Standardization of Edge Magnitude in Color Images

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***Abstract*—Edge detection is a useful task in low-level image processing. The efficiency of many image processing and computer vision tasks depends on the perfection of detecting meaningful edges. To get a meaningful edge, thresholding is almost inevitable in any edge detection algorithm. Many algorithms reported in the literature adopt ad hoc schemes for this purpose. These algorithms require the threshold values to be supplied and tuned by the user. There are many high-level tasks in computer vision which are to be performed without human intervention. Thus, there is a need to develop a scheme where a single set of threshold values would give acceptable results for many color images. In this paper, an attempt has been made to devise such an algorithm. Statistical variability of partial derivatives at each pixel is used to obtain standardized edge magnitude and is thresholded using two threshold values. The advantage of standardization is evident from the results obtained.**

***Index Terms*—Adaptive choice of parameters, color edge detection, edge magnitude, local standardization for thresholding, nonmaxima suppression, smoothing technique, thresholding, thresholding with hysteresis.**

I. Introduction

EDGE detection has been a challenging problem in low-level image processing. It becomes more challenging when color images are considered because of its multidimensional nature. Color images provide more information than grayscale images. Thus, more edge information is expected from a color edge detector than a grayscale edge detector [1]–[3]. In a grayscale image, edges are detected by detecting the discontinuities in the image surface, i.e., the discontinuities in the intensity of a sequence of pixels in a particular direction called gradient direction. The discontinuities in grayscale is easy to determine because gray values are partially ordered, but this freedom is not there in a color image. The simple difference between color vectors does not give the true distance between them. Sometimes, it is difficult to detect a low intensity [2] edge between two regions in grayscale, but in color image, the clarity is more because, without being much different in intensity there can be a substantial difference in hue. Almost 90% of edge information in a color image can be found in the corresponding grayscale image. However, the remaining 10% can still be vital in certain computer vision tasks [1]. Further, human perception of color picture is perceptually much richer than an achromatic picture [4].

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One of the earliest color edge detectors is proposed by Navatia [4]. The image data is transformed to luminance Y and two chrominance components T_1 and T_2 and Huckel's edge detector is used to find the edge map in each individual component independently, except for the constraint of having the same orientation. Shiozaki [5] found entropy in each component using a local entropy operator and merged the three values for color edge detection. Machuca *et al.* [6] transformed the image from RGB to YIQ and detected edge in the hue plane. Fan *et al.* [3] proposed a method where they find edges in YUV space. Edge magnitude is found individually and thresholded in each component and merged. They proposed an entropy-based method to automatically detect a threshold value for each component. This method is simple and may be faster in computation but produces less accurate results [7].

A multidimensional edge detection method using differential geometric approach was proposed by DiZenzo [8]. He considered the multi-images as a vector field and found the tensor gradient. Explicit formulas for the edge direction and magnitude in multispectral images are derived. He also shows that the earlier ways of finding edges by combining the output of difference operators in each component does not actually cooperate with one another. Cumani proposed an extension of the second-directional derivative approach to color images in [9]. He found the edge map by locating the zero crossings in image surface. Formulas for second order partial derivatives for finding zero crossings in multispectral images are derived. He defined the direction of maximal-contrast by the corresponding eigenvector of the largest eigenvalue of the 2×2 matrix formed from the outer product of the gradient vector in each component. Alshatti *et al.* [10] suggested a modification of the Cumani's approach to solve the problem of sign ambiguities and to reduce computational time involved in the selection of maximal directional contrast. Later, Cumani [11] proposed an efficient algorithm to get rid of this problem. The multidimensional gradient method is also used by Saber *et al.* [12] for edge linking in image segmentation. Some of the other related works can be found in [13]–[15].

Trahanias *et al.* [16], [17] proposed a class of edge detectors using vector order statistics. Three different ways of finding edge magnitudes using dispersion of color vectors from the median of the set of vectors in the neighborhood of a pixel are proposed. Toivanen *et al.* [18] have pointed out that R-ordering sometimes orders two different spectra into the same scalar value. They have proposed a different ordering method of multispectral image pixels. They further used self-organizing map (SOM) for this purpose. A class of directional vector operators are proposed to detect the location and orientation of edges in color images by Scharcansk *et al.* [19]. A comprehensive analysis of color edge detectors can be found in Zhu *et al.*'s [20] work.

Ruzon *et al.* [21] have proposed an algorithm using compass operator. It considers a disc at each pixel location. The disc is divided into several pairs of opposite semi discs by rotating the diameter over 180° with an interval of 15°. The color distribution of the pixels in each such semi disc is found after doing vector quantization. The distance between two semi discs generated by a single diameter is the distance between their color distributions. The distance between two distributions is found using the Earth Mover's Distance (EMD). The edge magnitude at the pixel is the maximum distance among all the distances found between each pair of opposite semi discs created by rotating the diameter.

There are some color edge detectors which are very specific in their objectives. Those are, color invariant edges by Geusebroek *et al.* [22] and photometric quasi-invariant color edge detector [23], avoiding unnecessary edges due to specular reflection by Tsang *et al.* [24], reflection-based color edge classification by Gevers [25] and Gevers *et al.* [26].

Various types of edge detection algorithms have been discussed above. All of them have their advantages and disadvantages. Some of these are pointed out here. The early approaches to color edge detectors, which are extensions of achromatic color edge detectors failed to extract certain crucial information conveyed by color [20]. R-ordering in certain cases orders two different spectra into the same scalar value, and as a result, can miss some parts of edges [18]. The edge detection approaches which simply add the gradient magnitudes of all the color components may fail to detect some crucial edge information in certain cases [8]. Thus, though several color edge detection algorithms are proposed in the literature several open problems still exist.

Most algorithms are concerned with finding edge magnitude and direction. This is expected and also justified because the quality of edge map depends on these two quantities. However, none of the algorithms except the work by Fan *et al.* [3] addressed the selection of thresholding parameters, although this is also an integral part in most of the algorithms. Edge detection algorithms discussed have reported good results when the values of the parameters involved are adjusted suitably. Though most of these algorithms produce good results, generally, none of them is designed to give uniformly acceptable results for all kinds of images with a fixed set of parameter values. Thus, there is a need to devise a method which can give uniformly acceptable results with a single set of parameter values. In this article, this problem is addressed.

This paper is organized in the following way. Section II gives a brief idea of the mathematical foundation of the method. In Section III, results of the proposed method are compared with other methods. The article is concluded in Section IV with concluding remarks.

II. Theoretical Foundation

This section describes the mathematical methodology of the algorithm. The proposed method basically follows the philosophy stated in [27] by Rakesh *et al.* and uses a different technique for finding the initial edge magnitude and the direction. Rakesh *et al.* have found the estimated image surface using the Priestly–Chao [28] kernel smoother. The Priestly–Chao kernel is used because, in statistics, it is a good estimator of a function when the independent variable is equally spaced which fits to the case of images as a function. Initial edge response and the direction of maximum contrast are found using the directional derivatives along x and y axes of the estimated image surface. Then, nonmaxima suppression [29] is performed on the initial edge response. The standardized edge magnitudes at these pixels which are not suppressed by nonmaxima suppression are found using the variability of the estimated image surface and the directional derivatives. In the end, a two-level thresholding is performed on the standardized edge magnitudes. In the proposed method, the Priestly–Chao kernel smoother is used to estimated the images surface in each component of the color image separately, i.e.,

$$f^c(x,y) = \frac{1}{\xi}\sum_{i=1}^{m}\sum_{j=1}^{n} K(x,i)K(y,j)I^c(i,j)$$
$$\text{where } \xi = 2\pi mnh^2, \quad K(a,b) = \Psi\left(\frac{a-b}{h}\right)$$
$$\Psi(x) = e^{-x^2/2}, \quad c = R, G, B. \tag{1}$$

$I^c(i,j)$ is the grey value at the (i,j)th pixel of the original image for the component c, h is the stiffness parameter, and m and n are the number of rows and columns of these, respectively. In the rest of this paper, the superscript c indicates that the operation is done on the corresponding component (i.e, R or G or B) of the image.

The directional derivatives along x and y directions of the estimated image surface are

$$f_x^c(x,y) = \frac{1}{\xi}\sum_{j=1}^{n} K(y,j)\left\{\sum_{i=1}^{m} K'(x,i)I^c(i,j)\right\} \tag{2}$$

$$\text{and } f_y^c(x,y) = \frac{1}{\xi}\sum_{i=1}^{m} K(x,i)\left\{\sum_{j=1}^{n} K'(y,j)I^c(i,j)\right\} \tag{3}$$

where $K'(x,i)$ and $K'(y,j)$ are the derivatives of $K(x,i)$ and $K(y,j)$, respectively. The estimate of data variability of the estimated image $f^c(i,j)$ is given by

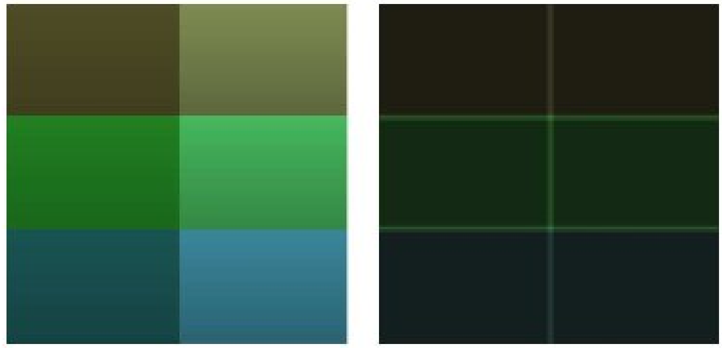
$$(\sigma^c)^2 = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}(I^c(i,j) - f^c(i,j))^2. \tag{4}$$

The edge magnitude λ of f at a pixel (x,y) is given by the largest eigenvalue of the 2×2 matrix [9], [11]

$$\begin{pmatrix} E & F \\ F & G \end{pmatrix} \tag{5}$$

and the direction of maximum contrast is given by the corresponding eigenvector. In the above expression

$$E = f_x^R f_x^R + f_x^G f_x^G + f_x^B f_x^B$$
$$F = f_x^R f_y^R + f_x^G f_y^G + f_x^B f_y^B$$
$$G = f_y^R f_y^R + f_y^G f_y^G + f_y^B f_y^B.$$



(a) (b)

Fig. 1. Two rectangles images, each of size 128 × 128: (a) Two horizontal edges in 43rd and 85th rows and one vertical edge in 66th column; (b) two vertical edges in 64th and 66th columns and four other horizontal edges.

Having the information of edge magnitude (λ) and the direction of maximum contrast at each pixel, edge location can be found precisely by using nonmaxima suppression [29]. The problem occurs in thresholding at the time of hysteresis. The edge magnitude found is generally not uniform for both low intensity and high intensity regions in an image. Thus, the edge detectors are unable to extract, simultaneously, all the edges in an image having edges of different intensities. They cannot extract all the edges in different images with a fixed set of threshold values. To get those edges, threshold values have to be tuned carefully for individual images. To overcome this problem this article proposed a technique to obtain standardized edge magnitudes. The standardization of edge magnitude is done using the variability of the partial derivatives and estimated image surface.

Let us define the derivative vectors for each component of the smooth image f at a pixel (x, y) to be $v^c = (f_x^c, f_y^c)^T$, and the statistic $S(x, y)$ as

$$S(x,y) = \sum_{c=R,G,B} (v^c)^T (\Sigma^c)^{-1} (v^c) \tag{6}$$

where

$$\begin{aligned}
\Sigma^c &= \begin{pmatrix} \sigma_{11}^c(x,y) & \sigma_{12}^c(x,y) \\ \sigma_{12}^c(x,y) & \sigma_{22}^c(x,y) \end{pmatrix} \\
\sigma_{11}^c(x,y) &= \left(\frac{\sigma^c}{\xi}\right)^2 \sum_{i=1}^{m}\sum_{j=1}^{n} K^2(y,j)K'^2(x,i) \\
\sigma_{22}^c(x,y) &= \left(\frac{\sigma^c}{\xi}\right)^2 \sum_{i=1}^{m}\sum_{j=1}^{n} K^2(x,i)K'^2(y,j) \\
\sigma_{12}^c(x,y) &= \left(\frac{\sigma^c}{\xi}\right)^2 \sum_{i=1}^{m}\sum_{j=1}^{n} K(x,i)K(y,j)K'(x,i)K'(y,j).
\end{aligned} \tag{7}$$

In the above expressions, c takes values R, G, and B. $S(x, y)$ is the standardized edge magnitude at a pixel (x, y). The value of S is used as the standardized edge response and is thresholded using two threshold values. Note that there is no need to estimate S for all the pixels. S is estimated only for those pixels, which are not suppressed by nonmaxima suppression.

Note: A simple way of standardization of edge magnitude is to consider the inverse of dispersion matrices of respective colors and add the standardized magnitudes for each color, which has been done above. A more generalized linear model may have given rise to different expressions for standardized edge magnitudes.

Algorithm: Edge_Detect(I)

Input: I- RGB Image. Output: Edge—Binary Image.

1) Let $h = 1.25$ (stiffness of gaussian), $T_u = 30$ (upper threshold), and $T_l = 5$ (lower threshold).
2) Find the directional derivatives f_x^R, f_y^R, f_x^G, f_y^G, f_x^B, and f_y^B from I as described in (2) and (3).
3) Find the initial edge magnitude (λ) and direction of maximum contrast (eigenvector corresponding to λ).
4) For each pixel (i, j)
   a) apply nonmaxima suppression [27];
   b) if it is not suppressed, find S as in (6);
   c) if $S > T_u$ $\mathrm{Edge\_Class}(i, j) = 2$ (edge pixel);
   else if $S > T_l$ $\mathrm{Edge\_Class}(i, j) = 1$ (edge pixel if any of its 8-neighbors is an edge pixel);
   else $\mathrm{Edge\_Class}(i, j) = 0$ (not an edge pixel).
5) Initialize an array $\mathrm{Edge}(i, j)$ of the size of the input image to zero.
6) For each pixel, (i, j) if $\mathrm{Edge\_Class}(i, j) = 2$ perform $\mathrm{Track\_edge}(i, j)$.

This $\mathrm{Track\_edge}(i, j)$ algorithm is the one described in [27].

III. Results and Comparisons

A method has been proposed above to get standardized edge magnitudes at each pixel location and two level thresholding is performed on the standardized edge magnitudes to obtain the final edge map. This has been implemented on many artificially created images as well as natural color images. Four artificial images among these are two images shown in Fig. 1, vertical bars in Fig. 2(a) and circles in Fig. 3(a). The vertical bars image is constructed by varying the intensity along the rows with fixed values of saturation and hue so that the edge profile is only due to the intensity. As the gray values in this image are periodic with the period of ten pixels, the edge profile of only the first twenty pixels of a row are shown in Fig. 2(b). A total of 200 images from the "Berkeley Segmentation Dataset and

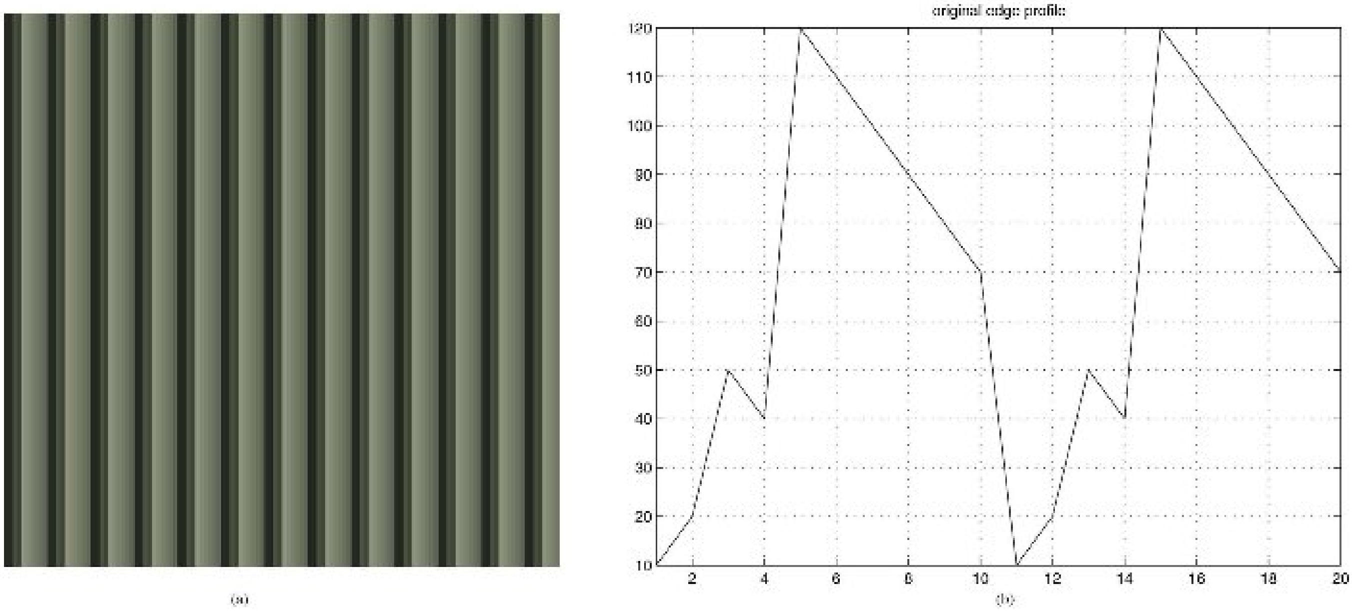
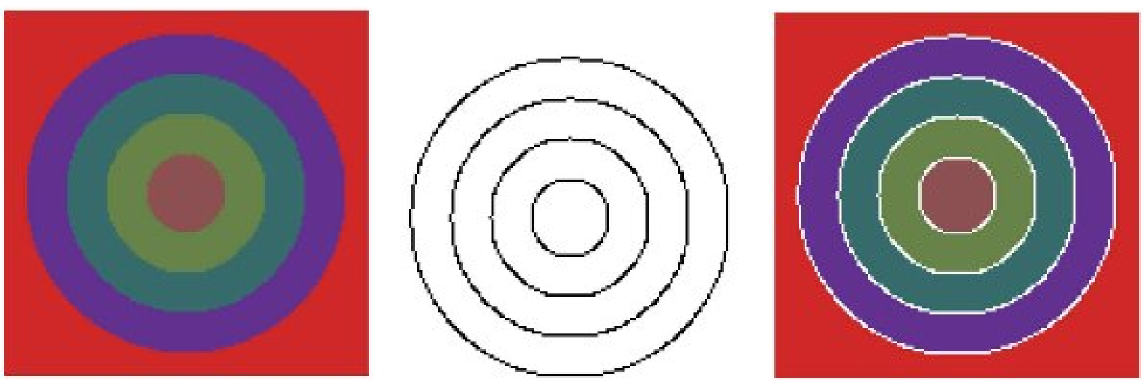


Fig. 2. Original vertical bars image and its edge profile. (a) Original vertical bars image. (b) Original edge profile of the first 20 pixels of a row of the image in Fig. 2(a).



(a) (b) (c)

Fig. 3. Results on circles image. (a) Original circles image. (b) Edge map obtained using proposed method with the fixed set of parameter values. (c) Edge map in Fig. 3(b) is super imposed on the original image.

Benchmark"(BSDB)[1] and six other images are considered to observe the performance of the proposed method. Out of these 206 images, 20 images are considered to obtain the threshold values for the proposed method. Three among the 20 images are used for threshold analysis, namely Lena [Fig. 4(a)], window [Fig. 4(b)] and balloon [Fig. 4(c)], are included here. Two different methods, one proposed by Cumani[2] [9] and second proposed by Ruzon[3] *et al.* [21], [30], have been considered for comparison.

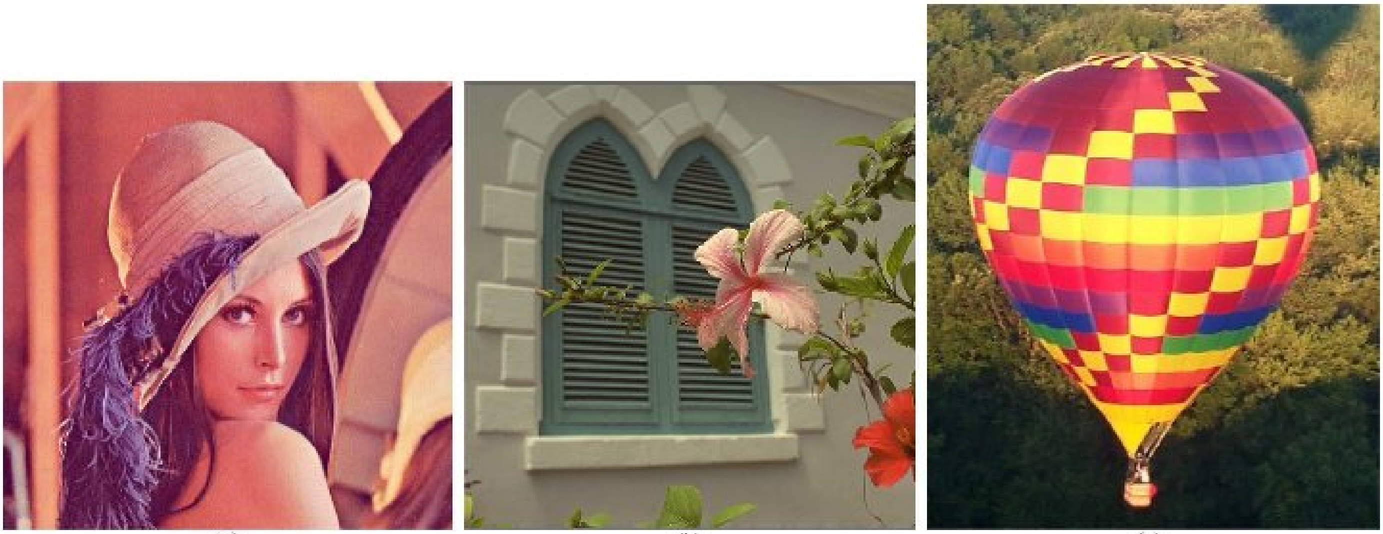
A. Standardization of Edge Magnitude by Proposed Method

Proposed method obtains the standardized edge magnitude at the maxima of the initial edge response of the image. The variability of the directional derivatives of the estimated image surface is used to obtain the standardized edge magnitudes. To verify it in reality, the edge magnitudes of 42nd row of Fig. 1(a) and 64th column of Fig. 1(b) before and after the standardization are plotted in Fig. 5. From the plots of edge magnitudes in Fig. 5, it can be seen that the edge magnitudes are enhanced after standardization but the rate of enhancement is not uniform in both the cases. It can also be observed that the edge magnitudes before the standardization is in the range from 0 to 12 in one image and it is between 0 to 4 in the other image, whereas after standardization the edge magnitudes are enhanced and the corresponding values are in the range of 0 to 1400 for both the images. This shows that the procedure suggested here standardizes the edge magnitudes. This helps to obtain a stable set of parameter values for obtaining uniform acceptable results for a wide variety of images. If we observe the edge profile of Fig. 1(b) before standardization (shown in the right side column of Fig. 5), the edge magnitudes between the two peaks are more than the edge magnitudes to the left of the left side peak and right of the right side peak. Actually, these

[1]BSDB is available at http://www.cs.berkeley.edu/projects/vision/grouping/segbench/

[2]Code available at http://www.ien.it/~cumani/

[3]Code available at http://robotics.stanford.edu/~ruzon/compass/



(a) (b) (c)

Fig. 4. Original Natural Images. (a) Lena image (256×256). (b) Window image (256×256). (c) Balloon image (320×373).

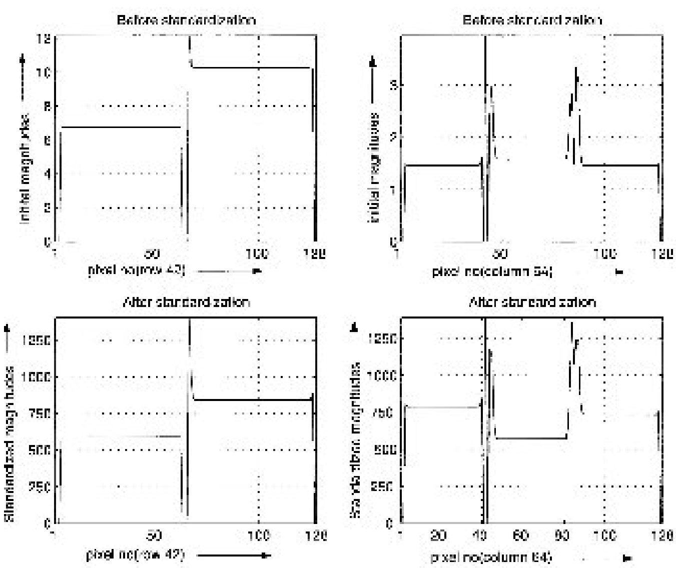


Fig. 5. Plots shown in the left column is the edge magnitudes plots corresponding to the horizontal edge at 42nd row of Fig. 1(a) and plots shown in the right column is the edge magnitudes plots corresponding to the vertical edge at the 64th column of Fig. 1(b). The top and bottom rows of this figure show the edge magnitudes before and after the standardization, respectively.

edge magnitudes are due to the edge corresponding to the two green rectangles in the middle row of Fig. 1(b). However, after standardization the middle edge magnitudes are less than both the right and left sides. This is happening because the variation of the color values in this region is more compared to the other two regions.

B. Analysis of Parameters for the Proposed Method

The judgement of good performance on the obtained results is a matter of concern because there is no appropriate method to judge the quality with 100% confidence. Pratt's figure of merit (FOM), which is used for comparing two edge detectors, needs the knowledge of the ground truth of the edge map. It is a quantitative evaluation procedure. Due to the difficulty of obtaining the ground truth of the edge map for natural images, quantitative method of judgement is ruled out and a qualitative method of judgement by visual evaluation is adopted.

1) Criteria of Selection for a Set of Parameter Values: The criteria of selection of a set of parameter values for a given image is that the resultant edge map should satisfy the following:

- it should contain most of the prominent edges;
- it should not contain too many spurious edges;
- it should be visibly pleasing.

The selection of edge maps is based on a process of elimination among a set of edge maps obtained using different parameter values. The elimination of an edge map has been done visually.

2) Selection of Parameter Values: The proposed method takes h the stiffness of gaussian, and two threshold values T_l and T_u as input parameters. T_l and T_u are the lower and upper threshold values respectively. To find a set of parameter values, several edge maps are generated for each image by varying the parameter h between 0.8 and 2 with an increment of 0.05, T_l between 0 and 10 with an increment of 1 and T_u between 5 to 50 with an increment of 1 subject to the condition that T_u is always greater than T_l.

There are several ways to obtain a fixed set of parameter values. A simple way is to examine the edge maps for a set of images and take that set of values which is producing acceptable edge maps for all the images in the set. When such an experiment is performed on the 20 considered images for threshold selection, the proposed method produced acceptable results with $h = 1.25$, $T_l = 5$, and $T_h = 30$.

3) Some of the Results Using Proposed Method: From the results on circles image [Fig. 3(c)], it can be seen that the proposed method has detected the boundaries of the discs in proper places in all the directions. In the vertical bars image, ideally, there should be only two edge locations one at the fourth pixel and another at the tenth pixel [Fig. 2(b)], and there should not be any edge between sixth and tenth pixels because the transition of intensity between these pixels is very smooth compared to the transition in intensity between the fourth and fifth pixels

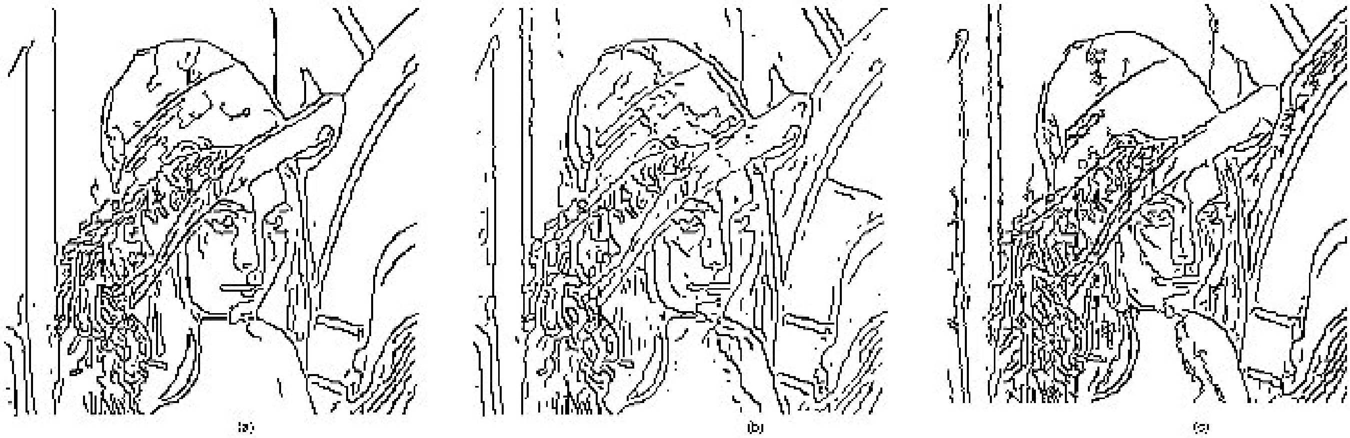


Fig. 6. Results on Lena image. (a) Proposed method ($h = 1.25$, $T_l = 5$, $T_h = 30$). (b) Cumani's method ($\sigma = 1.5$, $T = 15$). (c) Ruzon *et al.*'s method ($R = 1.5$, $low = 0.1$, $high = 0.3$).

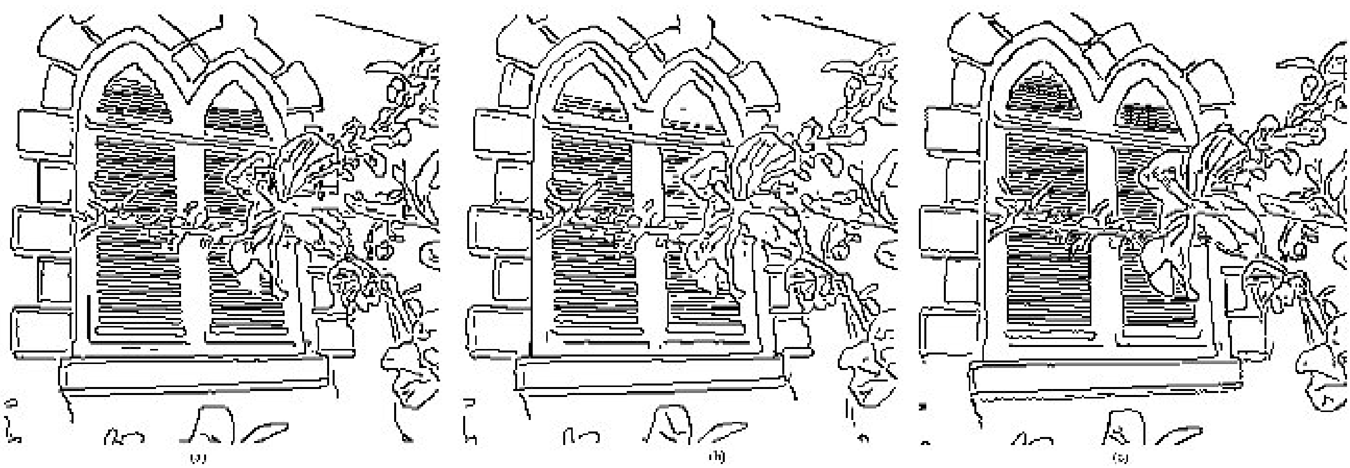


Fig. 7. Results on window image. (a) Proposed method ($h = 1.25$, $T_l = 5$, $T_h = 30$). (b) Cumani's method ($\sigma = 1.5$, $T = 15$). (c) Ruzon *et al.*'s method ($R = 1.5$, $low = 0.1$, $high = 0.3$).

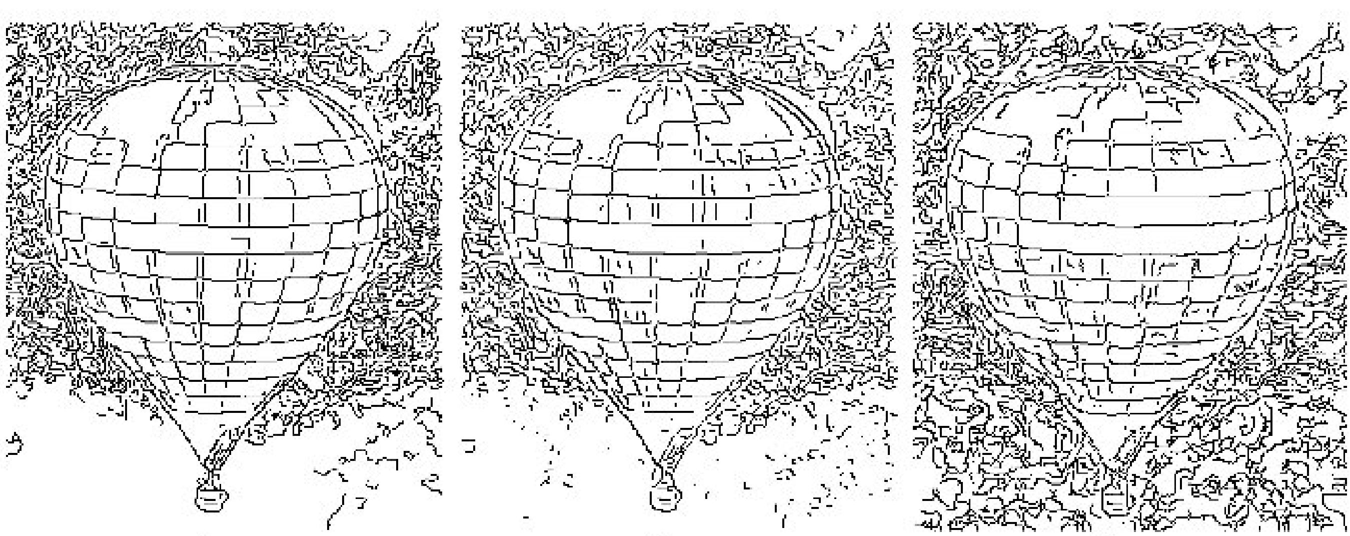


Fig. 8. Results on balloon image. (a) Proposed method ($h = 1.25$, $T_l = 5$, $T_h = 30$). (b) Cumani's method ($\sigma = 1.5$, $T = 15$). (c) Ruzon *et al.*'s method ($R = 1.5$, $low = 0.1$, $high = 0.30$).

and the tenth and eleventh pixels. The proposed method has found the edges at these two locations [Fig. 9(a)]. Results on the Lena, window, and balloon images using the proposed method are shown in Figs. 6(a), 7(a), and 8(a), respectively.

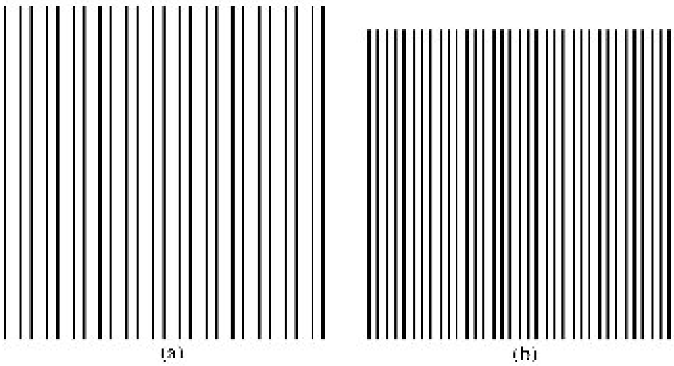


Fig. 9. Results on vertical bars image. (a) Proposed method ($h = 1.25$, $T_l = 5$, and $T_h = 30$). (b) Ruzon *et al.*'s method ($R = 1.5, 0 < low < high$, $0 < high < 0.46$).

C. Analysis of Parameters for Ruzon et al.'s Method

Ruzon *et al.*'s method takes stiffness of gaussian R, and two threshold values *low* and *high* as input parameters. For judging the performance of the algorithm, several edge maps are generated by varying R between 0.8 to 3 with an increment of 0.1, *low* between 0.0 to 0.60 with an increment of 0.01 and *high* between 0.1 to 0.60 with an increment of 0.1 subject to the condition that $high > low$. Results on the circles image over a wide range of parameter values are found to be appropriate; thus, no figure is included here. When the vertical bars image [Fig. 2(a)] is considered, one extra edge is detected [Fig. 9(a)] between the fifth and the tenth pixels in reference to Fig. 2(b) for the parameter values $h = 1.5$, $0 \leq low < high$, and $0 \leq high < 0.46$. Ideally, there should not be any edge between these two pixels because the transition of intensity between these two pixels is very smooth, which can be seen from Fig. 2(b). The correct edge map is obtained with $high = 0.46$ or above with $h = 1.5$ and $0 \leq low \leq high$. However, results on balloon and window images with the same parameter values $h = 1.5$, $low = 0.1$, and $high = 0.46$ are found to be unsatisfactory, since many prominent edges are missing (Figs. 10 and 11). It is also found that, when $high > 0.46$, some more edges are missing in window and balloon images. The results have not been shown here due to lake of space. It is apparent from these observations that no fixed set of parameter values exists for Ruzon *et al.*'s method that provide acceptable results in all cases.

Similar to the proposed method, a fixed set of parameter values, $R = 1.5$, $low = 0.1$, and $high = 0.3$, is obtained using visual evaluation of edge maps. Although this may lead to a slight reduction in the quality of results, the tedious task of parameter tuning is avoided here.

D. Analysis of Parameters for Cumani's Method

Cumani's method takes stiffness of gaussian σ and a threshold value T as input parameters. For this method, the edge maps with $0.8 \leq \sigma \leq 3$ with an increment of 0.1 and $0 \leq T \leq 50$ with an increment of 1 are observed to select the edge maps. Results on the artificial images over a wide range of parameter values using Cumani's method are found to be appropriate. Thus, no edge map using this method on artificial images is included here. However, results on many real life images by Cumani's method are either noisy or missing important edges. This can be seen from the results on Lena image [Fig. 6(b)]. There are many spurious edges present and at the same time many edges are disconnected. In particular, the upper boundary of the hat is disconnected. To get these edges connected, T has to be decreased. With the decrease in the value of T, more spurious edges will be introduced. When the threshold value is increased, many important edges would be lost. These results are not shown here due to lake of space. Similar phenomenon is found with the window image [Fig. 7(b)] and balloon image [Fig. 8(b)].

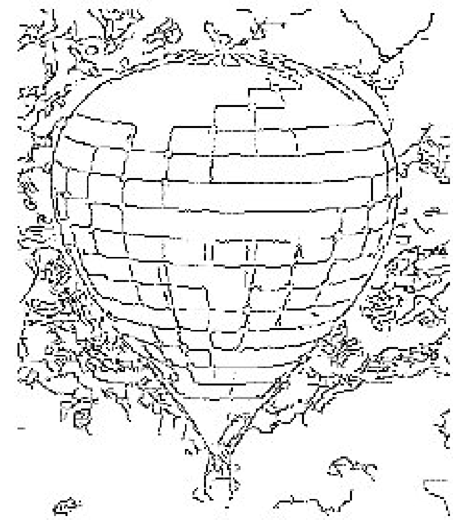


Fig. 10. Result using Ruzon *et al.*'s method on balloon image shown in Fig. 4(c) ($R = 1.5$, $low = 0.1$, $high = 0.46$).

Fig. 11. Result using Ruzon *et al.*'s method on window image shown in Fig. 4(b) ($R = 1.5$, $low = 0.1$, and $high = 0.46$).

IV. Conclusion, Discussion, and Future Works

The proposed method, along with the other two methods, have been compared on several images. It is found that the proposed method consistently produces acceptable results for all the images. It is difficult to get a single fixed set of parameter values which would give a visibly pleasing edge maps containing most of the prominent edges in the case of Ruzon *et al.* and Cumani's methods.

In the proposed method, the two fixed threshold values $T_l = 5$ and $T_h = 30$ have been used for detecting edges on more than 200 natural and artificial images. It is evident from the obtained results that the algorithm is producing results containing most of the important edges for all the images with these two threshold values. An intuitive reason for producing acceptable results is that it increases the edge response of all the detected edge pixels but not necessarily uniformly. This can be observed from two artificial images shown in Fig. 1 and from their edge profiles shown in Fig. 5.

In terms of computational complexity the proposed method is slower than Cumani's method but much faster than Ruzon *et al.*'s method.

The main advantage of the proposed method is that the parameters do not need fine tuning for getting acceptable results for an image. Thus, it may be handy for any computer vision task where extraction of edge maps is required for a large set of images. In the proposed method, basically, a linear model with fixed effects is assumed. The performance of the edge detector may possibly be better if a generalized method is assumed considering the correlations between channels, though the statistical analysis may be complicated. A comprehensive evaluation, like that of Heath *et al.* [31], is needed for color edge detectors.

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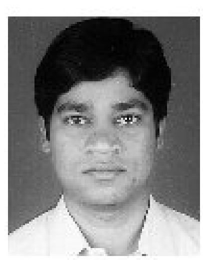

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