

# An edge contour extraction technique

Ivan Cabezas<sup>1</sup>, Maria Trujillo<sup>1</sup>, and Panos Liatsis<sup>2</sup>

<sup>1</sup> School of Systems and Computer Engineering, Universidad del Valle  
Ciudad Universitaria Melendez, Cali, Colombia

{mcabezas, mtrujillo}@univalle.edu.co

<sup>2</sup> Information and Biomedical Engineering Centre  
School of Engineering and Mathematical Sciences, City University,  
Northampton Square, London, United Kingdom  
p.liatsis@city.ac.uk

**Abstract.** – Gradient operators are used in image processing and computer vision to detect edges and estimate their local orientation. Most operators have to process the entire image. In this paper, an edge contour extraction technique is presented. The proposed technique is based on the gradient magnitude and a quantisation of gradient directions. Its distinctive aspect consists in that the technique does not process the entire image to extract edge contours. It detects an edge region and locates an edge. The pixel coordinates where the edge is located are used as an anchor for tracking an edge contour. Edges in a contour have a common quantised gradient direction. Experimental validation using ground-truth edge images is presented. The proposed technique is compared to the Sobel and the Canny operators. It produces results similar to the Canny edge detector, in terms of true positive rate, false positive rate and false positive edge probability.

**Keywords:** Image processing, computer vision, feature extraction, gradient operators, edge, contour.

## 1 Introduction

An edge can be described as a local luminance change for which a gradient can be measured [9]. An edge detector is an operator that describes a mapping from an input image to a final edge contour representation [1]. An edge contour is a thin feature that satisfies the single-response constraint [1], [2]. Edge detection is an essential low-level task in image processing and computer vision, which is still an area of active research [21]. In fact, edge detection is an ill-posed problem in the sense of Hadamard [10].

If an edge detector does not make any distinction about the feature that produces the luminance change, it can be considered as a non-contextual or general-purpose edge detector [9], [24]. Order-derivative operators consider a local neighbourhood using convolution. The convolution kernel can be expressed by several masks.

Differences between derivatives operators can be explained as differences in the masks employed. Operators such as Canny [1], [2], Prewitt [18], Roberts [19], and Sobel are based on the first-order derivative. A mask can correspond to a certain direction. Different responses to masks can be used to compute the gradient magnitude and the gradient direction. Edge detectors based on the first-order derivative are criticised given the small area they consider and for being sensitive to noise. Operators such as Laplacian, Marr-Hildreth (Zero-Crossing) [14], and ISEF (Shen-Castan) [20] are based on the second-order derivative. These operators use larger masks than the first-order derivative operators. Masks used are rotationally invariant. Rotationally invariant masks allow computing the gradient magnitude only.

There are alternative approaches for edges detection based on statistical concepts such as operators based on Student t-test [7], random field models [12], Bayesian inference [13], non-linear order statistics filters [16], and anisotropic diffusion [15]. Many of them rely on non-trivial statistical concepts that are in contrast to the simple process of convolution, making them difficult to deploy. Moreover, edge operators based on efficiently deployable statistical concepts, such as the rank filtering [17], lack thinning and linking steps.

The Canny operator is probably the most used general-purpose edge detector in vision community. The main contribution by Canny can be summarized as the introduction of optimality criteria in edge detection processes. Although there are alternative definitions of optimality in edge detection processes [4], [20], they can be described as modifications of that proposed in [1], [2]. Furthermore, these definitions of optimality do not cause a decrease in the computational effort required to achieve edge detection. In fact, the Canny operator requires a non-trivial computational effort. A computationally demanding edge detection process could lead an entire system to perform inadequately in specific domains. A balance between low-computational cost and high-quality output is required. An approach to pursue that balance could be by reducing the number of the gradient magnitude and the gradient direction computations to obtain edges.

In contrast to general-purpose edge detectors there are contextual edge detectors [24]. They selectively enhance only the luminance changes that are of interest in the context of a specific task. Operators capable of discerning between edges produced by textured areas and edges produced by objects contours are discussed in [9] and [11]. In fact, a general-purpose edge detector commonly produces meaningless tangled and random edges in a textured area [11]. A solution for avoiding this situation is the use of a high threshold. Nevertheless, this solution misses extended contours of low contrast. A surround suppression method and a post-processing method are added to the Canny operator in [9]. The former method aims to improve detection of contours and the latter method aims to suppress edges in textured areas [8]. An edge point classified as a contour point has both small complexity along its gradient direction and a strong continuity along the tangential direction of its gradient [11].

On the other hand, edge contours have been recently used in approaches for object recognition [3], [6], [21]. Contours are considered robust features due to they are largely invariant to lighting conditions, can efficiently represent image structures and vary smoothly as object pose changes [21].

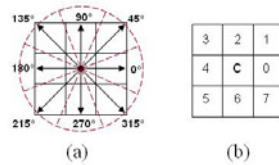
In this paper, an edge contour extraction technique is proposed. Edge contours are extracted based on the gradient magnitude and a quantisation of gradient directions.

Its distinctive aspect consists in that the technique does not process the entire image to extract edge contours. In a first step, it uses a selected set of rows and/or columns to detect an edge region. In a second step, it locates an edge point –which is called edgel. In a third step, the located edgel is used as an anchor to track down an edge contour.

The paper is organized as follows: the proposed technique is introduced in Section 2. Experimental validation is shown in Section 3. Finally, conclusions are presented in Section 4.

## 2 Proposed Technique

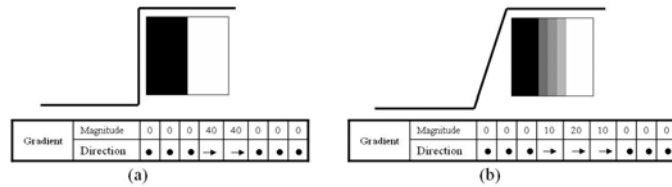
Most edge detection operators are based exclusively on the gradient magnitude [1], [18], [19], [23]. The proposed technique considers gradient magnitude and gradient direction to extract edge contours. It uses the Sobel masks to calculate gradient magnitudes and gradient directions. A quantisation of gradient directions is used to establish common gradient directions, as it is presented in Fig. 1(a). In fact, edgels in an extracted contour have a common quantised gradient direction. An edge contour is codified using a pair of coordinates – of the starting and the ending edgels – and a set of labels for following movements which link them. A movement from an edgel to the next one is represented using the labels shown in Fig. 1(b).



**Fig. 1.** Directional information: (a) quantisation of directions (b) 8-neighbourhood connectivity coding labels.

The technique uses a selected set of rows and/or columns for edge contour extraction process. For a given row or column the technique searches and detects edge regions. An edge region is a set of adjacent points with a gradient magnitude higher than a threshold and a common quantised gradient direction. Edge regions based on gradient magnitudes and gradient directions are illustrated in Fig. 2, using a ramp and a step edge profiles

An edgel is located in an edge region. An edgel is a point with maximum gradient magnitude in the perpendicular direction to its quantised gradient direction. An edge contour is tracked down using the coordinates of the located edgel. The technique splits the edge contour extraction process into three main steps: *edge region detection*, *edgel location* and *edge tracking*.



**Fig. 2.** Relation between image signal, gradient magnitude, and gradient direction in: (a) step edge profile, (b) ramp edge profile.

The technique can be sketched as:

1. Set a gradient magnitude threshold.
2. Choose a set of rows and/or columns.
3. Select a row or a column from the set. If the set is empty stop.
4. Move along the selected row or column for performing *edge region detection*.
5. Perform *edgel location* in a detected edge region.
6. Perform *edge tracking* using the coordinates of the located edgel.
7. If the selected row or column is not entirely processed go back to step 4. Otherwise remove the selected row or column from the set and go to step 3.

*Edge region detection, edgel location and edge tracking* are described as follows.

### 2.1 Edge Region Detection

It calculates gradient magnitude and gradient direction for every point in a given row or column. Edge regions are detected by comparing quantised gradient directions of contiguous points with gradient magnitude higher than the gradient magnitude threshold. Thus, there is a region when at least two contiguous points have the same quantised gradient direction.

### 2.2 Edgel Location

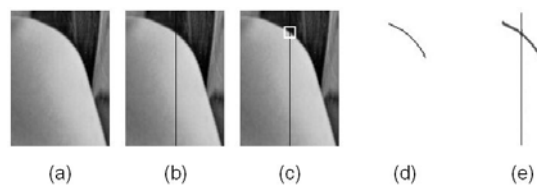
This step aims the fulfilment of the single response constraint. Once, a region is detected, *edgel location* computes and considers gradient magnitudes and quantised gradient directions of neighbouring points in the intersection of the given row or column with the detected region. An edgel is located by performing non-maximal suppression.

### 2.3 Edge Tracking

It uses as input the coordinates and the quantised gradient direction of the located edgel. The continuity of the edge region and the adjacency of located edgels allow tracking edgels and codifying edge contours. Starting from a located edgel, the next edgel is searched in a tangential direction to its quantised gradient direction. Following that direction, adjacent points are considered as candidates for being an

edgel. Among them, the one with maximum gradient magnitude is located. Directions followed in the tracking process among edgels are represented using the labels, in Fig. 1(b). The reported edge contour links edgels with maximum local gradient magnitude and a common quantised gradient direction.

The proposed technique is illustrated using a fragment of the Lenna image, in Fig. 3(a). A selected column is shown in Fig. 3 (b). An edge region is detected and an edgel is located, in Fig 3(c). An edge contour is tracked down using the coordinates of the located edgel, in Fig. 3 (d). The set of points processed during the search can be observed in Fig. 3 (e).



**Fig. 3.** Illustration of the proposed technique: (a) fragment of the Lenna image, (b) selected column, (c) edge region detected and edgel located, (d) edge contour traced, (e) points processed during the search.

### 3 Experimentation

The performance of the proposed technique is evaluated using the ground-truth edge images repository of South Florida University [22], [23], [5]. The quantitative evaluation is based on a confusion matrix, in Fig. 4(a). The confusion matrix calculation is illustrated in Fig. 4(b). Using the Canny optimality criteria, the edge localisation criterion considers a maximum tolerance of one pixel. For a quantitative evaluation, true positive rate (TPR), false positive rate (FPR), and the false positive edgel probability (FPP) are calculated.

#### 3.1 Inter-Technique Evaluation

The proposed technique is compared to the Sobel and the Canny operators. For comparison purposes, the proposed technique processes an entire image. A gradient magnitude threshold equal to 64 is used with the proposed technique and the Sobel operator. Parameters for edge detection using the Canny operator are:  $\sigma$  equals to 1.8, threshold low equals 0.3, and threshold high equals 0.9.

Inter-technique evaluation results using “Egg”, “Briefcase”, and “Stapler” ground-truth edge images are summarised in Table 1.

The Canny operator and the proposed technique produced similar FPP, TPR, and FPR results. On the other hand, the Sobel operator, which does not consider the single response criterion, produced the highest FPP, TPR, and FPR.

The “Egg” original image and its ground-truth edge image, in Fig. 5(a) and Fig. 5(b) respectively, are used for illustrating the performance of the Canny, the Sobel

and the proposed techniques. The edge maps for the “Egg” image generated by the Sobel operator, the Canny operator, and the proposed technique are shown in Fig. 5(c), Fig. 5(d) and Fig. 5(e), respectively.

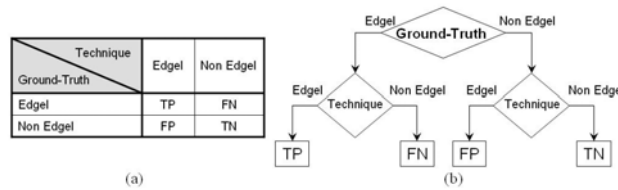


Fig. 4. Evaluation criteria using ground-truth map: (a) confusion matrix, (b) decision tree.

Table 1. Inter-technique evaluation using “Egg”, “Briefcase,” and “Stapler” images

Image	Technique	Extracted Edges	TP	FN	FP	TN	FPP	TPR	FPR
“Egg”	Sobel	15255	7535	298	7720	238463	0.50	0.96	0.031
“Egg”	Canny	6714	6098	1735	616	245567	0.09	0.78	0.002
“Egg”	Proposal	7077	6104	1729	973	245210	0.13	0.78	0.003
“Briefcase”	Sobel	37059	8679	110	28380	196690	0.77	0.98	0.126
“Briefcase”	Canny	6524	5346	3443	1178	223892	0.18	0.60	0.005
“Briefcase”	Proposal	6286	4856	3933	1430	223640	0.22	0.55	0.006
“Stapler”	Sobel	13354	4847	2198	8507	245990	0.63	0.68	0.033
“Stapler”	Canny	5713	3516	3529	2197	252300	0.38	0.49	0.008
“Stapler”	Proposal	6107	4215	2830	1892	252605	0.30	0.59	0.007

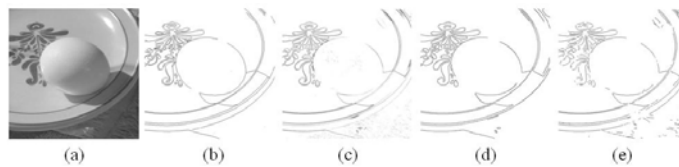


Fig. 5. Test images: (a) “Egg” original image, (b) “Egg” ground-truth edge map, (c) Sobel edge map, (d) Canny edge map, (e) proposed technique edge map.

### 3.2 Intra-Technique Evaluation

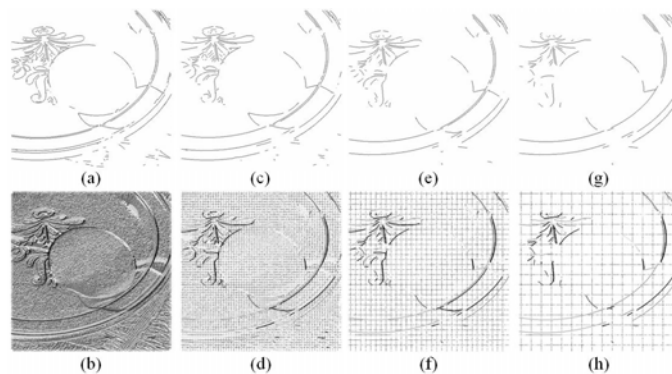
The proposed technique allows a decreasing on the computational effort required to achieve edge detection. Instead of sequentially evaluate the gradient in all points of an image, the proposed technique focuses and directs it computational effort to the regions where an edge contour could be extracted: the edge regions. Table 2 presents different search densities for illustrating this characteristic of the proposed technique. It summarises the computational effort and performance indicators of the proposed technique using the “Egg” image. The column rows and columns reflects the number of selected rows and columns used in the *edgel location* step. The column *image*

*analysed* reflects the percentage of points in the original image where the gradient magnitude and the gradient direction were calculated. An important remark in the analysis of Table 2 is that the proposed technique produces good performance indicators, such as a low FPP and a high number of true positive edges.

**Table 2.** Intra-technique evaluation of the proposed technique using the “Egg” image.

Rows and Columns	Gradient Operations	Image Analysed	Extracted Edges	TP	FN	FP	TN	FPP
494	253916	99.9%	7077	6104	1729	973	245210	0.13
247	194012	76.4%	6850	6058	1775	792	245391	0.11
124	121314	47.8%	6325	5673	2160	652	245531	0.10
62	70711	27.8%	4966	4518	3315	448	245735	0.09
31	41308	16.3%	4025	3733	4100	292	245891	0.07
16	25186	9.9%	3158	2941	4892	217	245966	0.06
8	15161	5.9%	2372	2277	5556	95	246088	0.04
4	8913	3.5%	1605	1523	6310	82	246101	0.05
2	3926	1.5%	619	543	7290	76	246107	0.12

Edge maps generated with the proposed technique using the “Egg” image and the search densities illustrated in Table 2 are shown in Fig. 6. It illustrates the performance of the proposed technique when the computational effort for achieving edge detection process is decreased.



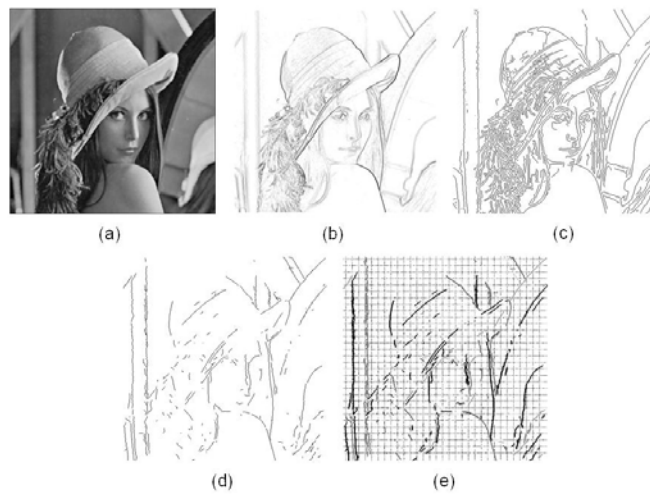
**Fig. 6.** Edge maps generated by the proposed technique and its respective search density: (a) and (b) using 247 rows and columns, (c) and (d) using 62 rows and columns, (e) and (f) using 31 rows and columns, (g) and (h) using 16 rows and columns.

### 3.3 Experimental Evaluation with the “Lenna” Image

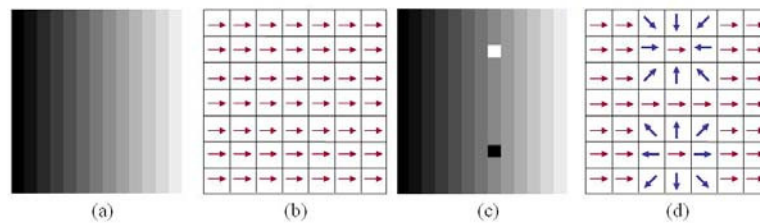
In this section the proposed technique is compared to the Sobel and the Canny operators using the “Lenna” image, in Fig. 7(a). In this comparison, the proposed technique does not process the entire image. A gradient magnitude threshold equal to 32 is used with the Sobel operator. Parameters for edge detection using the Canny

operator are:  $\sigma$  equals to 1, threshold low equals 0.0375, and threshold high equals 0.0938. The proposed technique uses a gradient magnitude threshold equal to 32 and a search density of 32 rows and 32 columns.

The Lenna edge maps generated by the Sobel operator, the Canny operator, and the proposed technique are shown in Fig. 7(b), Fig. 7(c) and Fig. 7(d), respectively. In this case, 18.5% of the Lenna image is processed by the proposed technique using a search density of 32 rows and 32 columns.



**Fig. 7.** The Lenna test image: (a) original image (b) Sobel edge map, (c) Canny edge map (d) proposed technique edge map and (e) proposed technique search density map.

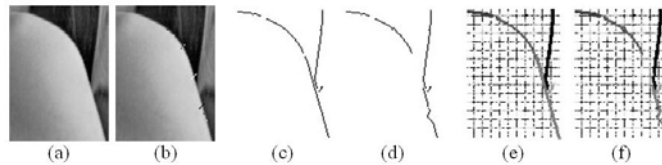


**Fig. 8.** Illustration of the impact of outliers in gradient directions: (a) original signal, (b) gradient directions, (c) signal plus outliers (d) gradient directions peculiarities.

### 3.4 Effects of Outliers

The presence of outliers in an edge region causes deterioration in edge maps computed by the proposed technique. An outlier point can have a high gradient magnitude but it causes a gradient direction peculiarity in its neighbourhood; seen in Fig. 8. Thus, an outlier point in an edge region cannot be reached by the proposed

technique. Effects of outliers in a fragment of the Lenna image are illustrated in Fig. 9. The falsely curved edge contour and the edge contour discontinuity are due to outliers, shown in Fig. 9(d).



**Fig. 9.** Effects of outliers in image: (a) Lenna fragment image, (b) Lenna fragment image plus outliers, (c) expected edge map, (d) deteriorated edge map, (e) expected search, (f) deteriorated search.

## 4 Conclusions

We presented an edge contour extraction technique. The proposed technique is based on the gradient magnitude and a quantisation of gradient directions. Extracted contours are one pixel width and links edgels with maximum gradient magnitude and a common quantised gradient direction. An outlier point in an edge region cannot be reached by the proposed technique. Inter-technique experimental evaluation using ground-truth edge images is presented. It shows that the proposed technique produces similar result to the Canny operator in terms of true positive rate, false positive rate and false positive edge probability. However, the distinctive aspect of the proposed technique consists in that it extracts and codifies edge contours using a set of rows or columns. This strategy allows a decreasing on the computational effort required to achieve edge detection. Intra-technique evaluation show that it is possible to obtain a edge contours by processing 50% or less than the entire image, depending on the image content.

## References

1. Canny, J.: Finding Edges and Lines in Images. AI-TR-720, MIT AI Lab, (1983)
2. Canny, J.: A Computational Approach to Edge Detection. In: IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 8, No. 8, pp. 679--698 (1986)
3. De Winter, J., Wagemans, J.: Contour-Based Object Identification and Segmentation: Stimuli, Norms and Data, and Software Tools. In: Behavior Research Methods, Instruments, and Computers, Vol. 36, No. 4, pp. 604--624 (2004).
4. Deriche, R.: Separable Recursive Filtering for Efficient Multi-Scale Edge Detection. In: Proc. International Workshop on Machine Vision and Machine Intelligence, pp. 18--23 (1987)
5. Fernandez-Garcia, N., Carmona-Poyato, A., Medina-Carnicer, R., Madrid-Cuevas, F.: Automatic Generation of Consensus Ground Truth for the Comparison of Edge Detection Techniques. In: Image and Vision Computing, Vol. 26, pp. 496--511 (2007)

6. Ferrari, V., Fevrier, L., Jurie, F., Schmid, C.: Groups of Adjacent Contour Segment for Object Detection. In: IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 30, No. 1, pp. 36--51 (2007)
7. Fesharaki, M., Hellestrand, G.: A new Edge Detection Algorithm based on a Statistical Approach. In: Speech, Image Processing and Neural Networks. Vol. 1, pp. 21--24 (1994)
8. Grigorescu, C., Petkov, N., Westenberg, M.: Contour detection based on nonclassical receptive field inhibition. In: IEEE Transactions on Image Processing, Vol. 12, No. 7, pp. 729--739 (2003)
9. Grigorescu, C., Petkov, N., Westenberg, M.: Contour and boundary detection improved by surround suppression of texture edges. In: Image and Vision Computing, Vol. 22, No. 8, pp. 609--622 (2004)
10. Hadamard, J.: Sur les Problèmes aux Dérivées Partielles et leur Signification Physique. Princeton University, No. 13, pp. 49--52 (1902)
11. Hsin, C., Chen, S., Lin, Y., Shin, S.: Separating contours from texture edges in natural images. In: IEEE International Conference on Electro/Information Technology, pp. 108-113 (2007)
12. Huang, T., Yang, G., Tang, G.: A Fast Two-Dimensional Median Filtering Algorithm. In: IEEE Transactions on Acoustics, Speech, and Signal Processing, Vol. 27, No. 1, pp. 13--18. (1979)
13. Konishi, S., Yuille, A., Coughlan, J., Zhu, S.: Statistical Edge Detection: Learning a Evaluating Edge Cues. In: IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 25, No 1, pp. 55--74 (2003)
14. Marr, D., Hildret, E.: Theory of the Edge Detection. In: Proc. Royal Soc. London, B 207, pp. 187--217 (1980).
15. Perona, P., Malik, J.: Scale-space and edge detection using anisotropic diffusion. In: IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 12, No. 7, pp. 629--639 (1990)
16. Pitas, I., Venetsanopoulos, N.: Nonlinear Digital Filters: Principles and Applications. Kluwer, (1990)
17. Poon, S., Ward, K.: A Simple and Effective Filter based on the Rank Difference. In: IEEE Proceedings International Conference on Image Processing, Vol. 1, pp. 900--903 (2000)
18. Prewitt, J.: Object Enhancement and Extraction. In: Picture Processing and Psychopictorics, Academic Press, (1970).
19. Roberts, L.: Machine Perception of Three-Dimensional Solids. In: Optical an electro-optical Information Processing. MIT Press, pp. 159--197 (1965)
20. Shen, J., Castan, S.: An Optimal Linear Operator for Step Edge Detection. In: Computer Vision, Graphics and Image Processing: Graphical Model and Understanding, Vol. 54, No. 2, pp. 112-133 (1992)
21. Shotton, J., Blake, A., Cipolla, R.: Multi-Scale Categorical Object Recognition Using Contour Fragments. In: IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 30, No. 7, pp.1270--1281 (2008)
22. South Florida University edge ground-truth repository, [http://marathon.csee.usf.edu/edge/edge\\_detection.html](http://marathon.csee.usf.edu/edge/edge_detection.html).
23. Yitzhaky, Y., Peli, E.: A Method for Objective Edge Detection Evaluation and Detector Parameter Selection. In: IEEE Transactions on Image Processing, Vol. 25, No 8, pp. 1027--1033 (2003)
24. Ziou, D., Tabbone, S.: Edge Detection Techniques – An Overview. In: International Journal of Pattern Recognition and Image Analysis, Vol. 8, pp. 537-559 (1998)