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A MULTI-SCALE MORPHOLOGIC EDGE DETECTOR

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Abstract—In this paper we present a morphologic edge detection methods using multi-scale approach for detecting edges of various fineness under noisy condition. It is shown that the proposed edge detector has the desirable properties that a good edge detector should have. Comparative study reveals its superiority over other morphologic edge detectors. © 1998 Pattern Recognition Society. Published by Elsevier Science Ltd. All rights reserved

Mathematical Morphology Multi-scale Edge Detection Morphologic Edge Detector
Nonmaxima suppression Performance evaluation

1. INTRODUCTION

Changes or discontinuities in image feature, such as intensity, are called edges. Edges in an image are formed due to variations of some of the physical properties, like surface illumination and shadows, geometry (orientation and depth) and reflectance of objects in the scene. Hence, one can say that edge points represent some features of a scene. The process of extraction of these feature points is called edge detection. More formally edge detection is a process which transforms a gray-level image to an edge image. In an edge image each pixel value indicates either the presence or absence of an edge. Edge detection is a fundamental step in computer vision.

One conventional approach to edge detection is based on use of spatial operators. The spatial intensity changes present in the image is enhanced by first-order differential operators[1–3] or by Laplacian operator.[4, 5] A threshold is then applied to get edge points at which intensity changes are significantly large. Some other edge detectors try to fit a function to the image intensity surface,[6–9] and then estimate edge point locations from the best fitting surface. These operators are computationally expensive than differential operators. The performance of all the above operators degrades with noise. To overcome this problem posed by noise, recently two new edge detectors were proposed.[10, 11] Canny[11] has shown that his method is better than that of Marr and Hildreth's[10] if both positional accuracy and amplitude sensitivity of the edge detector are considered. However, performance of most of the edge detectors improve if we adopt multi-scale approach whose information at various scales are integrated.

A new approach to image analysis was proposed using the theory of mathematical morphology.[12, 13] This approach is based on set-theoretic concepts of shape. In morphology objects present in an image are treated as sets. As the identification of objects and object features directly depend on their shape, mathematical morphology is becoming an obvious approach for various machine vision recognition processes. Several machine vision hardware manufacturers have started including morphological processors. These machines include Golay logic processor,[14] Leitz Texture Analysis System TAS,[15] the CLIP processor arrays,[16] and the Delft Image Processor DIP.[17] Initially, morphology dealt with binary image only, and basic operations were dilation and erosion, also known as Minkowski addition and subtraction.[18] Natural extension of morphologic transformations from binary image processing to gray-scale processing using max and min operations is done by Sternberg[19] and Haralick *et al.*[20]

Morphologic techniques are being used in various fields of Image processing. Peleg and Rosenfield[21] use it to generalize medial axis transform, Peleg *et al.*[22] use it to measure changes in texture properties as a function of resolution, Werman and Peleg[23] use it for feature extraction, and Favre *et al.*[24] use it for the detection of platelet thrombosis in cross sections of blood vessels. Lee *et al.*[25] have used gray scale morphology for edge detection. In this paper we present a morphologic edge detection methods using multi-scale approach for detecting edges of various fineness under noisy condition. The paper is

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organized as follows. Section 2 presents definitions of morphologic operations that are used to describe the algorithms. Existing morphologic edge detectors and their properties are discussed in Section 3. Multi-scale morphologic edge detector, proposed by us, and its performance is presented in Section 4. Experimental results obtained by applying the edge detectors on a real image with and without noise are presented in Section 6, and the results are evaluated qualitatively for comparison purpose.

2. DEFINITIONS

The morphologic operations work with *two* images: The original data to be processed and a structuring element. Each structuring element has a shape which can be thought of as a parameter to the operation. Most fundamental morphological operations are morphological *dilation* and morphological *erosion*. Based on these, two compound operations named as *opening* and *closing* are defined. We first give definitions of binary morphologic operations and then that related to gray-scale morphology. In the present work the objects and operations we deal with are in the two-dimensional discrete domain only.

Considering the case of binary image, let A be the set of points representing the binary one pixels of the original binary image and B be the set of points representing binary one pixels of structuring element.

Definition. Dilation of a binary image A by binary structuring element B, denoted by $A \oplus B$, is defined as

$$A \oplus B = \{b + a \mid \text{for some } b \in B \text{ and } a \in A\}.$$

Definition. Erosion of a binary image A by binary structuring element B, denoted $A \ominus B$, is defined as

$$A \ominus B = \{p \mid b + p \in A \text{ for every } b \in B\}.$$

Definition. Opening of a binary image A by a binary structuring element B, denoted by $A \circ B$, is defined as

$$A \circ B = (A \ominus B) \oplus B.$$

Definition. Closing of an image A by a structuring element B, denoted by $A \bullet B$, is defined as

$$A \bullet B = (A \oplus B) \ominus B.$$

The term *scale* stands for the largest size of a shape template that can fit inside an image region or object.[26] Suppose B is a compact connected subset. If we say that the base structuring element B has size one then the finite set

$$nB = \underbrace{B \oplus B \oplus \cdots \oplus B}_{n-1 \text{ times}}, \quad n > 0 \qquad (1)$$

defines a pattern of size n. By convention, $nB = \{(0, 0)\}$ if $n = 0$. Hence, for $n = 0, 1, 2, \ldots$ we have a family of shape templates parametrized by the *discrete size parameter n*.

A gray-scale image with a gray-level function $f(r, c)$ can be thought of a set of points $p = (r, c, f(r, c))$ in the Euclidian three-dimensional space. So gray-scale morphologic operations may be regarded as three-dimensional binary morphology. Hence, in gray-scale morphology, both the domain of the function $\{(r, c)\}$ and its value $f(r, c)$ are changed.

Definition. The *dilation* of a gray-scale image $f(r, c)$ by a gray-scale structuring element $b(r, c)$ is denoted by $(f \oplus b)(r, c)$ and is defined as

$$(f \oplus b)(r, c) = \max_{(i,j)}(f(r - i, c - j) + b(i, j)).$$

The domain of $f \oplus b$ is the dilation of the domain of f by the domain of b.

Definition. The *erosion* of gray-scale image $f(r, c)$ by a gray-scale structuring element $b(r, c)$ is denoted by $(f \ominus b)(r, c)$ and is defined as

$$(f \ominus b)(r, c) = \min_{(i,j)}(f(r + i, c + j) - b(i, j)).$$

The domain of $f \ominus b$ is the erosion of the domain of f by the domain of b.

Definition. The *opening* of a gray-scale image $f(r, c)$ by a gray-scale structuring element $b(r, c)$ is denoted by $(f \circ b)(r, c)$ and is defined as

$$(f \circ b)(r, c) = (f \ominus b)(r, c) \oplus b(r, c)$$

Definition. The *closing* of a gray-scale image $f(r, c)$ by a gray-scale structuring element $b(r, c)$ is denoted by $(f \bullet b)(r, c)$ and is defined as

$$(f \bullet b)(r, c) = (f \oplus b)(r, c) \ominus b(r, c).$$

3. MORPHOLOGIC EDGE DETECTION

A simple method of performing gray-scale edge detection in morphology is to take the difference between an image and its erosion/dilation image by a structuring element. This may be preceded by preprocessing or followed by postprocessing or both. The difference image is an image of edge strength. Most popularly used structuring element for edge detection is rod shaped with flat top. To define the gray-scale rod structuring element having flat top and rod-shaped domain, let (0, 0) denote center of local neighborhood and a point by (r, c) at an offset of r along row direction and c along column direction. Then the domain of rod structuring element, say, of radius 1 (using *city-block distance*) is denoted by D_{rod1} and is defined as

$$D_{rod1} = \{(0, -1), (0, 1), (0, 0), (-1, 0), (1, 0)\}$$

and its value is a mapping $b: D_{rod1} \rightarrow \{0, \ldots, 255\}$. Since rod is flat on top the gray scale value of $b(r, c) = 0, \ \forall (r, c) \in D_{rod1}$. This is represented diagramatically as

$$\begin{array}{ccc} & 0 & \\ 0 & * & 0 \\ & 0 & \end{array}$$

D_{rod1} = Domain of rod structuring element of radius one.
"*" indicates the origin. Hence, D_{rod1} is nothing but the 4-neighbour of the origin including it. Let us denote it also by N_4. Similarly, 8-neighbour of the origin including it is denoted by N_8.

The edge strength image due to *dilation residue edge detector* is given by

$$\begin{aligned} G_d(r, c) &= (f \oplus b)(r, c) - f(r, c) \\ &= \max_{(i, j4) \in D_{\text{rod}1}} (f(r-i, c-j)) - f(r, c) \qquad (2) \\ &= \max_{(i, j) \in N_{4(r,c)}} (f(i, j) - f(r, c)) \end{aligned}$$

The edge strength image due to *erosion residue edge detector* is given by

$$\begin{aligned} G_e(r, c) &= f(r, c) - (f \ominus b)(r, c) \\ &= f(r, c) - \min_{(i, j) \in D_{\text{rod}1}} (f(r-i, c-j)) \qquad (3) \\ &= \max_{(i, j) \in N_{4(r,c)}} (f(r, c) - f(i, j)) \end{aligned}$$

Both dilation residue edge detector and erosion residue edge detector are noise sensitive. Moreover these are biased in the sense that the former gives the edge strength to that side of an edge which has low value while the latter gives to the high value side. A position unbiased operator can be obtained by the combination of the operators $G_d(r, c)$ and $G_e(r, c)$. Three such combinations are defined using pixelwise minimum, maximum and sum. They are denoted by $G_{\min}(r, c)$, $G_{\max}(r, c)$ and $G_{\text{sum}}(r, c)$, respectively, and are defined as

$$G_{\min}(r, c) = \min\{G_d(r, c), G_e(r, c)\}, \qquad (4)$$

$$G_{\max}(r, c) = \max\{G_d(r, c), g_e(r, c)\}, \qquad (5)$$

$$G_{\text{sum}}(r, c) = G_d(r, c) + G_e(r, c). \qquad (6)$$

$G_{\max}$ and G_{sum} are still sensitive to noise. $G_{\max}$ is same as the 4-neighbour compass gradient in max sense.[27] G_{sum} results in thick edges and strength of detected edge is less than actual edge strength. $G_{\min}(r, c)$ is less sensitive to noise but cannot detect ideal step edges.

Lee *et al.*[25] suggested the following improved edge detectors which are less sensitive to noise but yet can detect ideal step edge. Before describing these operators we need to define the structuring elements. Consider four structuring elements which have flat top and have domains denoted by D_1, D_2, D_3, D_4 and D and are defined as

$$\begin{aligned} D_1 &= \{(-1, 0), (0, 0), (0, 1)\}. \\ D_2 &= \{(0, -1), (0, 0), (1, 0)\}. \\ D_3 &= \{(-1, 0), (0, 0), (0, -1)\}. \qquad (7) \\ D_4 &= \{(0, 1), (0, 0), (1, 0)\}. \\ D &= \{(-1, -1), (-1, 1), (0, 0), (1, -1), (1, 1)\}. \end{aligned}$$

Diagramatically,

$$\underset{D_1}{\begin{array}{cc} & 0 \\ 0 & * \end{array}} \quad \underset{D_2}{\begin{array}{cc} * & 0 \\ 0 & \end{array}} \quad \underset{D_3}{\begin{array}{cc} 0 & * \\ & 0 \end{array}} \quad \underset{D_4}{\begin{array}{cc} 0 & \\ * & 0 \end{array}}$$

and

$$\underset{D}{\begin{array}{ccc} 0 & & 0 \\ & * & \\ 0 & & 0 \end{array}}$$

Hence, $D_1 \cup D_2 \cup D_3 \cup D_4 = N_4$ and $D = N_8/N_4 \cup (0, 0)$, where the binary operator "/" represents set subtraction such that $A/B = \{x \mid x \in A \text{ and } x \notin B\}$.

Suppose dilation and erosion of $f(r, c)$ by the flat top structuring element whose domain is a is denoted

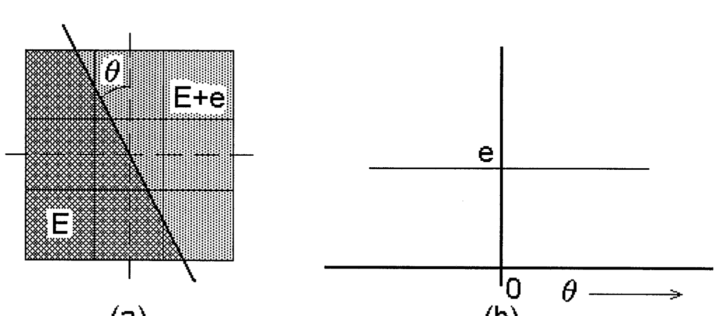


Fig. 1. Illustrates edge orientation response of multi-scale morphologic edge detector: (a) model of step edge with inclination θ about vertical axis; (b) edge strength (e) versus orientation plot.

by $dilation_a(r, c)$ and $erosion_a(r, c)$, respectively. Then the *improved dilation residue operator* is defined as

$$G'_d(r, c) = \min\{dilation_{D_{rod1}}(r, c) - f(r, c), dilation_D(r, c) - f(r, c), G''_d(r, c)\}, \quad (8)$$

where $G''_d(r, c)$ is defined as

$$G'''_d(r, c) = \max\{|dilation_{D_1}(r, c) - dilation_{D_2}(r, c)|, |dilation_{D_3}(r, c) - dilation_{D_4}(r, c)|\}$$

and the *improved erosion residue operator* is defined as

$$G'_e(r, c) = \min\{f(r, c) - erosion_{D_{rod1}}(r, c), f(r, c) - erosion_D(r, c), G''_e(r, c)\}, \quad (9)$$

where $G''_e(r, c)$ is defined by

$$G''_e(r, c) = \max\{|erosion_{D_1}(r, c) - erosion_{D_2}(r, c)|, |erosion_{D_3}(r, c) - erosion_{D_4}(r, c)|\}.$$

These improved operators are biased for ideal step edges and a natural resolution is to consider their sum. This leads to a new edge detector G'_{sum} defined as

$$G'_{sum}(r, c) = G'_d(r, c) + G'_e(r, c) \quad (10)$$

The shortcoming of this is that its capability to reduce effects of noise is limited.

Now recall that minimum of dilation residue and erosion residue as given by equation (4) is a good detector of ramp edge and is less sensitive to noise, but it cannot detect step edge. So before applying this operator if we blur the image by, say, simple mean filter our achievement is twofold: Effect of noise is further reduced and step edges are converted to ramp edges which can now be detected by the said operator. The resultant operator is what we call *blur-minimum edge detector*.[25]

Even though Blur-minimum operator is less sensitive to noise, the edge strength assigned to the edge pixel is less than edge contrast. This is due to the blurring of input image which diffuses the edge peaks over the blur neighborhood area. Hence, weak edge points may be undetected. Secondly, the thickness of the edge detected by blur-minimum operator increases as the slope of ramp edge decreases. This decreases the ability of the blur-minimum operator to localize edges correctly. To overcome these problems, Song and Neuvo[28] have proposed a new edge detector, named as *alternating sequential filter* (ASF) *edge detector*. This is basically an erosion residue edge detector using a rod structuring element preceded by noise suppression. Here noise is suppressed by alternating application of opening and closing morphological filters. So is the name of the edge detector.

4. MULTI-SCALE MORPHOLOGIC EDGE DETECTOR

The goal of edge detection is to detect and localize edge points even under noisy condition. Not all edges

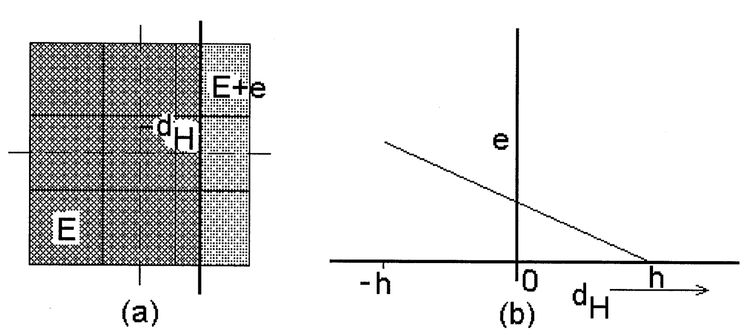


Fig. 2. Illustrates edge displacement response of multi-scale morphologic edge detector for vertical edge: (a) model of step edge with horizontal displacement d_H from vertical axis; (b) edge strength (e) versus horizontal displacement plot.

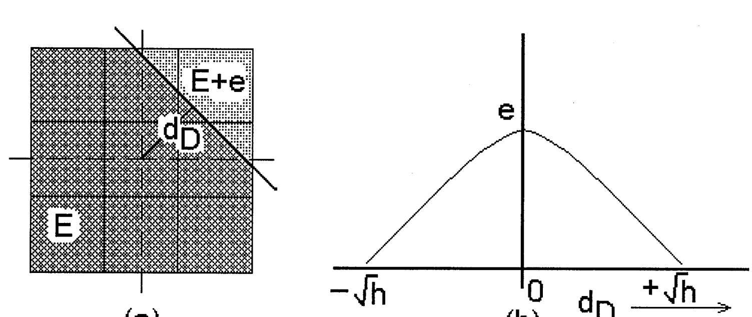


Fig. 3. Illustrates edge displacement response of multi-scale morphologic edge detector for diagonal edge: (a) model of step edge with diagonal displacement d_D from the centre; (b) edge strength (e) versus diagonal displacement plot.

with various fineness regarding spectral contrast and spatial geometry can be detected by a single operator. In fact, some detail that seem to be freak and noisy in one scale may become relevant in other scale. Hence, edges of different fineness are detected using operator at different scale, and then they are judiciously combined to produce all the edges of interest in an image.

The *multi-scale morphological edge detector* is able to differentiate these fine variations of gray-level surface, and yet can remove noise. As the name implies this is based on multi-scaling approach. Structuring elements of different sizes are used to extract features at different scale. The smaller the size of structuring element, lesser is the noise removing capacity and more the ability to detect fine edges. By using large size structuring element one can remove more noise but at the same time the thickness of edge increases causing smearing of closely spaced edges. Hence, to overcome these problems, one can combine judiciously different edge maps obtained with different size structuring elements. True edge points are extracted from this combined edge map. The following are the different steps involved.

1. Obtain edge strength maps using structuring elemens of different size.
2. Combine edge strength maps/images obtained in Step 1.
3. Extract the edge points lying on the ridge of the edge strength surface using non-maximal suppression technique.

The following paragraphs give a detailed description of each of the three steps of multi-scale morphologic edge detection method.

Step 1: *Obtain edge maps.* Consider four flat top structuring elements whose domains are nD_1, nD_2, nD_3 and nD_4 that are same as D_1, D_2, D_3 and D_4, respectively [defined by equation (7)] but have size n and $nD = nN_8/nN_4\ u(0, 0)$. Similarly, the domain of a flat top rod structuring element of radius n, denoted by D_{rodn}, is defined as $D_{rodn} = nD_{rod1}$. Thus, the edge strength map at scale n may be given as

$$G_d^n(r, c) = \min\{dilation_{nD_{rod1}}(r, c) - f(r, c),\ dilation_{nD}(r, c) - f(r, c),\ G_d^{n'}(r, c)\}, \qquad (11)$$

where $G_d^{n'}(r, c)$ is defined as

$$G_d^{n'}(r, c) = \max\{|dilation_{nD_1}(r, c) - dilation_{nD_2}(r, c)|,\ |dilation_{nD_3}(r, c) - dilation_{nD_4}(r, c)|\}.$$

A close examination of equation (11) reveals that this is similar to improved dilation residue operator [as defined in equation (8)] at scale n. So we may also define the edge strength by an operator similar to improved erosion residue operator or by sum of them.

Step 2: *Combining edge strength.* Suppose edge strength at scale n due to an image $f(r, c)$ is denoted by $f'_n(r, c)$. Thus, according to the operator presented in the step 1, $f'_n(r, c) = G_d^n(r, c)$. Now we combine these edge strengths of different scale, most naturally, by simple pixelwise summation, i.e.

$$f'(r, c) = \sum_{n=k}^{l} w_n f'_n(r, c),$$

where $[k, l]$ represents the range of scale that explicit the edges of interest and w_i's are respective weights

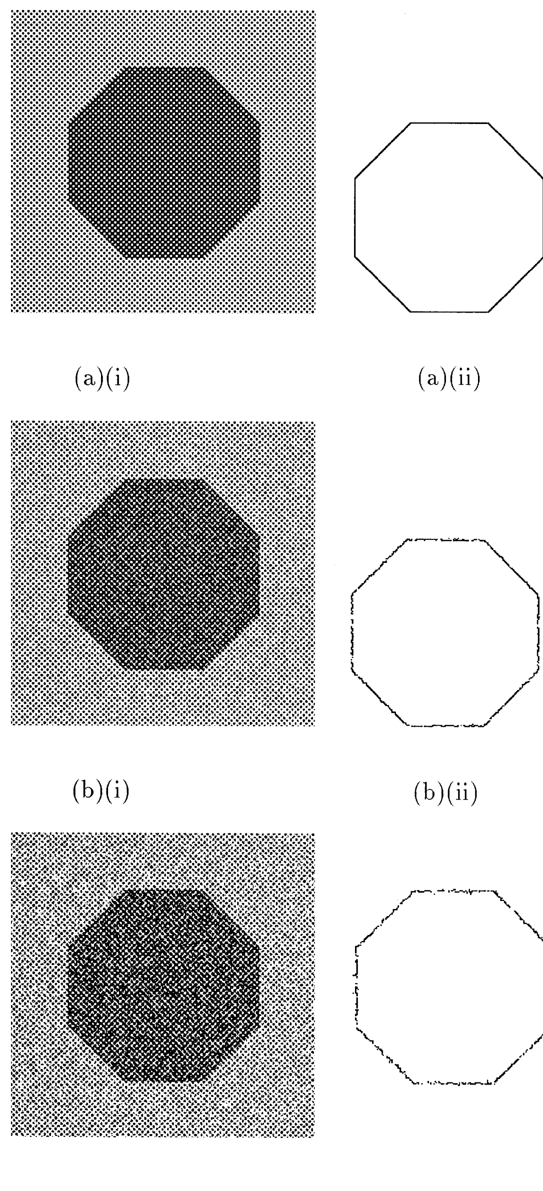


Fig. 4. Illustrates the study of noise sensitivity of the multi-scale morphologic edge detector: (a) original noise-free image of octagon; (b) noisy image of octagon (SNR = 30); and (c) noisy image of octagon (SNR = 10). (i) Gray-scale image, and (ii) edge map due to multi-scale morphologic edge detector.

that are supplied by the user. Note that other kinds of combination are also possible. Secondly, the edge strength map $f'(r, c)$ appears to contain long range of mountains and true edge lies along its ridge.

Step 3: *Non-maximal suppression.* As stated earlier true edge corresponds to the ridges of hilly terrain of the result of step 2. Therefore, to get the edge points and subsequently the edges we employ non-maxima suppression technique. The method is as follows. Let $a_1, \ldots, a_8$ be the values of pixels in the 3×3 neighbourhood of a pixel 'a', i.e.

$$\begin{matrix} a_1 & a_2 & a_3 \\ a_4 & a & a_5 \\ a_6 & a_7 & a_8 \end{matrix}$$

The pixel point "a" is said to be on the local ridge if any one of the following four conditions is true.

1. $a_1 + a_4 + a_6 < a_2 + a + a_7 > a_3 + a_5 + a_8$ (corresponding to vertical ridge).
2. $a_1 + a_2 + a_3 < a_4 + a + a_5 > a_6 + a_7 + a_8$ (corresponding to horizontal ridge).
3. $a_1 + a_2 + a_4 < a_3 + a + a_6 > a_5 + a_7 + a_8$ (corresponding to 45° ridge).
4. $a_2 + a_3 + a_5 < a_1 + a + a_8 > a_4 + a_6 + a_7$ (corresponding to 135° ridge).

If "a" is not a ridge point then it is replaced with the $\min\{a, a_1, \ldots, a_8\}$. To emphasize ridge points one may employ gray-scale thinning method too.[29]

5. EDGE DETECTOR PERFORMANCE

For evaluating performance of edge detector we need to distinguish variation in its response due to variation in orientation and location of edge; edge type, such as step or ramp or other; and its noise sensitivity.

5.1. *Edge orientation response*

Conventional operators, like Prewitt and Sobel operators, are directional sensitive. For example, Prewitt operator[2] is better for vertical edges, while Sobel operator[3] is for diagonal one. Because of rotational

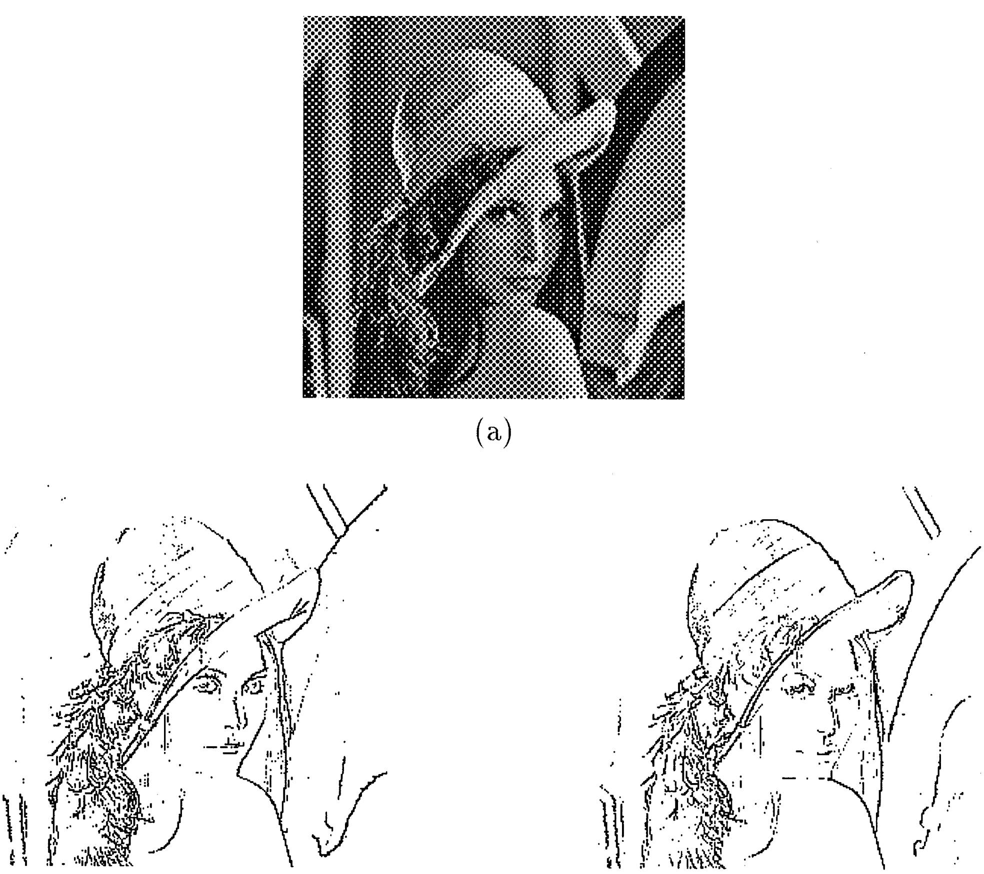


Fig. 5. Illustrates the study of performance of edge detectors on real image: (a) original noise-free image of Lena, edge map due to (b) dilation residue edge detector, (c) erosion residue edge detector, (d) blur-minimum edge detector, (e) ASF edge detector, (f) multi-scale morphologic edge detector, and (g) Canny's edge detector.

Fig. 5. (*Continued.*)

symmetry, the proposed morphological edge detector is not sensitive to edge direction. The curve shown in Fig. 1 illustrates these characteristics.

5.2. Edge position response

An important property of an edge detector is its ability to localize an edge. The proposed morphological edge detector exhibits a desirable sharp monotonic decreasing response as the edge moves away from the centre of the neighbourhood. The edge amplitude response curves for the displacement of the horizontal and the diagonal edges are given in Figs 2 and 3, respectively.

Ramp edges of extended width usually cause difficulties in localizing the edges. But proposed edge detector performs better than other morphological operators due to summation and non-maximal suppression. Combined edge strength image is expected to have a roof edge surface. Hence, non-maximal suppression results in thin edges. Even edges of small contrast can be detected and localized as shown in the experimental results.

5.3. Noise sensitivity

The three types of errors associated with edge detection are missing valid edge points, classification of noise fluctuations as edge points and failure to localize edge points. Pratt[30] has introduced a figure of merit defined as

$$R = \frac{1}{I_m} \sum_{i=1}^{I_a} \frac{1}{1 + wd^2},$$

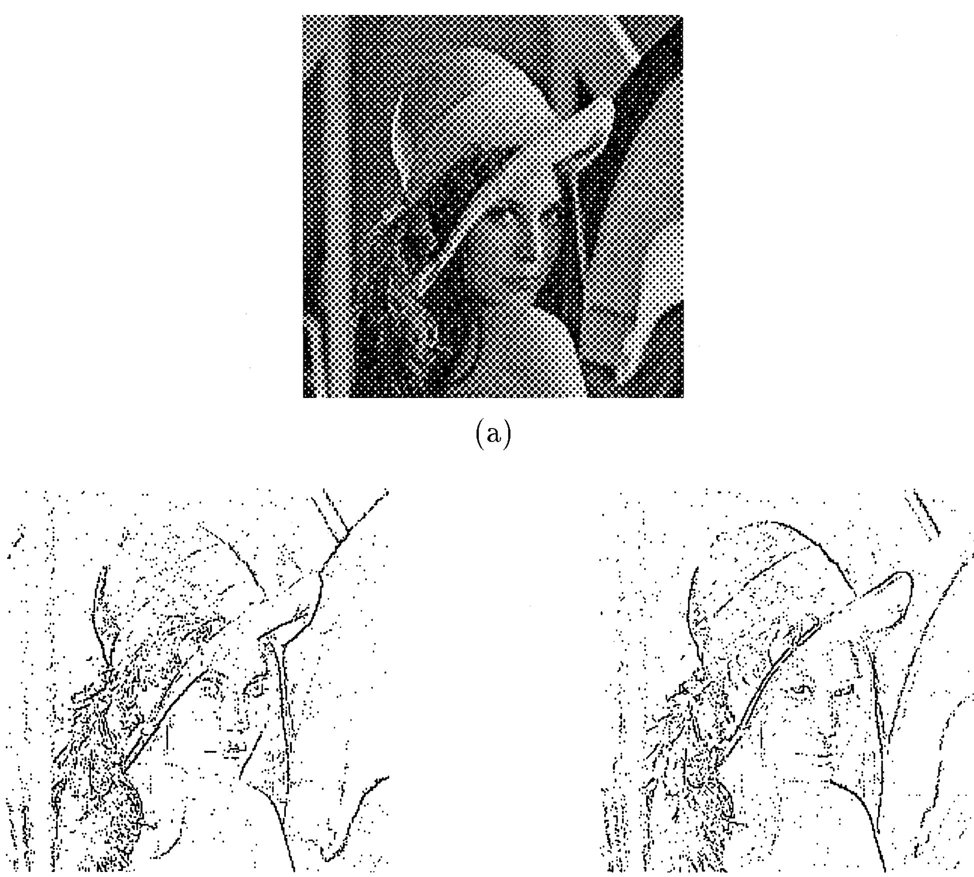
where I_i is the number of ideal edge map points, I_a the number of actual edge map points, $I_m = \max\{I_i, I_a\}$, w the scaling constant, adjusted to penalize edge points that are detected but offset from true position and d the separation distance of an actual edge point along a line normal to a line of ideal edge points.

The proposed edge detector is evaluated by a coincidence comparison of ideal edge map with the actual detected edge map. For studying the noise sensitivity we have considered a 256×256 size image containing an octagon that has edges with four different slopes: 0, 45, 90 and 135°. To this image white Gaussian noise of different standard deviations are added. The images of different signal-to-noise ratio are given in Fig. 4(a)–(c) (i) and corresponding edge maps due to the multi-scale morphologic edge detector are shown in Fig. 4(a)–(c) (ii). Finally, Fig. 4(a) (ii) is used as the ideal edge map, and Fig. 4(b) (ii) and Fig. 4(c) (ii) are used as actual edge map for the performance study. Value of the figure of merit is close to 1 as desired, and decreases with the decrease of signal-to-noise ratio.

6. EXPERIMENTAL RESULTS AND DISCUSSION

To study the performance of proposed multi-scale morphologic edge detector and to compare its performance with that of other morphologic edge detectors as well as Canny's edge detector, we have applied the edge detectors on the well known image of Lena (size 256×256) with and without noise. We have taken $w_n = 1$ for all n. Results are shown in Figs 5 and 6, and are evaluated qualitatively.

It can be observed that the proposed multi-scale morphological edge detector performs better than dilation residue and erosion residue edge detection methods under noisy conditions. The edges obtained by blur-minimum operator are not continuous and some edge points are missing. This is the point where ASF edge detector performs better than blur-minimum operator. This is due to initial morphological filtering (ASF) to remove noise. In fact, morphological opening and closing operations in ASF edge detector selectively remove some of the noisy features without disturbing the others. However, ASF edge detector cannot detect small and quick variations on gray-level surface. Multi-scale edge detector performs better than ASF edge detector for these cases. At the same time it performs better than the improved methods under noise conditions. It is possible to obtain thin edges or object boundaries with multi-scale operator which may not be detected with other morphological methods. This method detects weak edge points lying next to strong edge points without sacrificing the overall quality. Results obtained with Canny's method are comparable. But Canny's method is computationally expensive as it involves Gaussian convolution. Morphological edge detectors involve simple addition/subtraction operations and max/min operations. Finally, though Canny's edge detector perform best in the sense of robustness to noise (because of smoothing by Gaussian function), its result is inferior to morphologic edge detectors in terms of edge localization. Thus, the proposed edge detector is found to perform well considering both the robustness to noise and the edge localization.



(a) (b) (c)

Fig. 6. Illustrates the study of performance of edge detectors on real image: (a) noisy image of Lena (SNR = 30), edge map due to (b) dilation residue edge detector, (c) erosion residue edge detector, (d) blur-minimum edge detector, (e) ASF edge detector, (f) multi-scale morphologic edge detector, and (g) Canny's edge detector.

Fig. 6. (*Continued.*)

7. SUMMARY

Edge detection is an important task in any image analysis system. The response of the conventional edge detectors are largely dependent on the size of spatial filter (area of support) and the threshold(cut off level) used. The choice of those parameters remain heuristic due to the absence of proper image model. This problem is greatly reduced when a multi-scale approach for integrations of edge information, obtained from various size of filters, is used. The present work proposed one such multi-scale edge detector based on the theory of mathematical morphology. It is shown that the proposed detector has better noise immunity and orientational and positional response compared to most of the conventional morphologic edge detectors. This is computationally less expensive than sophisticated edge detectors like Canny etc., with comparable result.

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