Contextual and Non-Contextual Performance Evaluation of Edge Detectors

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Abstract

This paper presents two new evaluation methods on edge detectors. The first is non-contextual and it concerns the evaluation of performance of edge detectors in terms of detection errors. The second method is contextual and it concerns the evaluation of performance of edge detectors used in image compression. In both methods, we studied the influence of the image characteristics and edge detector properties on its performance. Seven detectors have been evaluated and their performance compared.

1 Introduction

Several edge detectors have been proposed, often different by their goals and their mathematical and algorithmic properties [19]. Consequently, a problem encountered by vision systems developers is the selection of an edge detector to be used in the considered application. This selection is primarily based on the definition of the influence of image characteristics and properties of detectors on their performance, which we call the performance evaluation of edge detectors [18]. Consequently, several performance evaluation methods have already been proposed. These methods can be regrouped in three classes. The first regroups subjective methods [11, 6], borrowed from the field of psychology, which use human judgment to evaluate the performance of edge detectors. More precisely, it consists of presenting a series of edge images to several individuals and asking them to give a score according to a given scale [11]. Even if these methods seem easy to put in practice, they have some inconvenience. The number of characteristics a human eye can distinguish is limited. For example, the eye cannot differentiate between two gray levels that are slightly different. Also the judgment depends on the individual's experience, his attachment to the method, and on the image type (e.g., multi-spectral, x-rays). The second class regroups objective methods [1, 8, 9, 13] that uses synthetic images to evaluate the performance of edge detectors by measuring different types of detection errors. This can be completed by experimentation or by using mathematical developments. The third method is hybrid. It combines a subjective method and an objective one [7]. These three evaluation methods can be completed taking the further use of edges into account [17, 15].

This paper presents two new performance evaluation methods on edge detectors: contextual and non-contextual. The non-contextual method concerns the evaluation of the performance of edge detectors in terms of detection errors. The detection errors include classical errors (omission, localization, multiple responses and sensitivity) and two new errors related to false edge suppression and orientation of the edges. The basic idea behind this method consists of running a given detector several times on an image with a known structure by varying the parameters of the detector and the image, and then to measure its performance. The back draw of this approach is that it does not completely characterize the performance of edge detectors, and it seems important to take into account their further use, that is to know if they satisfy the requirements of a particular application. For this reason we proposed a contextual performance evaluation method. This method concerns the evaluation of the performance of edge detectors in the context of image compression. It consists of measuring the performance of an edge detector according to the mean square difference between the reconstructed image from edges and the original one. In both methods, we studied the influence of the image characteristics and the detector properties on the performance of this latter. This paper is divided in six sections. The next describes the non-contextual method of performance evaluation. Section 3 describes the experimental results du to this evaluation method. Sections 4 and 5 are devoted to the contextual performance evaluation method and the experimental results obtained. Lastly, section 6 summarizes the main results.

2 Non-Contextual Performance Evaluation Method

The non-contextual method consists of running several times an edge detector on a image of known structure (e.g., synthetic image) by varying the image characteristics and the detector properties. We then determine the influence of these parameters on the performance of edge detectors. The detector performance is determined by comparing the obtained edges with the ideal edges, which are assumed to be known. For this purpose, a given edge pixel is classified in one of the following four classes: ideal, delocalized, multiple, or false. False edges do not belong to the support region of ideal edges (i.e., pixels in the vicinity of ideal edges). The width of the support region of the edge influences the performance. Figure 1.a presents an example of the ideal edges, identified in black. The pixels identified in gray belong to support region of ideal edges. Among edges detected within the support region, there are ambiguous edges corresponding to the multiple responses. All edges detected within the support region and which are not ambiguous are called unambiguous edges. Among the multiple responses of a detector to an ideal edge, the closest detected edge to ideal edge belongs to the unambiguous edges. The performance of an edge detector are defined by six errors that are the omission, localization, multiples responses, sensitivity, false edge suppression, and edge orientation. False suppression and orientation errors concern only the gradient detectors. A good detector must minimize all theses errors. Definitions of these performance measures are provided as follow:

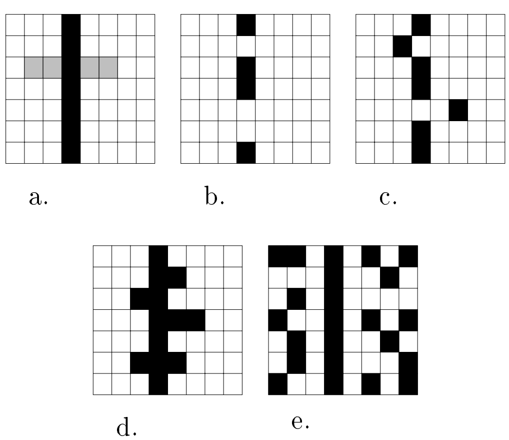
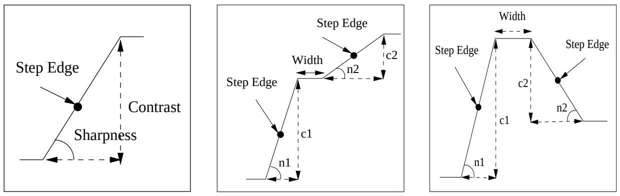


Figure 1: Detection errors. (a) Ideal edges, black pixels are ideal edges and grey pixels belong to the support region of ideal edges. (b) Omission error. (c) Localization error. (d) Multiples responses error. (e) Sensitivity error. False suppression and orientation errors are not easy to represent

- *Omission error.* It occurs when the detector omits to find ideal edge (Figure 1.b). The error is measured by the total number of omitted pixels on the total number of ideal edges.
- *Multiple responses error.* It occurs when multiple edges are detected in the vicinity of ideal edge (Figure 1.d). The error is defined by the total number of ambiguous pixels on the total number of unambiguous edges.
- *Localization error.* It occurs when the location of unambiguous edges is different from the location of ideal edges (Figure 1.c). The error is measured by the total distance between unambiguous edges and ideal edges on the total number of unambiguous edges.
- *Sensitivity error.* This error occurs when the detector localizes edges which do not belong to the support region of ideal edges (Figure 1.e). The error is defined by the total number of false edges on the total number of edges detected.
- *False suppression error.* Usually false edges suppression is done by a thresholding operation. The edges that have a gradient modulus below a given threshold are then suppressed. However, the gradient modulus of an unambiguous edge may be lower than the gradient modulus of a false edge. The false suppression error occurs when there is a suppression of unambiguous edges while false edges persist. Let us consider the distribution of the gradient modulus of false edges and the distribution of the gradient modulus of unambiguous edges, the false suppression error is measured by the overlapping between these distributions.
- *Orientation error.* It occurs when the estimated orientation of the detected edge is not equal to the given orientation. The error is defined by the sum of the absolute value of the difference between the estimated and the given orientations of unambiguous edges on the total number of unambiguous detected edges.

The considered parameters that influence the detector performance concerns the detector properties, the image characteristics, and the performance evaluation method. The parameters of the detector are scale, order of the differentiation operator and filter. The parameters of the image concerns the edges such as type, sharpness, signal-to-noise ratio and subpixel. The edge type we considered are the step, staircase and pulse (Figure 2). Another parameter related to the performance evaluation method, the size of the support region of ideal edges. The parameters that take their values in continuous intervals are sampled. We have considered large intervals for the parameters and a small step for the sampling, i.e, subpixel $\in [0.0, 0.5]$, sharpness $\in [1, 10]$, signal-to-noise ratio $\in [2, 5]$, scale $\in [0.95, 5.0]$, and support region size $\in [3, 11]$. This allows us to have a better idea on the detector performance.



a. b. c.

Figure 2: Profiles of (a) step, (b) staircase and (c) pulse.

Figure 3 presents an example of a synthetic image of 256x256 pixels and 256 gray level used in the evaluation. The image contains five edges where the type of each one are, from left to right, step, ascending staircase, descending staircase, pulse and inverted pulse. The vertical step edge is determined by the following equation:

Figure 3: Synthetic image

$$I(x,y) = \begin{cases} c * (1 - \frac{1}{2} e^{-\mu(x - Loc_{edge})}) & \text{if} \quad x \leq Loc_{edge} \\ \frac{c}{2} * e^{\mu(x - Loc_{edge})} & \text{if} \quad x > Loc_{edge} \end{cases}$$

where c is the contrast, μ the sharpness and Loc_{edge} the location of the edge. This location can be real (subpixel). The staircase and pulse edges are formed by the combination of two steps ; $I(x, y) + aI(x - \Delta, y)$ where $a < 0$ is a pulse and $a > 0$ is a staircase. To this image, we added white noise of a given standard deviation.

The edge detectors used are the gradient of Gaussian (DGG) [2], gradient of Deriche (DGD) [5], gradient of Shen (DGS) [16], Laplacian of Gaussian (DLG) [10], Laplacian of Deriche (DLD), Prewitt (PWT) and Sobel (SBL) [14]. There are several ways to implement the edge detector algorithms. To reduce the effect of the implementation method, all algorithms have been implemented by convolution masks. It is then possible to determine the influences of differentiation operators and filters on the obtained performance measures. For example, the difference in performance of Laplacian of Gaussian and gradient of Gaussian is due to the differentiation operator. Similarly, the difference in the performance of the gradient of Deriche and the gradient of Shen is due to the filter.

It should be recalled that to obtain the performance measures of the edge detectors, we ran them by varying the detection parameters mentioned above. Each error is a function of eight variables: differentiation operator, filter, scale, edge type, sharpness, signal-to-noise ratio, subpixel, size of support region. These functions are discrete and there are no efficient way to analyze them. To carry out the performance analysis, we chose to reduce the number of variables to five (i.e., edge type, filter, scale, differentiation operator, one of the image characteristics) by using a projection operation.

3 Experimental Results

In this section, we present the general observations derived from the results for the non-contextual method. Tables 1 and 2 present experimental results obtained in the case of a step edge. The first number indicates the mean error. In order to make easy the comparison of detectors, we normalized the errors by dividing each one by the highest one. In tables 1 and 2, the normalized errors are within brackets. For example, for DGS the omission error is 0.05, normalized omission error 0.56, false separation error 0.26, and normalized false separation error 0.93. The performance in the case of staircase and pulse are in Tables 3, 4, 5, 6.

False suppression	**Orientation**
DGG 0.18 (0.64)	DGG 31.22 (0.86)
DGD 0.21 (0.75)	DGD 33.42 (0.92)
DGS 0.26 (0.93)	DGS 35.12 (0.97)
PWT 0.27 (0.96)	PWT 35.79 (0.99)
SBL 0.28 (1.00)	SBL 36.13 (1.00)

Table 2: False separation and orientation errors of gradient detectors in the case of step edges. We used the same scale for the all detectors.

False suppression	**Orientation**
DGG 0.16 (0.57)	DGG 24.27 (0.77)
DGD 0.19 (0.68)	DGD 26.85 (0.85)
DGS 0.26 (0.93)	DGS 30.37 (0.96)
PWT 0.27 (0.96)	PWT 31.29 (0.99)
SBL 0.28 (1.00)	SBL 31.60 (1.00)

Table 4: False separation and orientation errors of gradient detectors in the case of staircase. We used the same scale for the all detectors.

By analyzing the obtained results, we conclude that:

- The ranking of detectors is the same in the case of multiple responses, sensitivity, separation and orientation errors. The sensitivity error of all detectors is comparable. The DGG has the lowest errors for multiple responses and sensitivity while

Omission	Localization	Multiple responses	Sensitivity
DLD 0.02 (0.22)	DGS 0.70 (0.87)	DGG 1.21 (0.52)	DGG 0.93 (0.97)
DLG 0.04 (0.44)	DGD 0.73 (0.92)	DGD 1.58 (0.68)	DGD 0.94 (0.98)
DGS 0.05 (0.56)	DGG 0.77 (0.97)	DGS 1.65 (0.71)	DGS 0.94 (0.98)
DGD 0.06 (0.67)	DLG 0.78 (0.99)	DLG 1.75 (0.76)	DLG 0.95 (0.99)
DGG 0.09 (1.00)	DLD 0.79 (1.00)	DLD 2.31 (1.00)	DLD 0.96 (1.00)

Table 1: Mean performance in the case of a step. The scale is between 1.0 and 2.5 for DGG and DLG, and between 0.82 and 1.82 for DGD, DGS et DLD.

Omission	Localization	Multiple responses	Sensitivity
DLD 0.02 (0.18)	DLD 0.25 (0.36)	DGG 0.74 (0.43)	DGG 0.86 (0.96)
DLG 0.06 (0.55)	DLG 0.49 (0.70)	DGD 0.97 (0.57)	DGD 0.88 (0.98)
DGS 0.07 (0.64)	DGS 0.67 (0.96)	DGS 1.08 (0.63)	DGS 0.88 (0.98)
DGD 0.08 (0.73)	DGG 0.69 (0.99)	DLG 1.38 (0.81)	DLG 0.89 (0.99)
DGG 0.11 (1.00)	DGD 0.70 (1.00)	DLD 1.71 (1.00)	DLD 0.90 (1.00)

Table 3: Mean performance in the case of a staircase. The scale is between 1.0 and 2.5 for DGG and DLG, and between 0.82 and 1.82 for DGD, DGS et DLD.

False suppression	Orientation
DGG 0.16 (0.57)	DGG 24.41 (0.77)
DGD 0.20 (0.71)	DGD 27.17 (0.86)
DGS 0.26 (0.93)	DGS 30.43 (0.96)
PWT 0.27 (0.96)	PWT 31.18 (0.97)
SBL 0.28 (1.00)	SBL 31.62 (1.00)

Table 6: False separation and orientation errors of gradient detectors in the case of a pulse. We used the same scale for the all detectors.

the DLD has the highest. At a comparable scale, PWT has the highest error of omission. A detector with low multiple responses and sensitivity errors has a high omission error and vice-versa.

- The performance are influenced by the differentiation operator. Laplacian detectors have lower omission error than their respective gradient detectors. However, these latter have lower multiple responses and sensitivity errors than their respective Laplacian detectors. This explain why the Laplacian detectors are not suitable for noisy and textured images. A Laplacian detector is more suitable for the localization of staircase and pulse edges. However, a gradient detector is more suitable to the localization of step edges.

- The performance are influenced by a filter. In the case of Gauss, Deriche, and Shen detectors, the filter that has lower separation and orientation errors has a higher omission error and lower multiple responses and sensitivity errors. The filter of Shen has the lowest omission error for all the edges. It is followed by the filters of Deriche and Gauss. The ranking is inverted for multiple responses and sensitivity errors. For the localization error, the ranking varies according to the scale and the types of edges. For a step edge, the ranking is DGS, DGD and DGG. For a staircase, the ranking is DGS, DGG and DGD, but we noticed that the difference between the DGG and DGD is small.

- The performance measures of detectors have also been compared by computing the correlation between them. All the results presented previously have been confirmed.

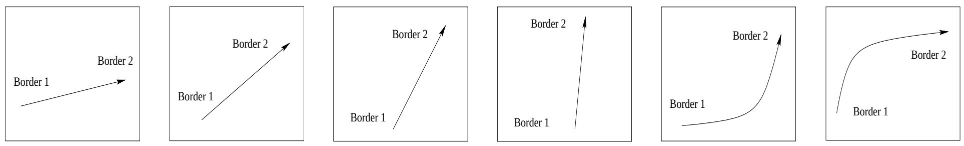
We will now deal with the influence of the considered parameters on the performance of a detector. As we mentioned before, the quantity of data generated by the non-contextual method is overwhelming (see [12]). In order to analyze the variations of performance, we proposed to define a "language" to describe the behavior of the detectors. Figure 4 defines the increasing curves (see [12] for the decreasing curves). Figures 4.a to 4.d present curves that increase linearly. Figure 4.e presents a curve that increases exponentially and figure 4.f presents a curve that increases logarithmically. The borders 1 and 2 are the interval of variation of the error.

To complete our "language", we needed to add three curves. The first represents quasi-linear measures (Figure 5.a). The second characteristic represents oscillating measures (Figure 5.b). Finally, it is possible that the measures oscillate between the two borders, that is they are not increasing nor decreasing (Figure 5.c).

Figure 6 presents an example of the performance of detectors as function of the signal-to-noise ratio in the case of a step. The observations below concerns all the type of edges, since the variation of the performance

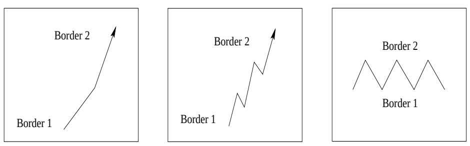
Omission	Localization	Multiple responses	Sensitivity
DLD 0.02 (0.18)	DLD 0.28 (0.41)	DGG 0.74 (0.47)	DGG 0.86 (0.95)
DLG 0.03 (0.27)	DLG 0.50 (0.72)	DGD 0.98 (0.62)	DGD 0.88 (0.97)
DGS 0.07 (0.64)	DGS 0.67 (0.97)	DGS 1.08 (0.68)	DGS 0.88 (0.97)
DGD 0.08 (0.73)	DGG 0.68 (0.99)	DLG 1.17 (0.74)	DLG 0.89 (0.98)
DGG 0.11 (1.00)	DGD 0.69 (1.00)	DLD 1.59 (1.00)	DLD 0.91 (1.00)

Table 5: Mean performance in the case of a pulse. The scale is between 1.0 and 2.5 for DGG and DLG, and between 0.82 and 1.82 for DGD, DGS et DLD.



a. b. c. d. e. f.

Figure 4: Increasing curves: (a), (b), (c) and (d) are linear, (e) is exponential and (f) is logarithm.



a. b. c.

Figure 5: Others curves.

measures as a function of the image characteristics is the same for the step, stair and pulse edges.

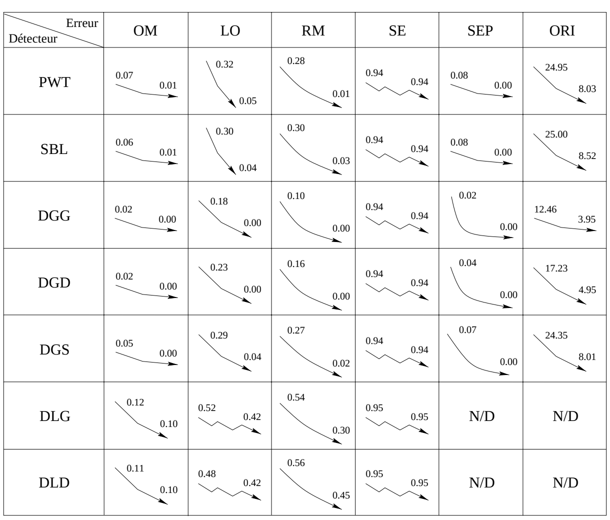


Figure 6: Performance of detectors as a function of the signal-to-noise ratio in the case of a step. Results obtained are rounded to two decimals; this explains why some borders are equal (e.g., column SE).

- When the subpixel increases, the omission error oscillates for gradient detectors and it increases linearly with oscillations for Laplacian detectors. The localization error increases linearly with oscillations for all detectors. The multiple responses error oscillates for gradient detectors and it decreases linearly for Laplacian detectors. The sensitivity error oscillates for all detectors. The separation and orientation errors oscillate for all gradient detectors.
- When the sharpness increases, the omission error decreases exponentially for all detectors. The localization and multiple responses errors decrease exponentially for gradient detectors and they decrease linearly with oscillations for Laplacian detectors. The sensitivity error decreases linearly with oscillations for all detectors. The separation and orientation errors decrease exponentially for all gradient detectors.
- When the signal-to-noise ratio increases, the omission and multiple responses errors decrease quasi-linearly for all detectors. The localization error decreases quasi-linearly for gradient detector and it decreases linearly with oscillations for Laplacian detectors. The sensitivity error decreases linearly with oscillations for all detectors. The separation error decreases almost linearly for PWT and SBL and it decreases exponentially for DGG, DGD and DGS. The orientation error decreases quasi-linearly for all gradient detectors.
- When the size of the support region increases, the omission error decreases exponentially, and the localization error increases logarithmically for all detectors. The multiple responses increase linearly for PWT, SBL, DLG and DLD, and it increases quasi-linearly for DGD and DGS, and it increases exponentially for DGG. The sensitivity error decreases linearly for all detectors. The separation er-

ror increases quasi-linearly for all detectors, except for DGG where it increases exponentially. The orientation error increases logarithmically for all detectors. We conclude that the non-contextual evaluation method is sensitive to the the size of the support region.

- When the scale increases, the omission error increases logarithmically for gradient detectors and it increases linearly for Laplacian detectors. The localization error increases exponentially for gradient detectors and it increases logarithmically for Laplacian detectors. The multiple responses error decrease linearly for gradient detectors and it decreases exponentially for Laplacian detectors. The sensitivity error decreases linearly for all detectors. The separation error decreases linearly with oscillations, and the orientation error increases logarithmically for DGG, DGD and DGS.

4 Contextual Performance Evaluation Method

This method consists of measuring the performance of the detectors in the context of image compression. The idea to compress an image from the coded data of the edge image was proposed by Carlsson [3, 4]. The image coding algorithm is based on the principle that important features like edges should be coded and reproduced as exactly as possible and no spurious features should be introduced in the image reconstruction process. The reconstructed image is smooth and is obtained as the solution to a heat diffusion equation. The back draw is that the decompressed image is degraded because there is a lost of information during the edge detection process. As we will show, the reconstructed image is influenced by the detector used and image characteristics. We are not interested in the image compression process; rather, our primary interest lies on the image reconstructed to characterize the performance of the edge detector used. The performance evaluation method is applied in two steps. The first consists of obtaining edges by performing an edge detection with a given detector. Figure 7 presents eight images used in the evaluation. These images have a size of 256x256 pixels and 256 gray levels. We also considered different types of edges in order to determine the influence of image characteristics on the detector performance (Fig., 7.a, 7.b, and 7.c). The second step consists of reconstructing the original image from the edge image by using the diffusion process.

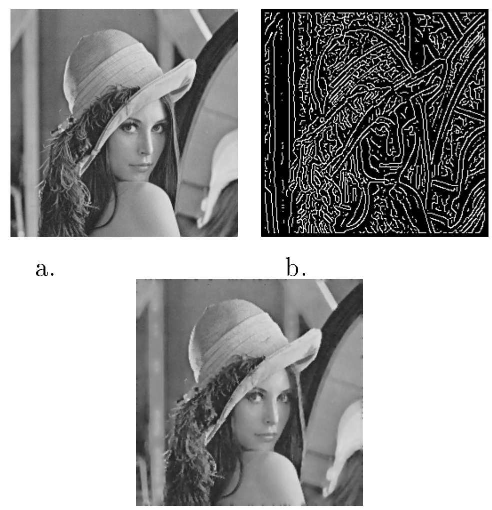
The considered edge detectors are DGG, DGD, DGS, DLG and DLD. The interval used for the scale is between 0.95 and 5.0. The performance of the detector is defined by the mean square difference between the reconstructed image I_{rec} and the original I_{ori}:

$$E_{quadratic} = \frac{\sqrt{\sum_x \sum_y (I_{rec(x,y)} - I_{ori(x,y)})^2}}{n}$$

where n is the image size. When $E_{quadratic}$ equals 0, it means that the reconstructed image is identical to the original one. The greater the value of $E_{quadratic}$, the more degraded the reconstructed image.

5 Experimental Results

This section presents the experimental results for the contextual method. Figure 8 shows an example of a reconstructed image. For each image, figure 9 presents the mean square difference between the reconstructed image and the original one as a function of the scale. We conclude that:



a. b. c.

Figure 8: Image reconstruction: (a) original image, (b) edge image, and (c) reconstructed image.

- The quadratic error depends on the scale. It increases when the scale increases for all detectors. In fact, at high scale there are few detected edges. The diffusion process, which is iterative, has fewer edges to begin with.
- The performance depends on the edge type. In the case of a step edge, the ranking for a small scale $\in [1.0, 1.6]$ is DGG, DGD, DGS, DLG, and DLD (see figure 9.a). The ranking for a greater scale $\in [1.6, 5.0]$ is DGS, DGD, DLD, DGG, DLG. In the case of staircase and pulse, the ranking for a small scale $\in [1.0, 1.6]$ is DGG, DGD, DGS, DLG and DLD (see figures 9.b and 9.c). We noticed that it is similar in ranking with the case of a step edge. The ranking for a greater scale $\in [1.6, 5.0]$ is DGS, DLD, DGD, DLG, DGG. A Laplacian detector has a lower error than its respective gradient one.

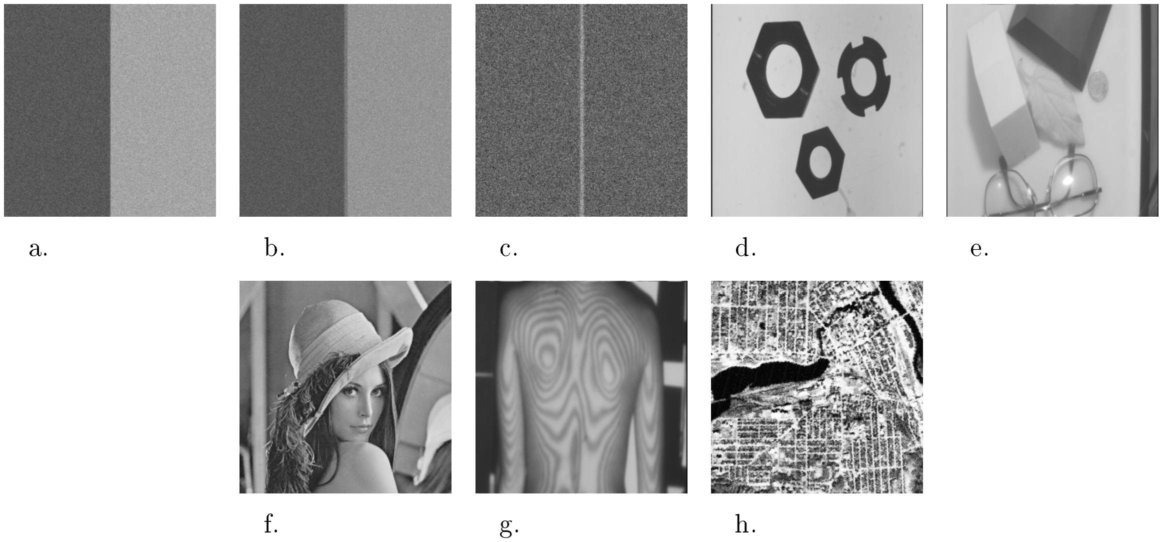


Figure 7: Synthetics images: (a) step, (b) staircase and, (c) pulse. Real images: (d) nuts, (e) glasses, (f) Lena, (g) back, and (h) Sherbrooke.

- For figures 9.d and 9.e, a gradient detector has a lower error than a Laplacian one. For figures 9.f and 9.g, a gradient detector has a lower error than its respective Laplacian one. For figure 9.h, a gradient detector has a lower error than its respective Laplacian one, except for the Gaussian detectors. We conclude that the performance is influenced by the differentiation operator.
- The performance is influenced by a filter. The filter of Shen has the best results. It is followed by the filters of Deriche and Gauss.

6 Conclusion

We presented in this paper two performance evaluation methods to measure the performance of edge detectors. The first one is non-contextual and concerns the evaluation of the performance of edge detectors in terms of detection errors. The main features of this method are:

- The detection errors include classical errors (omission, localization, multiple responses and sensitivity) and two new errors related to the separation and the orientation of the edges.
- The influence of the image characteristics and the properties of detectors on their performance is carried out. The image characterestics are the types of edges, subpixel, sharpness and signal-to-noise ratio. The detector parameters are the scale, order of the differentiation operator and filter. A last parameter, the size of the support region of ideal edges is used to measure the performance of the detectors.

The most of quantitative evaluation methods are non contextual. However, these methods do not completely characterize the performance of an edge detector. It is important to take into account the further use of the detector to know if it satisfies the requirements of a particular application. This is why we proposed a second evaluation method of the performance of edge detectors in the context of image compression. It consists of measuring the performance of an edge detector according to a mean square difference between the reconstructed image and the original one. In both methods we studied the influence of the images characteristics and the detector properties on the performance of this latter. This study help in the selection of an edge detector for the considered application. For example, it is better to use a gradient detector to localize a step and a Laplacian detector to localize a stair or a pulse.

However, several improvements can be done in order to make these performance evaluation methods more complete such as the definition of better synthesis of experimental results and the consideration of other types of edges.

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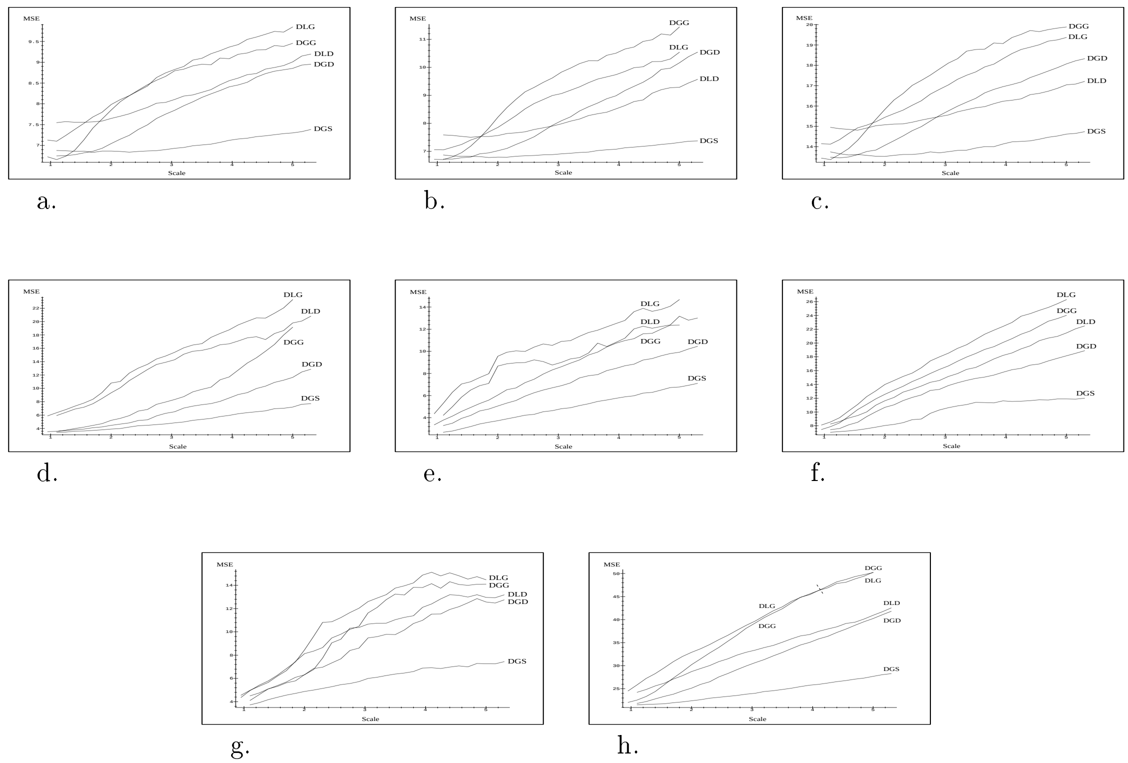

Figure 9: Mean square errors. Synthetic images: (a) step, (b) staircase and (c) pulse. Real images: (d) nuts, (e) glasses, (f) Lena, (g) back, and (h) Sherbrooke.

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