

The Canny Detector with Edge Region Focusing Using an Anisotropic Diffusion Process[¶]

E. A. S. Galvanin, G. M. do Vale, and A. P. Dal Poz

*São Paulo State University, Department of Cartography, 305 Rua Roberta Simonsen, Presidente Prudente,
São Paulo, 19060-900 Brazil*

e-mail: edineia@pos.prudente.unesp.br; gmval@pos.prudente.unesp.br; aluir@fct.unesp.br

Abstract—This paper proposes a methodology for edge detection in digital images using the Canny detector, but associated with a priori edge structure focusing by a nonlinear anisotropic diffusion via the partial differential equation (PDE). This strategy aims at minimizing the effect of the well-known duality of the Canny detector, under which is not possible to simultaneously enhance the insensitivity to image noise and the localization precision of detected edges. The process of anisotropic diffusion via the PDE is used to a priori focus the edge structure due to its notable characteristic in selectively smoothing the image, leaving the homogeneous regions strongly smoothed and mainly preserving the physical edges, i.e., those that are actually related to objects presented in the image. The solution for the mentioned duality consists in applying the Canny detector to a fine gaussian scale but only along the edge regions focused by the process of anisotropic diffusion via the PDE. The results have shown that the method is appropriate for applications involving automatic feature extraction, since it allowed the high-precision localization of thinned edges, which are usually related to objects present in the image.

DOI: 10.1134/S1054661806040067

1. INTRODUCTION

The properties of objects, such as geometrical and physical characteristics, are transferred to an image because they cause variations on the image's grayscale. Thus, to detect and to extract information from the objects, several image analysis techniques are used, among them, edge detection. Depending on the goal, edge detection can be considered as an end or as a pre-processing for subsequent processes of image analysis. Anyway, in order to obtain the desired result, it is necessary that the strategy of edge detection work properly.

In the current methodologies for edge detection, one of the common operations is the differentiation of the image, which allows the detection of both physical and spurious edges. To minimize this undesired effect, the image is smoothed before the differentiation, creating the duality between detection and precision of edge localization [8]. Namely, the higher the localization precision, the lower the signal-to-noise ratio and, consequently, the detection becomes more and more sensitive to the spurious details of the image. This duality is present in the Canny detector, thus influencing the efficiency and autonomy of a posteriori image analysis tasks. For instance, feature extraction methodologies, classified as automatic and that use the Canny edge detector, are dependent on the choice of the adequate scale parameter for a particular image, leading to an

undesired interaction of the operator with the extraction system. Therefore, the study of the duality “detection versus localization” is very relevant in the context of automatic feature extraction methodologies.

The nonlinear anisotropic diffusion via the partial differential equation (PDE) is an edge detection methodology that is, in principle, promising for solving the duality problem. The main idea of this methodology is to carry out a selective smoothing of the image in a previous stage [1]. This process smooths homogeneous regions of the image more intensively, removing spurious information usually related to noise. Consequently, the PDE detector preserves, in terms of completeness and localization, the edges of better contrast, making it possible to detect mainly the contour of the objects (road, buildings, limit of cultures etc.). This property is fundamental for automatic feature extraction methodologies in a digital image [3]. A disadvantage of the edge detector via PDE is the possibility of detecting edge regions with nearly constant gradient magnitude, thus bringing a possible difficulty for a precise localization of thinned edges.

The motivation for the combination of both detectors comes from the perception that is possible to take advantage of: (1) the main characteristic of the PDE detector in generating results with a good signal-to-noise ratio, including edge regions without displacement and with minimum fragmentation; (2) the characteristics of the Canny detector in detecting high-precision thinned edge at a fine scale. Thus, this paper proposes a solution for the duality problem of the Canny detector based on the application of this detector to a

[¶]The text was submitted by the authors in English.

fine scale, but only along the edge regions focused via a PDE detector.

This paper is organized into five main sections. Section 2 presents the theoretical foundation of the detectors related to the proposed methodology. This methodology is described in Section 3. In Section 4 the experimental results are presented and analyzed. In Section 5 the main conclusions are presented.

2. EDGE DETECTORS

As this paper proposes a combination of the Canny and anisotropic diffusion detectors, this section presents the basic theoretical foundation of both detectors. Algorithm details are left to relevant literature (see, e.g. [1, 4, 6, 7]).

2.1. Canny Detector

According to Canny (1986), any edge detection filter should meet three basic criteria. The first is the so-called error or detection ratio, and it consists in maximizing the signal-to-noise ratio (SNR). The higher the SNR, the more probable the detection of true edges in the image. The second criterion specifies that edge points should be well located; i.e., the distances among the points extracted by the detector and the respective true positions should be minimized. The localization criterion (L) is defined as the inverse of the distance between a detected point and the respective true position. Therefore, the higher L, the closer the true positions will be from the points detected by the filter. Thus, a detection filter designed to detect step edges involves the maximization of both criteria [2]:

$$\Sigma(f)\Lambda(f') = \left(\frac{\left| \int_{-w}^0 f(x) dx \right|}{\sqrt{\int_{-w}^{+w} f^2(x) dx}} \right) \left(\frac{|f'(0)|}{\sqrt{\int_{-w}^{+w} f'^2(x) dx}} \right), \quad (1)$$

where $f(x)$ is the impulse response of the filter defined in the interval $[-w; w]$ and $f'(0)$ is the slope of the filter $f(x)$ at the origin ($x = 0$), where step edges are assumed to be centered. $\Sigma(f)$ and $\Lambda(f')$ (the respective amounts in parenthesis in (1)) are two performance measures, which are related to SNR and L, respectively. It is possible to demonstrate that $\Sigma(f)$ and $\Lambda(f')$ vary inversely along the scale space, meaning that when the detection is privileged, the localization is not precise, and vice versa.

The optimal filter condition in (1) should meet yet a third criterion, the so-called multiple response crite-

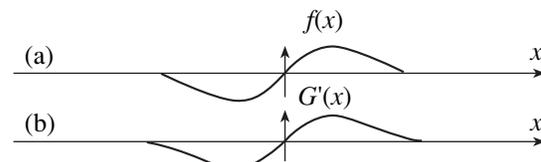


Fig. 1. Filter response, (a) Optimal filter, (b) Gaussian filter.

rion. The basic idea is that there should be only one edge point where only one true edge exists [2]:

$$x_{\max} = 2\pi \left(\frac{\int_{+\infty}^{+\infty} f'^2(x) dx}{\int_{-\infty}^{-\infty} f'^2(x) dx} \right)^{1/2}, \quad (2)$$

which is the mathematical expression for the distance (x_{\max}) between adjacent maxima in the filter response $f(x)$ that are due to the presence of noise. Thus, the maximization of the condition given by (1) must guarantee that x_{\max} be as large as possible, increasing the possibility of separation of the true maxima from the false ones in the filter response $f(x)$.

The response of optimal filter that satisfies the three Canny criteria is shown in Fig. 1a [2]. An important finding of Canny was the possibility of approximating the optimal filter $f(x)$ through the first derivative of the Gaussian function $G'(x)$ (Fig. 1b). This function is, in practice, quite attractive, because its analytical form is simple. Another advantage of this function comes from its well-known separability property, which allows its two-dimensional extension to be quite simple.

Notice that both filter responses (Fig. 1) are very similar, which intuitively suggests a similar performance.

2.2. Anisotropic Diffusion Detector via the PDE

The process of edge detection is very dependent on the type of smoothing applied a priori to the image. Thus, a lot of research has been carried out with the goal of solving the problems related to image smoothing. Perona and Malik [7] developed a model whose goal was the selective smoothing of the image. This model carries out a nonlinear anisotropic diffusion consisting in an algorithm for edge detection and image enhancement. Using insight from Perona and Malik model, some authors developed models for image selective smoothing. Nordström [6] developed a model that resulted in unification of the nonlinear diffusion model with a regularization term. This term has a function of keeping the generated images in the optimal smoothing time, next to the original image. Barcelos et al. (2002) proposed a model that consists in selectively smoothing the image, leaving the homogeneous regions

strongly smoothed and mainly preserving the physical edges, i.e., those that are really related to objects presented in the image.

The mathematical model proposed by Barcelos et al. [1] is based on the nonlinear anisotropic diffusion equation. This model follows the idea formulated by Perona and Malik [7], mathematically expressed as

$$\frac{\partial u}{\partial t} = \bar{g} |\nabla u| \operatorname{div} \left(\frac{\nabla u}{|\nabla u|} \right) - \lambda (1 - \bar{g})(u - I), \quad (3)$$

$$u(x, y, 0) = I(x, y), \quad (x, y) \in \mathcal{R}^2,$$

where $\bar{g} = \frac{1}{1 + k|\nabla(G_T u)|^2}$ ($0 \leq \bar{g} \leq 1$), ∇ is the gradient operator, div denotes the divergent operator, λ is a parameter that acts as a weight for the term $(1 - \bar{g})$, k is a constant in the function \bar{g} , I represents the original image, u is the smoothed image from I at the scale t , T represents the smoothing optimum level necessary to obtain an adequate level of smoothing, and G_T is the Gaussian function.

The term $|\nabla u| \operatorname{div} \left(\frac{\nabla u}{|\nabla u|} \right)$ in (3) diffuses the image u along the orthogonal direction to its gradient u . Then, the image u is smoothed on both sides of an edge with minimal smoothing along the own edge.

The mathematical model given by (3) has the purpose of selectively smoothing the image. The function \bar{g} in (3) is used to control the diffusion speed; that is, the selective smoothing is carried out at speeds that are lower in the surroundings of a point where the term $|\nabla(G_T u)|$ is small. Consequently, the second term in the denominator of function \bar{g} will be very small. Under these conditions, $\bar{g} \sim 1$; thus, the term $(1 - \bar{g}) \sim 0$ in (3). Therefore, the term $(u - I)$ that preserves the edge does not act in the model. Consequently, the diffusion accomplished by the first term of (3) will be higher within homogeneous regions. On the other hand, if the term $|\nabla(G_T u)|$ were high, then the analyzed point would be considered an edge point. If this occurs, the second term in the denominator of function \bar{g} will be high, so $(1 - \bar{g}) \sim 1$ in (3) when $\bar{g} \sim 0$. In this case, the term $(u - I)$ will act strongly in the image, keeping the original characteristics of edges. Thus, the diffusion process carried out by the first term of (3) will have an insignificant effect along the edge regions.

The Gaussian function used in (3) was slightly modified by substituting the scale parameter σ by $(aT)^{1/2}$, i.e., $\sigma^2 = aT$ (a is a real constant). This relation indicates that the smoothing optimum level (T) depends on the parameter σ , which controls the smoothing intensity of

Gaussian kernel. The modified Gaussian function is given by

$$G_T(x, y) = \frac{1}{2a\pi T} e^{-(x^2 + y^2)/2aT} \quad (x, y) \in \mathcal{R}^2. \quad (4)$$

The smoothing optimum level concept introduced by Barcelos et al. [1] is then given by

$$T = \frac{\sigma^2}{a}. \quad (5)$$

The temporal evolution (t) in the model of anisotropic diffusion is directly related to the smoothing optimal level (T):

$$t = \frac{T}{\Delta t}, \quad (6)$$

where Δt represents the step size of temporal evolution.

The model consists of an iterative process, controlled by the temporal evolution defined in (6). The process continues up to a smoothing optimal level (T). The estimation of parameter σ is subjective, meaning that the choice of a suitable threshold is difficult and involves trial and error.

After the application of the PDE model (3) to the image, the result will be a smoothed image. With the smoothed image, the second stage can be carried out, consisting in detecting edges in the image. The function used in the second stage is

$$g(|\nabla u|) = \frac{1}{1 + k_1 |\nabla u|^2}, \quad (7)$$

where k_1 is the constant in the function g , with $0 \leq g \leq 1$.

After the application of (7) to the smoothed image u , the pixels whose values of g are next to the unitary value are changed to a null gray value, and the pixels with values of g with a next to null value are changed to a unitary gray value. The result is a binary image where the edge pixels are white and the background pixels are black.

3. CANNY DETECTOR WITH EDGE STRUCTURE FOCUSING

Automatic and semiautomatic feature extraction processes commonly depend on preprocessing involving edge detection from images. Within this context, the basic objective of feature extraction processes is polygon extraction (for example, representing the contour of the roof of a building) accurately representing the contour of the respective object. As a result, the edge detection results should be linear chains (i.e., thinned edges) of accurately located pixels. Thus, detected edges with displacement are highly undesired but, as can be seen later, edge structures without displacement do not warrant precise extraction of linear pixel chains. Another highly desirable characteristic of an edge detector in the context of feature extraction is

that it should respond only to physical edges, avoiding spurious ones coming from the noise and texture of the image. In summary, an ideal edge detector should allow the following:

- (1) physical edge detection, avoiding spurious edges related to noise and texture of the image;
- (2) edge detection without fragmentation; and
- (3) precise localization of the point sequence that best represents the interest object contour, which is efficiently accomplished by the well-known process of nonmaxima suppression.

If an edge detector with the above characteristics existed, the a posteriori stages of feature extraction processes that attempt to assign meaning to the objects present in the image would be easier. Since a perfect edge detector does not exist, strategies that allow results as close as possible to ideal in the feature extraction process have been researched. A potential strategy is presented below, consisting in the application of the Canny detector after edge structure focusing by anisotropic diffusion via a PDE detector. In order to better understand the logic of this strategy, fundamental characteristics of both detectors are discussed beforehand. The table presents these characteristics.

In the Canny detector, four basic stages can be identified: smoothing, differentiation, nonmaxima suppression, and hysteresis. The first two stages generate an intensity surface where, for each pixel position of the original image, its gradient magnitude is determined. On that surface, the ridges will correspond to image edges. If that surface is transformed into an image, which is usually called a gradient image, the edges will be visualized as lines several pixels in width. The thinning of the ridges is accomplished by the nonmaxima suppression process. The hysteresis process is the last applied step, and it consists in the complementation of the thinned edges and elimination of the remaining spurious edges. The edge detector based on anisotropic diffusion via PDE has two basic stages. The first one consists in accomplishing the anisotropic diffusion process, generating a smoothed image without displacing the prominent structures of the image. In the second stage, a simple thresholding of the gradient image is used, based on (7). The Canny detector is a complete process because its result is already an image of thinned edges, ready to be used in feature extraction processes. The PDE detector provides similar results to the ones obtained by the first two stages of the Canny detector. In principle, it would be enough to apply the processes of nonmaxima suppression and hysteresis to obtain similar results to the ones obtained by the Canny detector. However, we demonstrate below that the results may not be appropriate for the feature extraction process.

Returning to table, the first characteristic refers to the displacement of edges obtained by the first two stages of the Canny detector or by the edge detector based on anisotropic diffusion. Therefore, the displace-

Main characteristics of Canny and PDE detectors

| Features | Detectors | |
|--|---|---|
| | CANNY | PDE |
| Edge displacement | Worthless at fine scale, and the coarser the scale, the higher it becomes | None |
| SNR | SNR is smaller at fine scales and higher at coarse scales | SNR is smaller at fine scales and higher at coarse scales |
| Localization precision of thinned edge | High precision is obtained at fine scales | High precision and uniqueness are not guaranteed |

ment refers to ridges on the gradient magnitude surface or to the edges on the gradient image. Although displaced edges imply necessarily in localization imprecision of the corresponding thinned edges (third characteristic, according to table), non-displaced edges do not necessarily imply in accurately thinned edges. Thus, the first and third characteristics should be discussed separately. Regarding the first characteristic, the edge structure obtained by the first two stages of the Canny detector is just preserved at a fine scale (e.g., $\sigma = 1$ in the illustrative example presented in Fig. 2a). The Canny application to a coarse scale ($\sigma = 8$, Fig. 2b) can cause an edge displacement of several pixels. As the Figs. 2c and 2d show, the edge detector based on anisotropic diffusion is not affected by the edge displacement along the diffusion process. This characteristic had already been discussed under the theoretical viewpoint in Section 2.2. In relation to SNR (second characteristic) of both detectors, the behavior is similar for both detectors (see Figs. 2a–2d). The higher the SNR, the less sensitive is the detector to the noises and texture of the image, enabling it to detect mainly the physical edges present in the image. Thus, the application of both detectors to a coarser scale would produce, at first, a satisfactory result because the physical edges would prevail. However, from the first characteristic, the Canny detector demonstrates unfavorable performance due to the displacement of the edge structure. The application of the two edge detectors to a fine scale would be disadvantageous for both detectors due to low SNR, with the consequent high sensitivity to the noise and texture of the image. Regarding the third characteristic, the precision of the localization of the thinned edges depends basically on three factors. The first one is directly related to the existence or not of edge structure displacement, according to the above-mentioned first characteristic. The second factor is related to the ridge shape on the gradient magnitude surface. The ridge shape generated by the Canny detector, mainly at a fine scale, possesses high curvatures along its traverse

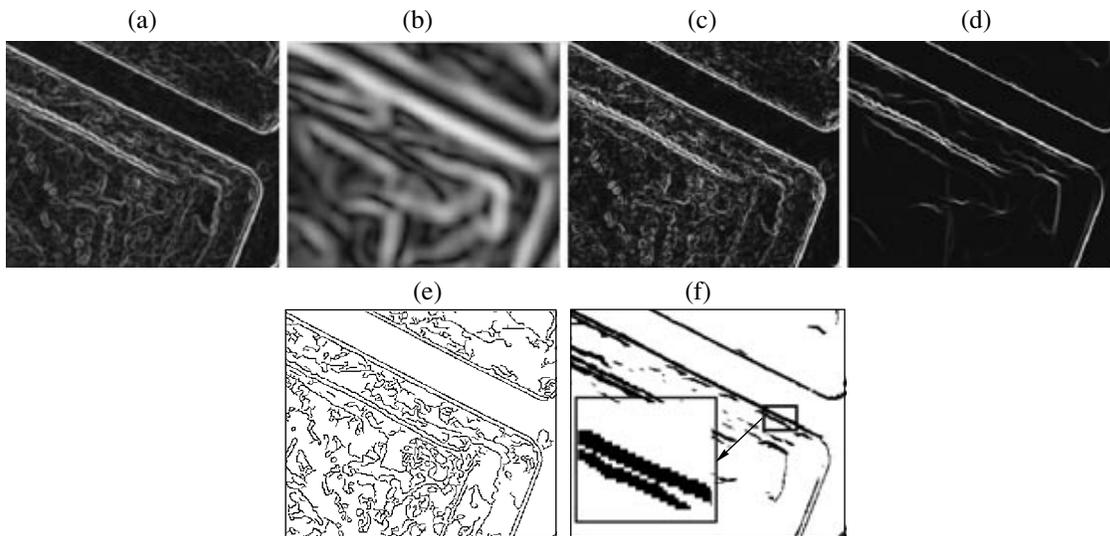


Fig. 2. Main characteristic of the Canny and anisotropic diffusion via PDE detectors: (a) No thinned edges, detected by Canny ($\sigma = 1$) without nonmaxima suppression and hysteresis, (b) Similar to (a), but at coarse scale ($\sigma = 8$), (c) No thinned edges, detected via the PDE at the beginning of the diffusion process, (d) Similar to (c), but at the end of the diffusion process. (e) High-precision thinned edges detected by the Canny detector for $\sigma = 1$, (f) Edges detected via the PDE and thinned by the no-maxima suppression.

sections. As a result, the nonmaxima suppression process possesses high discrimination power for detecting the maximum points along the traverse sections of ridge, allowing high precision in edge thinning (Fig. 2e). The same does not happen with the edge detector based on anisotropic diffusion. This detector can generate transverse sections of ridges with low curvature or even with too flat curvature, due to its capacity for homogenizing areas with similar characteristics, e.g., narrow and elongated edge regions. Consequently, nonmaxima suppression becomes an inaccurate process and it can even prove unable to find the localization of the thinned edges. An example where the nonmaxima suppression process does not extract thinned edges is shown in Fig. 2f.

The analysis above allows us to conclude that the PDE detector is not appropriate for application in feature extraction problems. This conclusion could be justified taking into consideration the third characteristic of the method (table), by which the thinned edges may not be extracted with high accuracy or it may not even be unique. However, the first two characteristics enable the method to be an excellent finder of physical edges in the image.

The proposed solution consists in applying the Canny detector to a fine scale, but just on the edge structures focused by the edge detector of anisotropic diffusion via the PDE. This procedure allows the minimization of disadvantages of each detector, because mainly high-precision thinned edges are detected. Moreover, the SNR of the final results drastically increases due to the previous isolation of noise and texture areas of the image. Thus, both methods work

together, though without suffering any theoretical or algorithmic modification.

Figure 3c shows the result obtained by application of the Canny detector for $\sigma = 1$ only on the edge structure detected by anisotropic diffusion via the PDE detector (Fig. 3a). Comparison of the results in Fig. 3c to the one obtained by using only the Canny detector with the same scale ($\sigma = 1$) (Fig. 3b) verified that mainly high-precision physical edges are detected. The zoomed window in Fig. 3d shows the result of the proposed methodology (Fig. 3c) overlaid on the original image, where it is possible to verify the precise localization of edges and the absence of fragmentation of important edges in the image.

4. EXPERIMENTAL RESULTS

In this section, some results and an evaluation of the Canny edge detection process with edge region focusing are presented. The edge detection process was applied in two real sets of image data. From Canny theory, the higher (τ_1) and lower (τ_2) hysteresis thresholds were fixed at 30% and 80% of the gradient magnitude range respectively. The standard deviation of the Gaussian used by Canny detector was fixed ($\sigma = 1$) in both experiments. In relation to the PDE detector, the optimal smoothing parameter was also fixed ($\sigma = 70$).

In order to show the efficiency of the method, the results obtained with two test images of different noise density are presented and analyzed. The second image is noisier than the first image, characteristic that is difficult to be observed in images showed in Figs. 4d and 5d. In this case, this difference in noise density is mainly related to the great difference of spatial resolu-

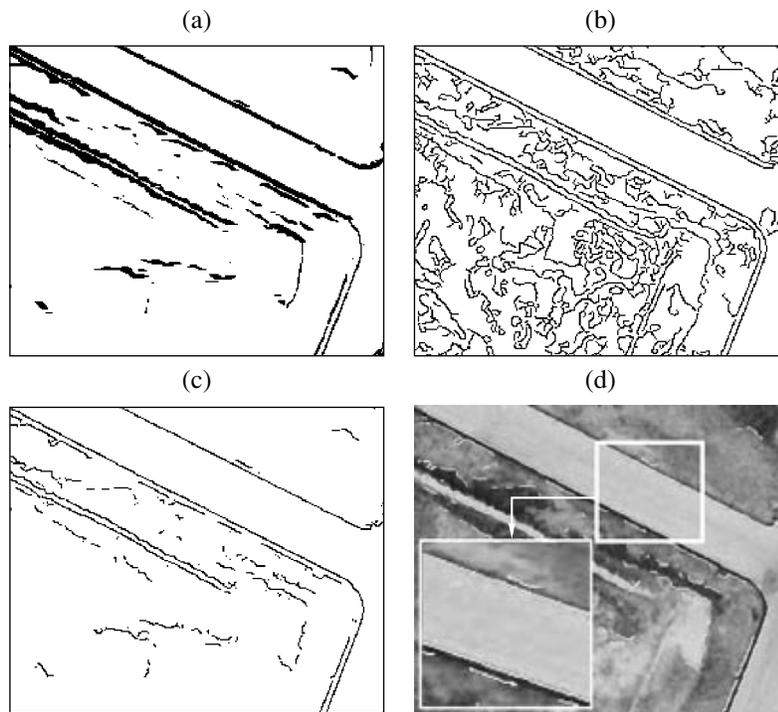


Fig. 3. Example of application of the Canny detector with a priori edge focusing. (a) Edges detected via PDE at the end of the diffusion process, (b) High-precision thinned edges detected by the Canny detector for $\sigma = 1$, (c) High-precision edges detected by the Canny detector with edge region focusing, (d) Edges of Fig. 3c overlaid on the original.

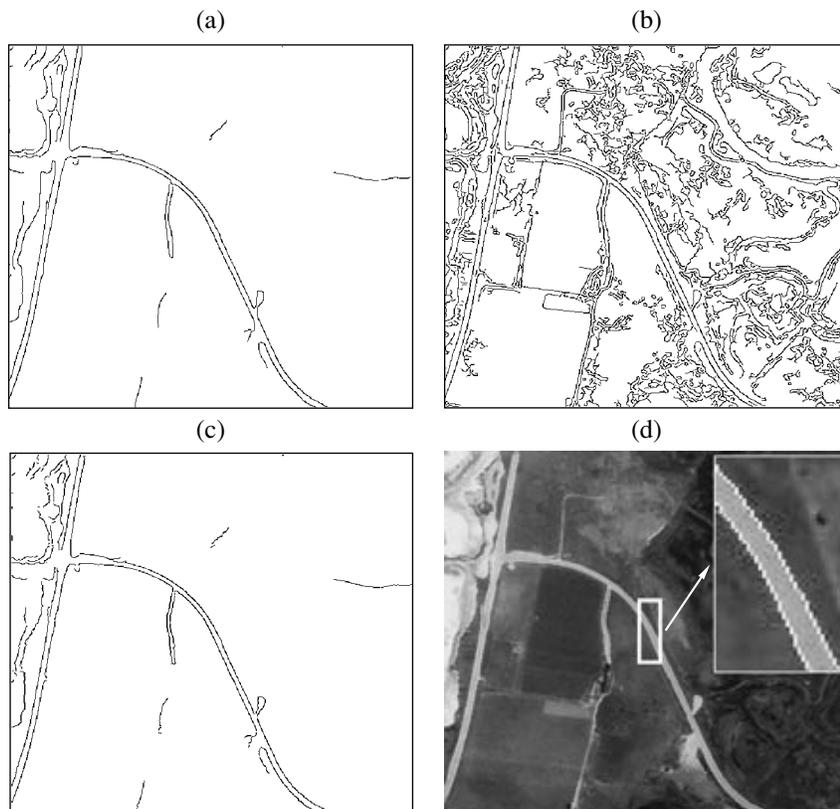


Fig. 4. Example of the application of the Canny detector with edges a priori focused. (a) Thinned edges, detected via the PDE on the coarse scale ($\sigma = 70$), (b) High-precision thinned edges detected by the Canny detector ($\sigma = 1$), (c) Edges detected by the Canny detector with focused edge regions, (d) edges detected by the proposed methodology overlaid on the original image.

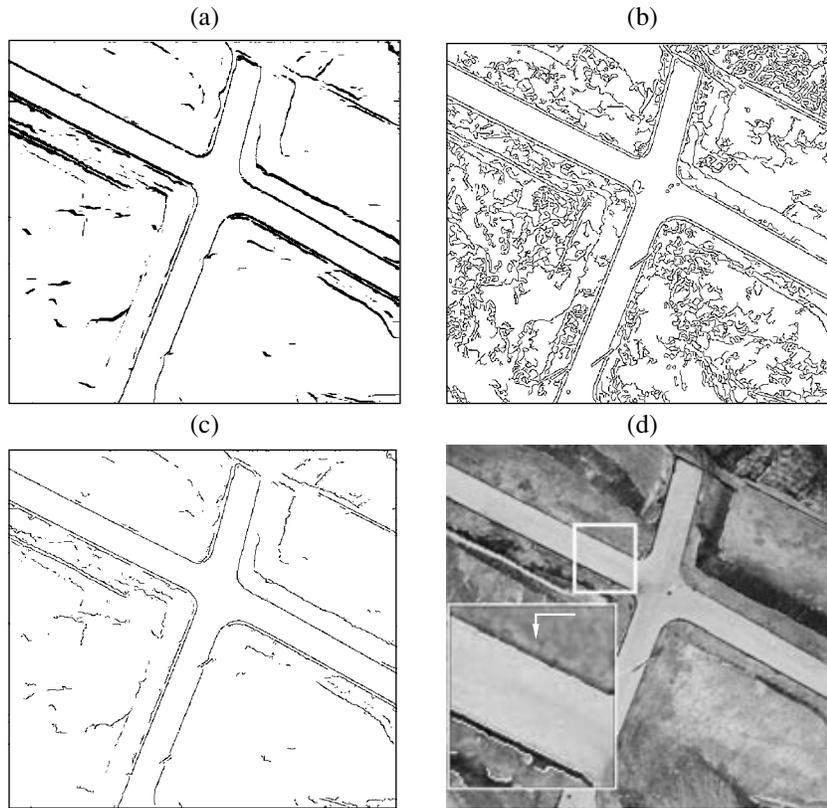


Fig. 5. Example of application of the Canny detector with edges a priori focused, (a) Thinned edges detected via the PDE on the coarse scale ($\sigma = 70$), (b) High-precision thinned edges detected by the Canny detector ($\sigma = 1$), (c) Edges detected by the Canny detector with focused edge regions, (d) Final results overlaid on the original image.

tion of both images. The first image (Fig. 4d) has spatial resolution of 2 meters and the second image (Fig. 5d) has 0.5 meter of spatial resolution. On the other hand, the contrast of the first image is better than the second image. These images were then selected with the purpose of verifying the potential of the method with images of different noise content.

Figure 4a shows the result obtained with PDE detector, followed by the application of nonmaxima suppression and hysteresis. For this image type, i.e., with low-resolution and good contrast, the method based on PDE usually makes it possible to obtain good results, i.e., thinned and well-located edges. Figure 4b shows the result obtained by the Canny detector with $\sigma = 1$. These results show, in addition to physical edges, many other edges associated with the noise and texture of the image. Figure 4c shows the result of application of the Canny detector on edge regions detected by the PDE detector.

It is possible to see that the results obtained by using only the PDE detector (Fig. 4a) are similar to the one obtained with the Canny detector with focused edge regions detected by the PDE detector (Fig. 4c). This occurred due to two main factors, namely, the low resolution and good contrast of image. Figure 4d shows the results of the proposed methodology overlaid on

original image. Anyway, the obtained results show mainly physical edges related to the road network, which would facilitate the automatic extraction of this structure.

The results obtained with second test image are shown in Fig. 5. Figure 5a shows that the PDE detector with edge thinning was inefficient in obtaining thinned edges. Transverse sections of edge regions in higher resolution images are usually described by a greater number of pixels than ones in lower resolution images. Due to the notable characteristic of the PDE detector in homogenizing image regions, even the narrow and elongated edge regions, which are wider in high-resolution images, it may detect “flat” edge regions. On the other words, the diffusion process may generate, for high-resolution images, homogeneous areas corresponding to the edge regions proper. As a result, the edge thinning by nonmaxima suppression may not be an efficient process. Figure 5b shows the results using only the Canny detector. Due to the high-resolution input image, the amount of spurious edges resulting from noise and texture of the image is too large. Figure 5c presents the results obtained with the proposed methodology. It is possible to observe, from the application of the proposed methodology to this image test, that the spurious edges were significantly reduced, and

the remaining edges are adequately thinned. Figure 5d shows the results (Fig. 5c) overlaid on the original image. Therefore, the Canny detector with a priori edge focusing using the PDE proved much more effective than the Canny detector for high-resolution images.

5. CONCLUSIONS

This paper presented the theoretical bases and the experimental evaluation of the Canny edge detection process with a priori edge focusing. With the purpose of verifying the theoretical expectative, experiments using real images with different characteristics were presented.

The Canny edge detection process with a priori edge focusing proved quite robust, because all parameters and thresholds remain unchanged for all test images. This characteristic is highly desirable in the context of automatic feature extraction methodologies. For the Canny edge detector, the scale parameter (σ) and the hysteresis thresholds (τ_1 and τ_2) depend on the noise density of the input image. In general, the proposed methodology makes it possible to obtain high-quality contour information. In addition, the proposed methodology enables the detection of mainly physical edges.

As expected, the proposed methodology is quite advantageous when the input image used in the process is of high resolution. This is because the PDE detector usually produces edge regions with low curvature along their transverse sections, and this makes the nonmaxima suppression process inefficient. For low-resolution and medium-resolution images, little advantage is expected of the proposed methodology. Thus, the use of the Canny detector with a priori edge focusing is usually more appropriate for applications involving automatic or semiautomatic feature extraction processes from digital images, especially high-resolution ones.

6. ACKNOWLEDGMENTS

The authors thank CAPES for the financial support, in form of scholarships to PhD students Edinéia Aparecida dos Santos Galvanin and Giovane Maia do Vale. This work is also the result of a project supported by FAPESP (Fundação de Amparo à Pesquisa do Estado de São Paulo), grant no. 2001/01168-5; and CNPq (Conselho Nacional de Desenvolvimento Científico e Tecnológico), grant no. 301114/2003-0 and CNPq.

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Edinéia Aparecida dos Santos Galvanin (born 1971). Graduated from São Paulo State University (2000). MS in Cartographic Sciences, São Paulo State University (2002). PhD student at São Paulo State University. Member of the Brazilian Society of Applied and Computational Mathematics. Areas of research: Digital Image Processing and Image Analysis. Author of 16 papers.



Giovane Maia do Vale. (born 1969) Graduate of São Paulo State University. MS (Math.), São Paulo State University (2003). PhD student at São Paulo State University. Member of the Brazilian Society of Applied and Computational Mathematics. Area of research: Digital Photogrammetry and Image Analysis. Author of 13 papers.



Aluir Porfírio Dal Poz (born 1960). Graduated São Paulo State University (1987). MS (Geodetic Sci.), Paraná Federal University (1991). PhD (Eng.), São Paulo University (1996). Associate Professor at São Paulo State University. Member of the Brazilian Society of Cartography, Brazilian Society of Applied and Computational Mathematics, and Canadian Institute of Geomatics. Associate Editor of the Series in Geodetic Science and member of the editorial board of *Brazilian Journal of Cartography*. Awards: Scientific Beginner in Cartography (1995) and Cartographic Merit (1999), both awarded by Brazilian Society of Cartography. Areas of research: Digital photogrammetry and image analysis. Author or coauthor of 100 papers and one book.