An Intelligent Method for Edge Detection based on Nonlinear Diffusion

C. A. Z. Barcelos and V. B. Pires

Abstract Edge detection is an important task in the field of image processing with broad applications in image and vision analysis. In this paper, we present a new intelligent computational mechanism using nonlinear diffusion equations for edge detection. Experimental results show that the proposed method outperforms standard edge detectors as well as other methods that deploy inhibition of texture.

1 Introduction

The conventional edge detectors as the Canny edge detector and others [5, 8, 17], do not make distinction between isolated edges and edges originating from texture. Therefore many false edges usually deriving from textures and noises are detected by these algorithms.

Significant advances have been achieved with the use of more sophisticated techniques such as the algorithms based on nonlinear diffusion [1, 3, 13] and inspired by the human visual system (HSV) [7, 9, 12], among others.

In this paper, we present a new intelligent computational method to effectively edge detect in natural images. We incorporate a nonlinear diffusion equation to the Canny edge detector, and show that this results in a method more effective to edges detection in presence of texture. The proposed method can be divided into two stages. The first consists of the application of a nonlinear diffusion equation, whose main idea is to accomplish, the selective smoothing of the image of interest, removing the irrelevant information, usually related to noise and texture elements. The

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second stage consists of the application of the Canny edge detector to the smoothed image, in an attempt to obtain as a final result only those edges of interest [14].

The proposed method is able to minimize the inconvenience effect of false edge detection (usually deriving from textures and noises) and improve the performance of the traditional Canny edge detector. Results obtained from various natural images are used to demonstrate the performance of proposed method. Comparing our new method with other edge detection methods, better performance in terms of removing texture in the edge detection process was obtained.

This paper is organized as follows: section 2 describes the proposed edge detection method. The experimental results that exemplify the performance of the proposed method and the numerical implementation of the method are described in section 3, and finally section 4 presents the paper's conclusion.

2 Proposed Edge Detection Method

Motivated by the difficulty found by standard edge detectors to remove noises and textures, we proposed an intelligent computational method for edge detection in digital images adding the nonlinear diffusion method introduced in [3] to the Canny edge detector [6].

The proposed method for edge detection can be divided into two stages. The first stage consists of the application of a nonlinear diffusion equation for selective smoothing of the image of interest, in an attempt of minimize the false edge detection originating from noise and irrelevant features. In the second stage, our goal is to apply the Canny edge detector in fine scale Gaussian on the smoothed image, since noises and texture elements were effectively removed by smoothing process of the considered diffusion model, in an attempt to obtain a map with its edges refined as a final result.

2.1 Edges Detection via Nonlinear Diffusion Equations

Several smoothing methods can be found in literature, however undesirable effects such as edge deterioration, loss of relevant information, make some of these methods unviable when one desires to eliminate just irrelevant information such as noise and at the same time maintain the edges intact.

During the last few years, many mathematical models have been proposed in the attempt to solve these problems related to image smoothing. We can cite, for example [1, 3, 10, 13] which are briefly described as follows.

Perona and Malik [13] developed a model through an anisotropic diffusion equation in the attempt to preserve the exact location of an edge point.

The mathematical formulation of the model is given by:

$$u_t = div(g(|\nabla u|)\nabla u), \quad x \in \Omega, t > 0, \tag{1}$$
$$u(x,0) = I(x), \quad x \in \Omega \subset R^2,$$

where $I(x)$ is the original image, $u(x,t)$ is its smoothed version on the scale t, g is a smooth non-increasing function, such that $g(0) = 1$, $g(s) \geq 0$ and $g(s) \rightarrow 0$ when $s \rightarrow \infty$. The usual choice for g is given by $g(s) = \frac{1}{1+ks^2}$ where k is a parameter.

This model provides edges and contours that remain stable through the scale t. However, this model presents many theoretical and practical difficulties. For example, if the image is very noisy, the "size" of the gradient ∇u will be very large at almost all of the points on the image and, as a consequence the function g will be almost null at these same points. In this way, all the noise on the image remains even when the image is processed by the smoothing process introduced by this model.

As this equation is not able to preserve the edges localization, Alvarez, Lions and Morel proposed in [1] the following nonlinear parabolic equation:

$$u_t = g(|\nabla G_\sigma * u|)|\nabla u|\; div\left(\frac{\nabla u}{|\nabla u|}\right), \quad x \in \Omega, t > 0, \tag{2}$$
$$u(x,0) = I(x), \quad x \in \Omega \subset R^2,$$

where $u(x,0) = I(x)$ is the initial image, $\frac{\partial u}{\partial \eta}|_{\partial\Omega \times R_+} = 0$ is the boundary condition and $g(|\nabla G_\sigma * u|) = \frac{1}{1+k|\nabla G_\sigma * u|^2}$, with $k > 0$ being a parameter and G_σ being the Gaussian function.

This model dislocates the level curves of the image u in the orthogonal direction ∇u with speed $g(|\nabla G_\sigma * u|)K$, where $K = div(\frac{\nabla u}{|\nabla u|})$ is the local curvature of the iso-intensity contour. Therefore, the image is smoothed along both sides of the edges with minimal smoothing of the edge itself, and this is carried out at speeds which are lower near the edges and higher in the interior of homogeneous regions which makes the preservation of the edges of the image possible.

Another modification in the Perona and Malik model Eq.(1) was proposed by Nordström [10]. He added a forcing term $(u - I)$ to the Perona and Malik model Eq.(1) forcing $u(x,t)$ to maintain itself close to the initial image $I(x)$.

The presence of the forcing term in Eqs.(1) and (2) reduces the degenerative effects of the diffusion to very acceptable levels; however, the models with this forcing term do not eliminate noise satisfactorily [3].

In the attempt to obtain ever better results, Barcelos, Boaventura and Silva Jr. [3] also presented a mathematical model for the smoothing and segmentation of digital images through a diffusion equation given by:

$$u_t = g\,|\nabla u|\, div\left(\frac{\nabla u}{|\nabla u|}\right) - \lambda\,(1-g)(u-I), \quad x \in \Omega, t > 0, \tag{3}$$
$$u(x,0) = I(x), \quad x \in \Omega \subset R^2,$$

$$\frac{\partial u}{\partial \eta}\bigg|_{\partial\Omega\times R_+} = 0, \quad x \in \partial\Omega, t > 0,$$

where $g = g(|\nabla G_\sigma * u|)$, $I(x)$ is the original image, $u(x,t)$ is its smoothed version on the scale t, λ is a parameter, $(u - I)$ is the term suggested by Nordström and $(1-g)$ is the moderation selector introduced in this model.

The balanced diffusion of the image allows the homogeneous regions $g \sim 1$ to be smoothed even more in relation to the edge regions $g \sim 0$. This is obtained through the moderation selector $(1-g)$ which by being in function with g allows for the identification of these different regions on the image [3].

Experimental results obtained with the application of this model show its efficiency in the smoothing process of natural images.

2.2 Canny Edges Detector

Among the edge detection methods found in literature, the Canny edge detector is considered to be one of the most used algorithm for edge detection.

The Canny edge detection process is based upon three basic performance criteria: good detection, good localization, and single response [2, 6]. The main objective of Canny work is to develop an optimal detector.

The implementation of the Canny edge detector [6] follows the steps below.

First, the input image $I(x)$ is smoothed to remove irrelevant details like noises and texture. The smoothing is obtained by convolution of the image $I(x)$ with a Gaussian function G_σ.

Second, determine gradient magnitude $|\nabla I(x)|$ and gradient direction at each pixel (x) in the smoothed image.

In the third step, non-maxima suppression technique is performed. In this process, all the pixels (x) for which the gradient magnitude $|\nabla I(x)|$ has a local maximum in the gradient direction will be considered edge pixels.

Fourth, hysteretic thresholding is performed to remove the weak edges. In this process, two different thresholds are used: the low threshold t_L and the high threshold t_H. All candidate edge pixels with the gradient magnitude below the low threshold t_L are considered as non edges. Only the pixels with the gradient magnitude above the low threshold t_L that can be connected to any pixel with magnitude above the high threshold t_H are considered as edge pixels.

3 Computational Details and Experimental Results

Obtaining the edges of natural images, such as animals in their natural habitat or objects on textured background, is not an easy task. The more sophisticated edge detection algorithms try to find an edge map that approximates the ideal edge map, which is usually drawn by hand more closely.

In the paper, we use natural images with different complexity levels and their corresponding ground truth maps to evaluate the performance of the proposed edge detection method. The natural images and ground truth contour maps were obtained in http://www.cs.rug.nl/ imaging/papari/JASP/results.html.

3.1 Performance Measure

To compare our method with the the Canny edge detector [6] and the single scale surround inhibition algorithm [9], we use the performance measure introduced in [9].

Let DO be the number of correctly detected edge pixels, FP the number of false positive pixels, i.e. pixels considered as edges by the detector while they belong to the background of the desired output and FN the number of false negative pixels, i.e. desired output edge pixels missed by the operator. The performance measure introduced in [9] is defined as:

$$P = \frac{DO}{DO + FP + FN} \tag{4}$$

Note that if $FN = 0$, i.e. all true edge pixels are correctly detected and if $FP = 0$, i.e. no background pixels are falsely detected as edge pixels, then $P = 1$. On the other hand, if FP (edge pixels falsely detected) and/or FN (true edge pixels missed by the detector) are greater, the value of P will be lower.

For the implementation of the above measure, we consider that an edge pixel is correctly detected if a corresponding ground truth edge pixel is present in a 5×5 square neighborhood centered at the respective pixel coordinates.

3.2 Numerical Implementation

Numerical solution of the mathematical model Eq.(3) is obtained by applying appropriate finite difference methods [11, 15, 16].

The images are represented by NxM matrices of intensity values. Let u_{ij} denote the value of the intensity of the image u at the pixel (x_i, y_j) with i = 1, 2,..., N and j = 1, 2,..., M. The evolution equation obtains images at times $t_n = n\Delta t$ where Δt is the step time and n = 1, 2,... . We denote $u(x_i, y_j, t_n)$ by u^n_{ij}.

Let

$$\mathscr{L}(u) = g\,|\nabla u|\,div\left(\frac{\nabla u}{|\nabla u|}\right) - \lambda\,(1-g)(u-I). \tag{5}$$

We can write Eq.(3) in the form $u_t = \mathscr{L}(u)$. The time derivative u_t at (i, j, t_n) is approximated using the Euler method $\frac{u_{ij}^{n+1} - u_{ij}^{n}}{\Delta t}$, so the discretization of the Eq.(3) is given by

$$u_{ij}^{n+1} = u_{ij}^{n} + \Delta t \mathscr{L}(u_{ij}^{n})$$

where $u_{ij}^{0} = I(x_i, y_i)$.

The diffusion term

$$|\nabla u|\, div\left(\frac{\nabla u}{|\nabla u|}\right) = \frac{u_x^2 u_{yy} - 2u_x u_y u_{xy} + u_y^2 u_{xx}}{u_x^2 + u_y^2} \tag{6}$$

in Eq. (3) is approximated using central differences, i.e:

$$u_x(x_i, y_j) \approx \frac{u_{i+1,j} - u_{i-1,j}}{2h},$$

$$u_y(x_i, y_j) \approx \frac{u_{i,j+1} - u_{i,j-1}}{2h},$$

$$u_{xx}(x_i, y_j) \approx \frac{u_{i+1,j} - 2u_{i,j} + u_{i-1,j}}{h^2},$$

$$u_{yy}(x_i, y_j) \approx \frac{u_{i,j+1} - 2u_{i,j} + u_{i,j-1}}{h^2},$$

$$u_{xy}(x_i, y_j) \approx \frac{1}{4h^2}\left[u_{i+1,j+1} - u_{i+1,j-1} - u_{i-1,j+1} + u_{i-1,j-1}\right],$$

with $i = 1, ..., N$ and $j = 1, ..., M$.

The function g is given by

$$g = \frac{1}{1 + k|\nabla G_\sigma * u|^2} \tag{7}$$

where k is a parameter and G_σ is given by

$$G_\sigma(x, y) = \frac{1}{\sigma\sqrt{2\pi}}\, e^{-\frac{x^2+y^2}{2\sigma^2}}.$$

3.3 Results

Here we present some results obtained with the application of the proposed edge detection method in several natural images with different complexity levels. We evaluate the performance P of proposed edge detector, and compare it to the performance of two other edge detection algorithms: the Canny edge detector [6] and the single scale edge detector with surround inhibition proposed in [9].

The obtained results using 5 test images are shown in Fig. 1. The first column shows the original images while the second column shows the ground truth. The third and fourth column show the results obtained by the proposed edge detection method and by the Canny edge detector [6], respectively. The fifth column shows the results obtained from the single scale surround inhibition algorithm proposed in [9]. These results can be found in http://www.cs.rug.nl/ imaging/papari/JASP/results.html and they are being used in this paper for comparison purpose only. The performance measures P concerning the three algorithms cited above are displayed at the bottom of each image.

As we can see, for all cases presented our method (third column) gives the best performance in terms of edge detection. The proposed method has the advantage of minimizing the inconvenience effect of false edge detection. On the other hand, the worst result in terms of performance is presented by the Canny edge detector (fourth column) which does not remove effectively texture elements, while the results obtained with the single scale surround inhibition algorithm (fifth column) present a significant advantage in terms of performance measurement once it uses texture suppression mechanism.

The implementation of the proposed method uses the following parameters: the used step size, Δt, for the temporal evolution of u_t was fixed at $\Delta t = 0.25$; the constant k was chosen in a manner which allows function $g(s)$ to carry out its role, which is $g \sim 1$ when s is large (edge points) and $g \sim 1$ when s is small (interior points); the constant λ was fixed at $\lambda = 1$, this means that the balance between the smoothing and the forcing term was unweighted. In [4], the authors describe the choice of parameters with more details.

The Canny edge detector parameters used were: σ, as the standard deviation of a Gaussian derivative kernel and two thresholds t_L and t_H. In our experiments, we fixed $\sigma = 1$ and $t_L = 0.4t_H$.

Table 1 shows the parameters used in the experiments.

Test images	Parameters of the Proposed Method					
	Nonlinear Diffusion Equation				Canny	
	λ	Δt	k	Iterations	σ	t_H
Elephant	1.0	0.25	0.003	100	1.0	0.183
Rhino	1.0	0.25	0.0015	100	1.0	0.289
Goat	1.0	0.25	0.003	100	1.0	0.391
Car	1.0	0.25	0.0007	100	1.0	0.28
Golfcart	1.0	0.25	0.0008	100	1.0	0.3

Table 1 Parameters used for each tested image.

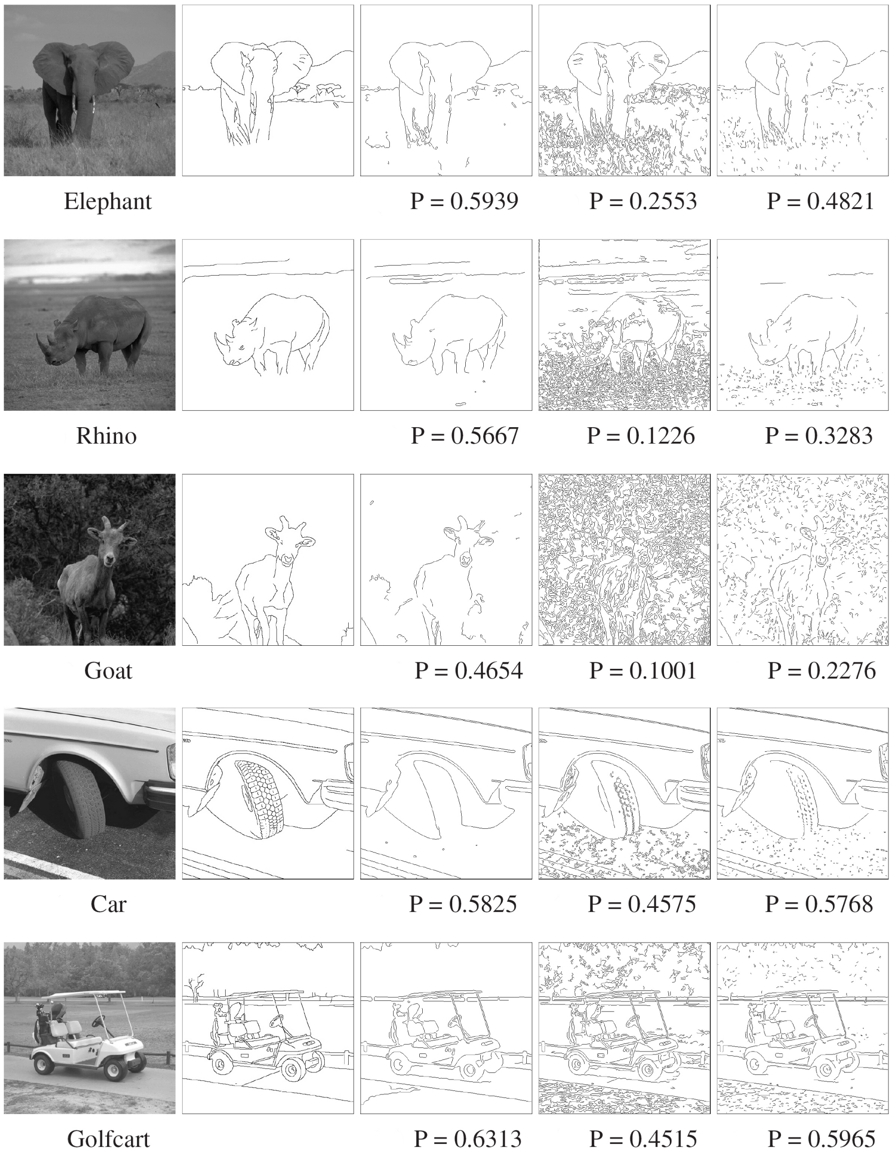

Fig. 1 Natural images (first column); Ground truth edge map (second column); Obtained results from the proposed method (third column); Obtained results from the Canny method (fourth column); Results from the single scale surround inhibition algorithm [9] (fifth column).

4 Conclusions

In this paper an edge detection method was proposed that outperforms all the considered edge detectors, even when the images background is textured.

Through the addition of the nonlinear diffusion method introduced in [3] to the Canny edge detector [6], we showed that the proposed edge detection method has the advantage of minimizing the inconvenience effect of false edge detection and at the same time to be efficient in the detection of true edges.

Due to the capacity that the nonlinear diffusion equations have to smooth an image and at the same time preserve the edges of interest, for a subsequent analysis via edge detector, we believe that the nonlinear diffusion equation introduced in [3] can also be extended the other conventional edge detectors improving the performance of same.

In summary, in this work we have shown that the proposed method is a useful computational mechanism which reflects human perception well.

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