges are two challenging areas of research in image enhancement and image segmentation. In this article, the proposed method is designed to solve this problem in comparison to certain other cutting-edge techniques to demonstrate its effectiveness. There are many algorithms for image segmentation. All of them have their merits and demerits. To overcome the problem of the existing method the proposed method is designed and experimentally compared with other methods. Experimental results show the proposed method is the best compared to other methods. The limitation of existing methods is loss of edge information, blurry and foggy output, over-segmentation, and so forth. The present research work is designed to find out sharp edge lines and visually pleasant image segmentation results.

Histogram equalization is a useful feature in digital image processing since it improves the contrast of the image [1]. Many histogram-based contrast enhancement studies have been conducted to increase image color and contrast. Various statistical strategies employ histogram clipping to decrease the occurrence of over-enhancement. In this regard, histogram equalization is a standard technique [1]. The least-squares approach [2] can be used to discover the polynomial with the lowest overall error for a given degree.

The remaining paper will be written as follows. A literature review is presented in section two. The proposed work is described in the third section. The compared algorithm and the suggested approach are presented in sections four and five. Section six describes the experiment and its results, whereas section seven brings the study to a conclusion.

2. Related Work

Karanwal presents a method of edge detection using multiple scales [3] is a technique for detecting edges at multiple scales. The research focuses on how noise decreases as scale values rise, as well as how real edges sometimes vanish as scale values rise. In 2021, Dhar et al. suggested a skin lesion detection [4] method using Fuzzy and CNN for classification. A deep convolutional neural network (CNN) is based on deep learning models; however, it requires a lot of processing time and a lot of data. Gupta et al. (2018) proposed a novel method [5] of facial recognition using a deep neural network. The extracted facial features reduce the complexity and achieve 97.05 % accuracy tested on the Yale faces dataset. Robinson compass mask edge detection method uses eight key compass angles [6], and each compass may convey the edges in the orientation of the compass. The zero-crossing edge detection [7] approach scans the image for zero-crossings before filtering it. Morphological function [8] such as ‘bwmorph’ is used in a binary image to find out the outline of objects. Meng et al. developed an edge detection approach based on adaptive canny and modified Hough transform to automatically identify and quantify the size of the particles in diverse frequencies, and unusual situations [9]. A modified canny [10] based edge detection approach is suggested by XM Zhao et al. The polynomial differentiation function [11-12] may be utilized to calculate the derivative of the polynomial. Polynomial evaluation [12] function is used for polynomial assessment. The Direcedge approach [13] with a Gaussian kernel and directional information can be used to identify grayscale image edges. In contrast to other current approaches, the experimental results demonstrate that the suggested method precisely locates the edges of desired image objects while maintaining the best possible image quality. The available published papers in journals and conferences have supplied a great number of methodologies such as Sobel [14], Prewitt [15], Roberts [16], Laplacian of Gaussian [17], and Canny [18] for edge detection of images. The proposed techniques were found to be suitable for detecting edges of images that have low contrast. Image enhancement is an important aspect [1] for contrast improvement using various image enhancement methods described in [19-20] on the source images. Edge detection from a contrast-enhanced image yields somewhat better outcomes than identifying edges from a source image, according to the performance of the suggested method. Additionally, it can be seen via Matlab simulation [21] results derived from different image quality matrices that the suggested technique outperforms current edge detection techniques already in use. Quantitative evaluation is made using various metrics like Edge-based contrast measure [22] (EBCM), Performance ratio [23] (PR), F-Measure [23], and Edge strength similarity for image quality assessment (ESSIM) [24].

2.1 The research objectives

The proposed methodology does an image enhancement with the use of histogram equalization algorithms, to increase the image contrast. Thus present algorithm improves the overall image quality which helps to find out clear edge lines. Experimental results show how image enhancement helps in finding better edge results by comparing edge detection without image enhancement.

3. The Proposed Edge Detection Algorithm on Contrast Enhanced Image

3.1 Pre-processing: Image Enhancement

Step 1: The input color image is transformed into a grayscale image and histogram processing is done by dividing it into two parts and further divided into four parts based on the harmonic mean value of image intensity.

Step 2: Histogram threshold is calculated by using a clipping threshold calculated based on mean absolute deviation to restrict the over enhancement.

Step 3: Histogram equalization is done on each sub histogram for the processing of sub-images.

Step 4: All the sub-images are combined into a final enhanced image.

3.2 The proposed edge detection algorithm procedures

Stage 5: The very first step of edge detection is the computation of image gradient on the improved image acquired in step 4.

Step 6: A histogram of the contrast-improved image is formed, and then a polynomial differentiation-based curve fitting approach is used to the histogram count data and grey level areas for more analysis.

Step 7: A polynomial evaluation is then performed on the coefficient values obtained in step 6 to accomplish the smoothing operation and then the first-order difference is computed on the obtained smoothed data values.

Step 8: The threshold value is determined by the minimal value obtained through the second-order difference.

Step 9: Two-dimensional convolution is performed on the image gradient obtained in step 5 with a threshold value obtained in step 8.

Step 10: At last a morphological operation is performed using image thinning to produce the final edge detection result.

4. Methodology

4.1 Histogram Clipping Through Mean Absolute Deviation

Histogram clipping is a technique for limiting an image over enhancement proportion. Histogram pixels with a higher value than the clipped threshold level are limited to the boundary [17]. The clipping threshold is computed by the mean absolute deviation on the histogram. Mean absolute deviation is a statistical parameter related to some data. This is a parameter that indicates the mean of the dispersion of each data. This parameter is equal to the arithmetic mean and the calculated value has a central tendency in the data set, for the clipping of the histogram in the same way as to mean, the standard deviation was used.

Calculation of the total number of samples for an image is represented by *T* in (1) as follows:

$$T = \sum_{i=1}^{N-1} H(\mathrm{i}) \tag{1}$$

$$MDV = \frac{1}{N}\sum_{i=1}^{N}\left(|\,\mathrm{H(i)} - \overline{M}\,|\right) \tag{2}$$

MDV returns the histogram clipping threshold computed in 2 by mean deviation on the image histogram. Here, $H(i)$ refers to image histogram data, and the mean value is denoted by $\overline{M}$ shown in 3.

$$\overline{M} = \frac{1}{N}\sum_{i=1}^{N} H(\mathrm{i}) \tag{3}$$

4.2 Histogram Division Through Harmonic Mean

$$HM = \frac{N}{\sum_{i=1}^{N} \frac{1}{H(\mathrm{i})}} \tag{4}$$

HM is a harmonic mean calculated on histogram data.

$$X_a = HM[H(i)] \tag{5}$$

The original histogram is first bisected based on harmonic mean intensity value X_a as calculated in (4) and (5). Here, X_a is a histogram separation point.

$$Q_l(i) = \frac{H(i)}{T_l} \text{ for } i=0,1,\ldots,X_a-1 \tag{6}$$

$$Q_u(i) = \frac{H(i)}{T_u} \text{ for } i= X_a, X_a+1,\ldots,N-1 \tag{7}$$

Here $Q_l(\mathrm{i})$ and $Q_u(i)$ are two sub-histograms divided based on the harmonic mean. Equations (6) and (7) depict the calculation of sub-histograms. T_l and T_u are the total numbers of pixels in the lower and upper histogram respectively.

$$X_{al}=\sum_{i=0}^{X_{a-1}} Q_l(\mathrm{i})\times \mathrm{i} \tag{8}$$

$$X_{au}=\sum_{i=x_a}^{N-1} Q_u(i)\times i \tag{9}$$

These discrete sub-histograms are segmented into two small sub histograms and their mean value X_{al} and X_{mu} are computed as shown in equations (8) and (9) respectively. The histogram is subdivided into four sub-images as V_{Nl}, V_{Nu}, V_{Ml}, and V_{Mu} which range is from gray-level 0 to X_{al}, $X_{al}+1$ to X_a , X_a+1 to X_{au} and $X_{au}+1$ to $N\text{-}1$.

4.3 Probability Density Function (PDF)

$R_{Nl}(e)$, $R_{Nu}(e)$, $R_{Ml}(e)$, and $R_{Mu}(e)$ are computed PDF of these sub images are shown in Eqs. (10)– (13).

$$R_{Nl}(\mathrm{i}) = \frac{H_c(i)}{T_{Ni}} \text{ for } 0 \le \mathrm{i} \le X_{al} \tag{10}$$

$$R_{Nu}(\mathrm{i}) = \frac{H_c(i)}{T_{Nu}} \text{ for } X_{al}+1 \le \mathrm{i} \le X_a \tag{11}$$

$$R_{Ml}(\mathrm{i}) = \frac{H_c(i)}{T_{ml}} \text{ for } X_a+1 \le \mathrm{i} \le X_{au} \tag{12}$$

$$R_{Mu}(\mathrm{i}) = \frac{H_c(i)}{T_{mu}} \text{ for } X_{au}+1 \le \mathrm{i} \le \mathrm{N}\text{-}1 \tag{13}$$

T_{Nl}, T_{Nu}, T_{Ml}, and T_{Mu} are the total number of pixels in sub-images V_{Nl} , V_{Nu} , V_{Ml} , and V_{Mu}.

4.4 Cumulative density function (CDF)

$CF_{Nl}(i)$, $CF_{Nu}(i)$, $CF_{Ml}(i)$, and $CF_{Mu}(i)$ are calculated CDF of sub images and CDFs is expressed as Eqs. (14) – (17)

$$CF_{Nl}(\mathrm{i}) = \sum_{i=0}^{X_{al}} R_{Nl}\left(i\right) \tag{14}$$

$$CF_{Nu}(\mathrm{i}) = \sum_{i=X_{al}+1}^{X_a} R_{Nu}\left(i\right) \tag{15}$$

$$CF_{Ml}(\mathrm{i}) = \sum_{i=X_a+1}^{X_{mu}} R_{Ml}\left(i\right) \tag{16}$$

$$CF_{Mu}(\mathrm{i}) = \sum_{i=X_a+1}^{N-1} R_{Mu}\left(i\right) \tag{17}$$

4.5 Transfer function

TF_{Ni}, TF_{Nu}, TF_{Ml}, and TF_{Mu} are the transfer functions expressed in equations (18)-(21) utilized for equalizing the sub-histograms individually.

$$TF_{Ni} = X_{al} \times CF_{NI} \tag{18}$$

$$TF_{Nu} = (X_{al}+1) + (X_a - X_{al} + 1) \times CF_{Nu} \tag{19}$$

$$TF_{Ml} = (X_a + 1) + (X_{mu} - X_a + 1) \times CF_{Ml} \tag{20}$$

$$TF_{Mu} = (X_{mu+1}) + (N - X_{mu+1}) \times CF_{Mu} \tag{21}$$

The next step is to equalize all the four-sub histograms using the transfer function to produce the final contrast-enhanced image. Then edge detection operation is performed on the resultant enhanced image.

The BSD database image [25] of 'Butterfly' and its histogram are shown in Fig.1 (a) and (b) (e). Fig. 1 (b) and 1(f) show the image enhancement results obtained using the suggested technique. The BSD image of 'Swimmer', as well as its histogram, are presented in Fig. 1 (c) and 1 (g), and its contrast improved image by the suggested approach is displayed in Fig. 1 (d) and 1(h).

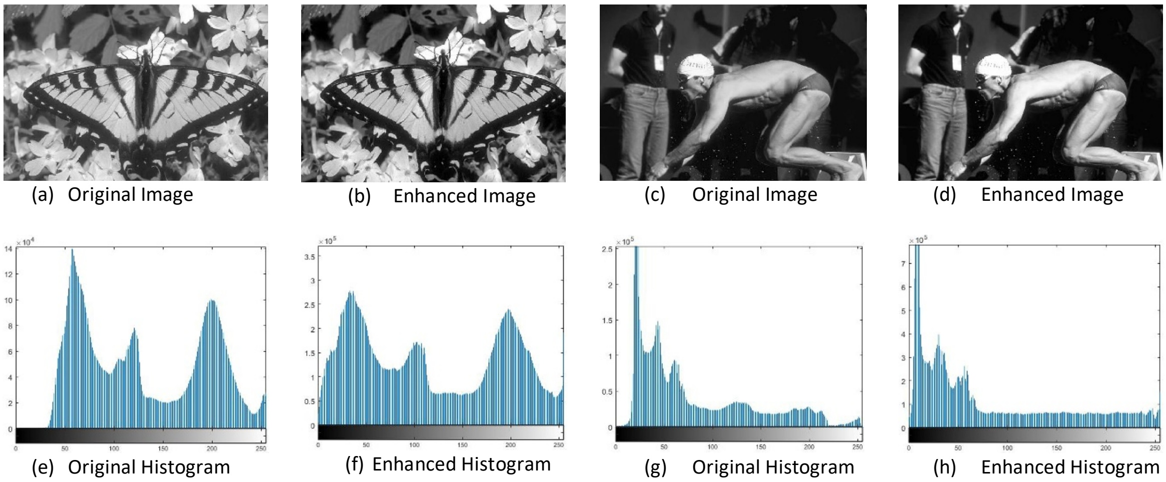

Fig. 1. (a), (c), (e), and (g) Original BSD image of 'Butterfly' and 'Swimmer' and their histograms and Fig.1 (b), (d), (f) and (h) enhanced image and histograms of 'Butterfly' and 'Swimmer' by the proposed method.

5. Edge Detection of Sub Image Histogram Equalization by Using Polynomial Threshold

A polynomial is a quantitative statement that contains variables, and coefficients. A polynomial is composed of non-negative integer exponent, subtraction, addition, multiplication, coefficients, and variables.

5.1 Instances of polynomials

Polynomials of degree 1

$$X + 7 \tag{22}$$

Polynomials of degree 2

$$2x^2 - 4x + 1 \tag{23}$$

polynomials of degree 3.

$$2x^3 - 4x + 1 \tag{24}$$

5.2 Derivatives of Polynomials

Using power rule derivatives of polynomials is achieved.
For a real number *r*, the derivative can be defined as :

$$f(x) = X^r \tag{25}$$

$$\frac{d}{dx} f(x) = rx^{r-1} \tag{26}$$

An instance:

$$if\ \ f(x) = 2x^2 + 7x + 3$$

$$f^{'}(x) = 2\times 2x + 1\times 7$$
$$= 4x + 7$$
$$f^{'}(x) = 11.$$

5.3 Polynomial Derivative Based Threshold

The histogram of the image is processed by a polynomial derivative [11-12] where the pixel value exposed varies according to the levels of intensity. When such a polynomial is subjected to a derivative method, the frequency of variation of levels of intensity concerning the image's pixel numbers is obtained. The derivative of the product between *HB* and *HC* is given by *DP*. *HB* stands for histogram bin locations (*HB*) while *HC* stands for histogram counts (*HC*).

$$DP(I) = \frac{d}{dx}\left[HB(I)\,\mathrm{HC}(I)\right] \tag{27}$$

Image histogram bin (HB) on image *I,* and polynomial derivative denoted by *DP* are utilized for polynomial assessment, as well as the function of *DP* is displayed in (28).

$$DP(I) = DP_1 I^{n} + DP_2 I^{n-1} + DP_3 I^{n-2} + ... + DP_n I \ + DP_{n+1} \tag{28}$$

The polynomial differentiation method yields the derivative of the polynomial signified by the coefficients.

6. Quantitative Evaluation

The Berkeley Segmentation Database (BSD) images are the subject of experiments for the suggested methods based on qualitative and quantitative assessment [25]. The approaches are simulated in MATLAB R2018a, on hardware configuration such as an Intel Core i7 CPU and 8 GB Ram, and Windows 10 Pro operating system software.

6.1. Quantitative Assessment

A. Edge-Based Contrast Measure (EBCM)

It is knowledgeable that peoples are very sensitive to the edges of an image. It is anticipated that an enhanced digital image should produce more edge pixels compared to the original image. The image intensity of edge pixels is counted in small windows of the image by EBCM [22] parameters. Input image *I* contrast *CT(i,j)* for a pixel positioned at *(i, j)* is expressed in (*29)*

Table 1. Average EBCM outcome of various methods

BSD Image	Ground Truth	Canny	Sobel	Roberts	log	Direcedge	Robinson	Proposed
126039	5.0886	13.082	12.916	12.484	27.684	46.761	34.708	86.082
176035	6.1721	17.006	15.744	14.214	34.969	123.64	26.179	97.116
202012	7.9702	88.055	23.593	10.449	76.296	125.36	94.048	143.81
227040	7.8749	31.657	21.726	14.454	46.495	96.640	54.426	94.190
239096	7.5896	19.127	20.087	17.706	34.399	29.047	33.436	68.389
12074	2.3673	24.358	15.716	16.407	25.568	16.529	25.367	56.064
Average	**6.17711**	**32.2141**	**18.297**	**14.2856**	**40.9018**	**72.9961**	**44.694**	**90.9418**

$$CT(i,j) = \frac{|\,x(i,j) - e(i,j)\,|}{|\,x(i,j) + e(i,j)\,|} \tag{29}$$

$$EBCM(I) = \sum_{i=1}^{C}\sum_{j=1}^{R}(\mathrm{i,j})\,/\,CR \tag{30}$$

C x R pixels where *C* indicates height and *R* indicate the width of the image *I*. EBCM outcomes were received from Table 1 and the average EBCM of the proposed method is found *90.9418* and this is better than the other values of the compared methods. Its high value measures human pleasure by the presence of more image pixels on the edges present in the enhanced image. The edge detection results observed in Table 1 is shown the average EBCM value of the proposed algorithm is higher. The second-best result is given by the Direcedge edge detection method. Its average EBCM value is *72.9961*.

B. Performance Ratio (PR)

Performance Ratio (PR) [23] signifies the ratio of true to false edges in an image. It is calculated in equation (*26*). *PR* is obtained from Table 2 and its high value is always desired as it indicates the presence of real pixels on the edges of the image surpassing the false presence of the pixels in the image. The simulation results are obtained from Table 2. It shows the proposed algorithm gives a higher average *PR* value of 13.2079. The second-best average *PR* is 11.0246 which is given by the Robinson edge detection method.

Table 2. Performance Ratio (PR) and the results of various method

BSD Image	Canny	Sobel	Robert	Log	Direcedge	Robinson	Proposed
126039	6.5571	6.5363	6.7854	8.5955	9.888	16.823	17.025
176035	1.5944	1.9625	1.798	2.553	7.8803	3.9053	5.8414
202012	10.745	3.2121	1.7244	9.0165	12.523	13.961	16.218
227040	6.3379	4.7663	3.6472	8.4397	17.759	13.157	15.362
239096	6.1247	4.5925	4.4358	7.2103	8.0295	13.044	14.20
12074	8.9997	6.736	8.0094	7.5988	9.2688	5.2577	10.601
Average	**6.7264**	**4.6342**	**4.4000**	**7.2356**	**10.8914**	**11.0246**	**13.2079**

$$PR = \frac{TE}{FE + NEP} \times 100 \tag{31}$$

PR denotes the ratio of true to false edge detected objects in an image. Here, *TE* signifies the pixel's true edges detected as edges of an image. *FE* represents false edges identified as edges and *NEP* denotes those pixels edge discovered as non-edge pixels.

Table 3. F-MEASURE outcome of the different edge detection algorithm

F-MEASURE	Sobel	Canny	Roberts	Log	Direcedge	Robinson	Proposed
126039	0.007759	0.006828	0.006721	0.012499	0.026397	0.017032	0.030675
176035	0.006730	0.004411	0.003802	0.006469	0.00986	0.009901	0.011188
202012	0.005859	0.017578	0.002859	0.015019	0.02363	0.023873	0.025542
227040	0.005677	0.008310	0.004867	0.010395	0.016397	0.015802	0.019308
239096	0.003203	0.004078	0.002211	0.006322	0.014656	0.009103	0.016467
12074	0.005849	0.008260	0.004412	0.010012	0.013548	0.013832	0.019647
Average	**0.005846**	**0.008244**	**0.004145**	**0.010119**	**0.017414**	**0.014923**	**0.020471**

C. Measure [20]

$$PR = TP / (TP + FP) \tag{32}$$

$$RE = TP / (TP + FN) \tag{33}$$

The F-measure is the harmonic mean of Precision and Recall defined as

$$F = 2((PR * RE) / (PR + RE)) \tag{34}$$

Here, PR denotes precision value, *TP* is true positive pixels, FP indicates false positive, *RE* is recalled and *F* is F-Measure. The results of the F-Measure are demonstrated in Table 3 and are always expected to be of high value. A high exposure value suggests better contrast. It provides a measure of precision and recall of a digital image by using the harmonic mean value of the pixel levels. The arithmetic means value determines the level of the ground truth of the processed enhanced image. The precision of quality and to maintain recall and good attribute for the interaction between the storage device and the processor and harmonic mean value of the pixels is found to be responsible for the above-mentioned performance. Observations made based on the findings show that the suggested approach produces a better average F-Measure value of 0.020471. The Direcedge method gives the second-best F-Measure result which is 0.017414.

Table 4. Edge strength similarity for Image quality assessment (ESSIM) results of various method

BSD Image	Canny	Sobel	Robert	Log	Direcedge	Robinson	Proposed
126039	0.99306	0.99304	0.99306	0.99317	0.99309	0.99333	0.99357
176035	0.99656	0.99657	0.99657	0.99658	0.99669	0.99658	0.99664
202012	0.99419	0.99391	0.99386	0.99417	0.99431	0.99425	0.99441
227040	0.9943	0.99425	0.99422	0.99441	0.99465	0.99446	0.99460
239096	0.99452	0.99448	0.99447	0.9946	0.99458	0.99463	0.99481
12074	0.99695	0.99691	0.99692	0.99693	0.99685	0.99704	0.9970
Average	**0.99493**	**0.99486**	**0.99485**	**0.99497**	**0.99502**	**0.99504**	**0.99517**

D. Edge Strength Similarity for Image Quality Assessment (ESSIM)

ESSIM [24] image quality metric is based on the similarity of edge-strength which described the visual quality, expressed as

$$ESSIM\,(fm, gm) = \frac{1}{N}\sum_{i=1}^{N} \frac{2E(fm,i)E(gm,i)+CP}{(E(fm,i))^2+(E(gm,i))^2+CP'} \tag{35}$$

Here, *fm* and *gm* are calculated via the likeness amongst the strength of the edge maps. Where the parameter *CP* has two meanings. Primarily, it is presented to ignore the denominator to be zero. Then, it can be observed as a scaling parameter. Various *ESSIM* scores can be generated by the different magnitudes of *CP*.

$$CP=(BC*LD)^2 \tag{36}$$

Here, *BC* denotes a predefined constant, and *LD* signifies the dynamic range of the edge strength. The total number of pixels is denoted by *N*, the image pixel is represented by *i*, and edge strength is denoted by *E*, more detail in [24]. A higher value of ESSIM indicates that the edge quality is better than those obtained by other methods. The *ESSIM* results demonstrated in Table 4 is shown the average *ESSIM* value of the proposed algorithm is higher which is 0.99517. The second-best result given by the Direcedge edge detection method is 0.99502.

Table 5 shows the outcome of different edge detection matrices through the proposed edge-detection method without using the proposed image enhancement algorithm. Results show the average EBCM is 86.505, PR is 13.187, F-MEASURE is 0.022657, and ESSIM is 0.99498.

Table 5. Proposed edge detection method without Image enhancement

BSD Image	EBCM	PR	F-MEASURE	ESSIM
126039	71.166	15.207	0.028983	0.99347
176035	93.119	14.024	0.016080	0.99455
202012	147.18	10.258	0.020859	0.99635
227040	87.074	15.076	0.033578	0.99374
239096	72.098	14.716	0.017240	0.99482
12074	48.398	9.8419	0.019203	**0.99698**
Average	**86.505**	**13.187**	**0.022657**	**0.99498**

Table 6. Comparison of proposed edge detection method with and without Image enhancement

Average Results	Edge Without Enhancement	Using Proposed Enhancement	Increased Rate by Enhancement	Decreased Rate Without Enhancement
EBCM	86.5058	90.9418	5.13%	Nil
PR	13.1871	13.2079	0.16%	Nil
F-Measure	0.02265	0.02047	Nil	9.62%
ESSIM	0.99498	0.99517	0.02%	Nil

Table 6, demonstrates the average results of different edge quality matrices through the proposed edge detection method. It is observed from the outcomes that the proposed edge detection method applying to the image produced by the proposed image enhancement algorithm returns better results compared to the outcomes returned by the proposed edge detection method without using the proposed image enhancement method. Matlab simulation results demonstrate that EBCM is increased by 5.13%, PR is increased by 0.16%, and ESSIM increased by 0.02% by applying proposed edge detection to the proposed enhancement method. Only, F-Measure is decreased by 9.62% by applying edge detection on the proposed enhancement algorithm. But in both cases, the overall performance of the proposed edge detection method is superior to compared edge detection methods.

6.2. Qualitative Assessment

The qualitative assessments are illustrated in Fig. 2-5 to measure the visual quality, and the results reveal that the suggested approach outperformed other existing methods.

The BSD image ‘126039’ of ‘Missionaries of charity’ and its detected edges obtained through various method are demonstrated in Fig.2 Sobel edge detector result shows broken edges with some missing information. The output of Canny is found slightly better than Sobel but some edge features are not present. Robert's method gives edges with less information. The edge obtained from the Log filter is acceptable with some missing information. The direction detector produces lines with artifacts that cannot be identified. Although the result of the Robinson compass detectors is of high quality, significant edge data is indeed missing. The proposed methodology delivers edges of the highest quality along with all relevant data. It prominently displays the cloud's edges which are missing in Sobel, Canny, Robert, and direction detector methods. Log and Robinson's method are showing cloud edges but to a small extent.

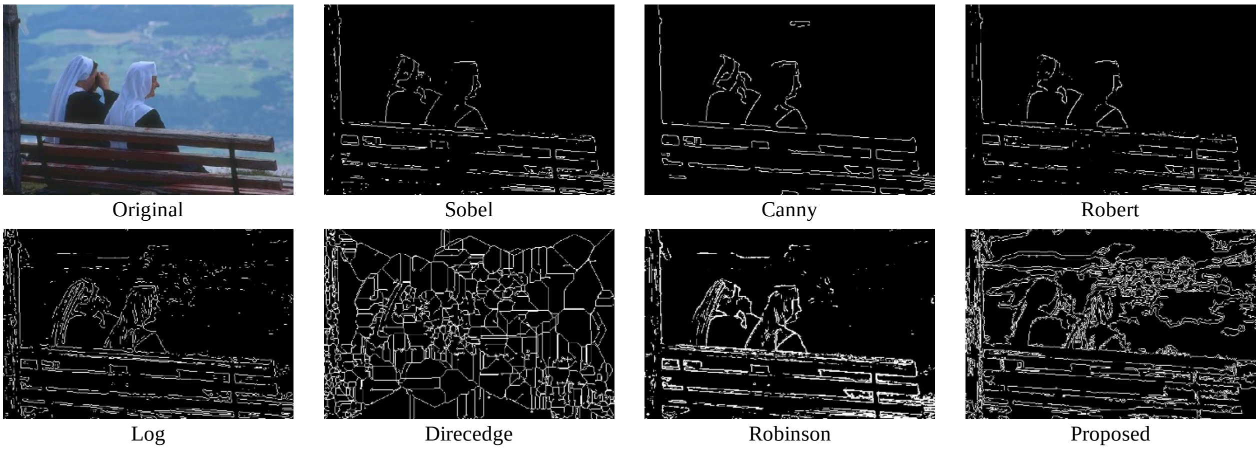

Fig. 2. Original BSD image ‘126039’ of ‘Missionaries of charity’ and output of various edge detection methods

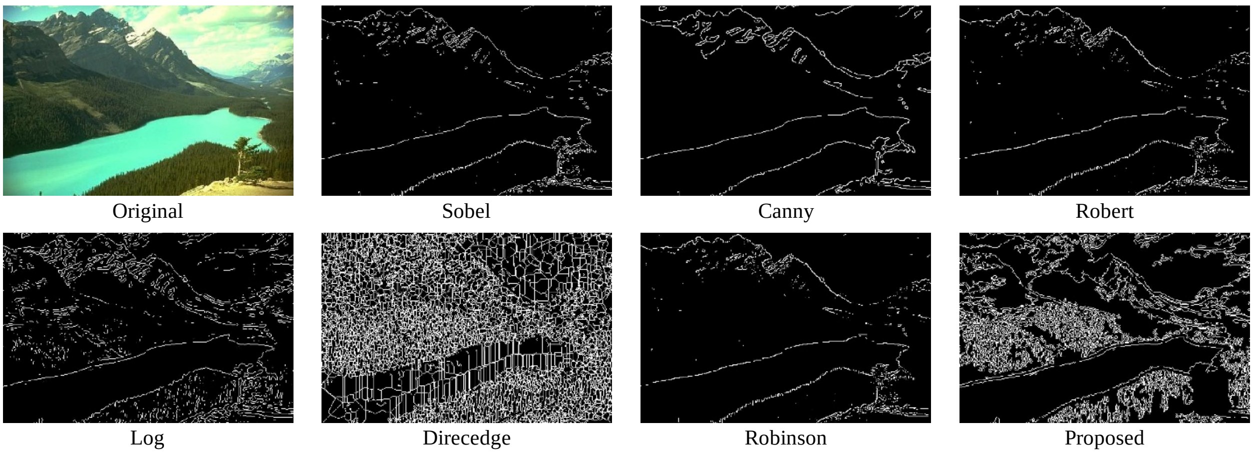

Fig. 3. Original BSD image ‘176035’ of ‘River and mountain’ and output of various edge detection methods

The BSD image ‘176035’ of ‘River and mountain’ and its edges of it found through various methods are shown in Fig.3. Sobel filter output is satisfactory but much information is still absent. The output of Canny is found clean but all detail about the edge is not present. Robert filter shows loss of edge lines. The edge obtained from the Log filter is good but still, some edge information is missing. The direction detector is not improved and the edges are scattered and contain artifacts. Robinson compass detector output is good quality but some information is still missing. The proposed algorithm gives the best quality of edges with all the vibrant information. It shows the details of both the cloud and mountain areas which are not present in existing compared methods to a large extent.

The BSD image ‘202012’, of ‘Cow plowing’ and its edge found using various methods are exposed in Fig.4. Sobel filter output is good quality but some information is still missing. The output of Canny is found clean but all detail about the edge is not present. Roberts filter output displays less significant output with lighter edges. The edge obtained from the Log filter is not improved and the edges are lighter and scattered. The direction detector is not improved and the edges are lighter and scattered. Robinson compass detector output is good quality but some information is still missing. The proposed algorithm is found to give the superiority of edges with large details of grass and soils.

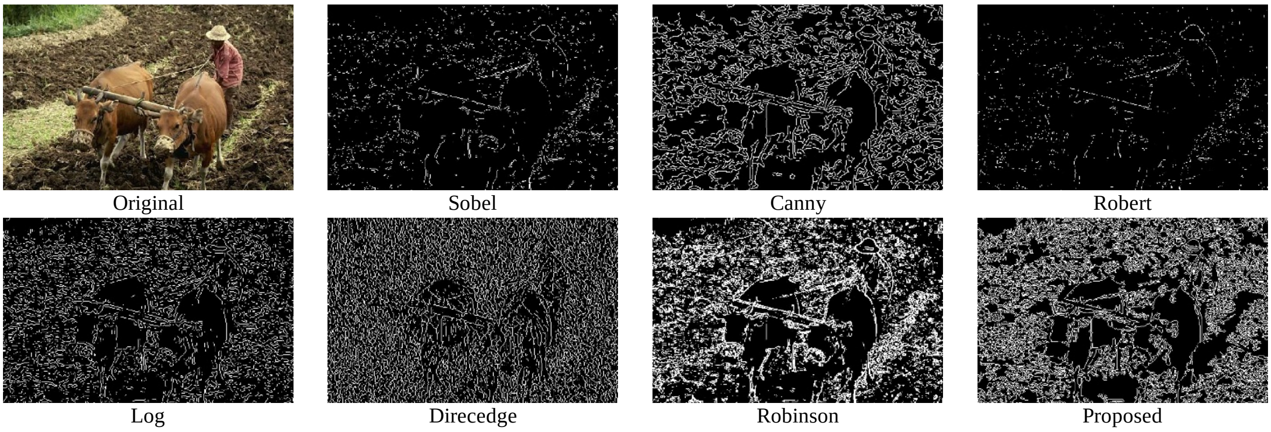

Fig. 4. Original BSD image ‘202012’ of ‘Cow plowing’ and output of various edge detection methods

The BSD image ‘239096’ of ‘Girl with flowers’ and its edges found through numerous method are shown in Fig.5. It is observed, the Sobel filter output is missing some vital edge information. The result of Canny displayed more clean edges than Sobel but few edge details are missing. Roberts filter output is close to Sobel and displays less significant output with broken edges. The edges got from the Log filter are good but still, some information is missing. The edges found through the direction detector method are not recognizable and have many artifacts. Robinson compass detector output is good quality but with thick lines and missing edges. The proposed algorithm is showing the best quality of edges with all details. It displayed the flower object on the right side of the image which is missing in other compared state-of-art algorithms.

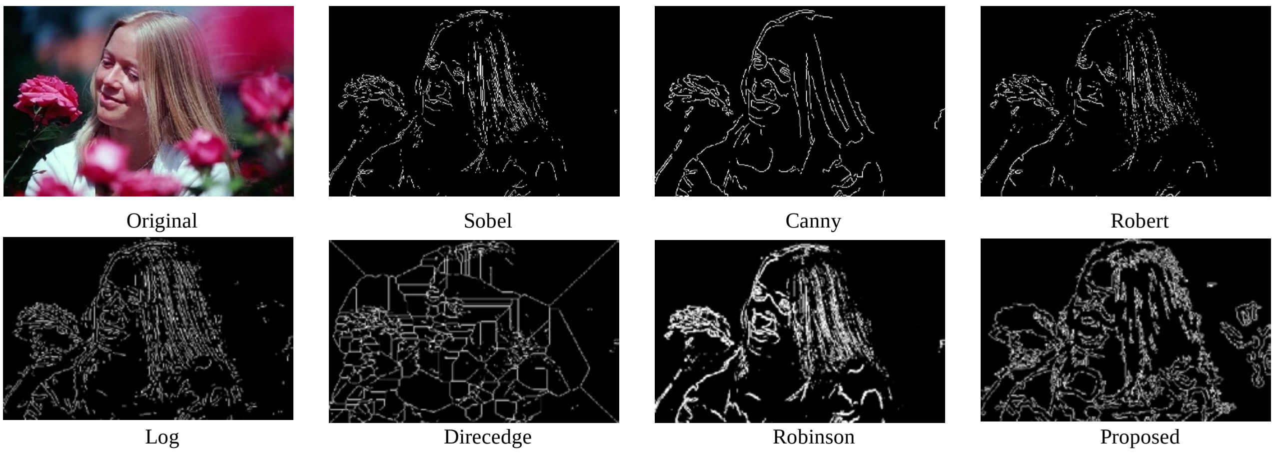

Fig. 5. Original BSD image ‘239096’ of ‘Girl with flowers’ and output of various edge detection methods

7. Conclusion

In the suggested research study, to improve the contrast of the image harmonic mean value is utilized to divide the histogram, and the mean absolute deviation is used to compute the clipped threshold to prevent excessive enhancement. Then polynomial differentiation curve fitting techniques on the contrast-enhanced image is accomplished to find out the edges of objects. Matlab experimental results demonstrate that the proposed methods produce superior results than other compared methods in terms of EBCM, Performance Ratio, F-Measure, and ESSIM. The present work advances in the field of edge detection from the present state of knowledge by producing better quantitative and qualitative results evaluated through various experiments. Experimental results show EBCM is increased by 5.13%, PR is increased by 0.16%, and ESSIM increased by 0.02%, by using the suggested edge detection method to the images, and by applying the proposed image enhancement method to the images. In future studies, the present algorithm can be extended by introducing other curve fitting methods with smoothing techniques.

References

[1] Gonzalez, R.C., R.E. Woods, S.L. Eddins, Digital Image Processing Using MATLAB, New Jersey, Prentice Hall, 2003, Chapter 11.
[2] Peli, T., & Malah, D. (1982). A study of edge detection algorithms. Computer graphics and image processing, 20(1), 1-21.
[3] Shekhar Karanwal, "Implementation of Edge Detection at Multiple Scales ", International Journal of Engineering and Manufacturing, Vol.11, No.1, pp.1-10, 2021.
[4] Prashengit Dhar, Sunanda Guha, "Skin Lesion Detection Using Fuzzy Approach and Classification with CNN ", International Journal of Engineering and Manufacturing, Vol.11, No.1, pp. 11-18, 2021.
[5] Priya Gupta, Nidhi Saxena, Meetika Sharma, Jagriti Tripathi,"Deep Neural Network for Human Face Recognition", International Journal of Engineering and Manufacturing, Vol.8, No.1, pp.63-71, 2018.
[6] P. Čisar, S. M. Čisar and B. Markoski, "Kernel sets in compass edge detection," 2013 IEEE 14th International Symposium on Computational Intelligence and Informatics (CINTI), Budapest, 2013, pp. 239-242.
[7] Haralick, R.M. 1984. Digital step edges from zero crossing of second directional derivatives. IEEE Trans. on Pattern Analysis and Machine Intelligence, 6(1):58–68.
[8] B. Meihua, G. Siyu, T. Qiu, and Z. Fan, “Optimization of the bwmorph Function in the MATLAB image processing toolbox for binary skeleton computation,” in Proc. Int. Conf. Comput. Intell. Nat. Comput., Wuhan,China, 2009, pp. 273–276.
[9] Y Meng, Z Zhang, H Yin et al., "Automatic detection of particle size distribution by image analysis based on local adaptive canny edge detection and modified circular Hough transform[J]", Micron, vol. 106, pp. 34, 2017.
[10] X M Zhao, W X Wang & L P Wang (2011) “Parameter optimal determination for canny edge detection”, The Imaging Science Journal, 59:6, 332-341.
[11] Acharya, Kuldip & Ghoshal, Dibyendu. (2020). Edge detection using polynomial differentiation method. 85-87. 10.26480/cic.01.2020.85.87. DOI: http://doi.org/10.26480/cic.01.2020.85.87
[12] Polynomial evaluation, https://in.mathworks.com/help/matlab/ref/polyval.html, (accessed March, 2022).
[13] Lihaotiansky, Edge-Detectors/direcedge. https://github.com/lihaotiansky/Edge-Detectors/blob/master/direcedge.m (accessed 7 January 2020).
[14] Sobel, I., Feldman, G.: A 3x3 isotropic gradient operator for image processing. Presented at the Stanford artificial intelligence project (SAIL), 1968.
[15] Prewitt, J.M.: Object enhancement and extraction. Pict. Process.Psychopict. 10(1), 15–19 (1970).
[16] G. Roberts, Machine perception of three-dimensional solids, in Optical and Electrooptical Information Processing (J. T. Tippett et al., Eds), pp. 159-197, MIT Press, Cambridge, Mass., 1965.
[17] Laplacian of Gaussian, https://in.mathworks.com/help/images/ref/edge.html?searchHighlight=Log%20edge&s_tid=doc_srchtitle.
[18] Canny, J.: A computational approach to edge detection. IEEE Trans. Pattern Anal. Mach. Intell. 6, 679–698 (1986).
[19] Ref: A. Beghdadi and A. L. Negrate, “Contrast enhancement technique based on local detection of edges,” Comput. Vis. Graph. Image Process., vol. 46, no. 2, pp. 162–174, May 1989.
[20] Singh, K., Kapoor, R.: ‘Image enhancement via median-mean based subimage-clipped histogram equalization’, Optik, 2014, 125, (17), pp. 4646–4651
[21] MATLAB 2018a. A Natick ed. Massachusetts, United States: The MathWorks, Inc.; 2018.
[22] Azeddine Beghdadi, Alain Le Negrate, Contrast enhancement technique based on local detection of edges, Computer Vision, Graphics, and Image Processing, Volume 46, Issue 2, 1989, Pages 162-174, ISSN 0734-189X, https://doi.org/10.1016/0734-189X(89)90166-7.
[23] Intawong K., Scuturici M., Miguet S. (2013) A New Pixel-Based Quality Measure for Segmentation Algorithms Integrating Precision, Recall and Specificity. In: Wilson R., Hancock E., Bors A., Smith W. (eds) Computer Analysis of Images and Patterns. CAIP 2013. Lecture Notes in Computer Science, vol 8047. Springer, Berlin, Heidelberg.
[24] X. Zhang, X. Feng, W. Wang and W. Xue, "Edge Strength Similarity for Image Quality Assessment," in IEEE Signal Processing Letters, vol. 20, no. 4, pp. 319-322, April 2013.
[25] Arbelaez, P., Maire, M., Fowlkes, C., et al.: ‘Contour Detection and Hierarchical Image Segmentation’, IEEE Transactions on Pattern Analysis and Machine Intelligence., 2011, 33, (5), pp. 898-916.

Authors’ Profiles

Kuldip Acharya received his M.Tech in Computer Science and Engineering (CSE) from Tripura University (a central university), India in 2012. He is doing Ph.D in Computer Science & Engineering from National Institute of Technology Agartala, India from 2013 onwards. His research area is Digital Image Processing.

Dr. Dibyendu Ghoshal was awarded Postdoctoral Research Associateship in 1996 and Ph.D. in Radio physics & Electronics from CU in 1997 with a specialization in Microwave and millimeter-wave systems. His research interest includes micro & millimeter wave, and Digital Image Processing.

How to cite this paper: Kuldip Acharya, Dibyendu Ghoshal, "Polynomial Differentiation Threshold based Edge Detection of Contrast Enhanced Images", International Journal of Image, Graphics and Signal Processing(IJIGSP), Vol.15, No.2, pp. 35-46, 2023. DOI:10.5815/ijigsp.2023.02.04