Edge Detection Method for Noisy Images Based on Improved Gaussian-Laplacian Operator (Postprint)

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Abstract

To address the susceptibility of existing gradient operators to noise in image edge detection, this paper proposes an improved edge detection method based on the Gaussian-Laplacian operator. Edge detection in noisy images constitutes a critical task; however, several commonly employed gradient operators, including the previously proposed Gaussian-Laplacian operator, have failed to achieve satisfactory performance. The proposed method enhances the traditional Laplacian edge detection operator and integrates it with a Gaussian filter. Specifically, a Gaussian filter is first applied to smooth the image and suppress noise; subsequently, edge detection is performed using the Laplacian gradient edge detector; finally, experiments were conducted on 10 images selected from the ImageNet dataset, comparing the proposed Gaussian gradient edge detector with conventional edge detectors. Evaluation results demonstrate that the proposed method achieves a higher Peak Signal-to-Noise Ratio (PSNR) and a lower Mean Squared Error (MSE) compared to baseline algorithms. Experimental results indicate that the proposed method can effectively enhance the quality of edge detection in noisy images in practical applications.

Full Text

Preamble

Noise Image Edge Detection Based on Improved Gauss-Laplace Operator

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Abstract: Existing gradient operators for image edge detection suffer from high sensitivity to noise. To address this problem, this paper proposes an improved Gaussian-Laplacian edge detection method. Edge detection in noisy images is a critical task; however, several commonly used gradient operators, including the previously proposed Gaussian-Laplacian operator, have failed to achieve satisfactory results. The proposed method improves upon the traditional Laplacian edge detection operator and combines it with a Gaussian filter. First, a Gaussian filter is applied to smooth the image and suppress noise. Then, edge detection is performed based on the Laplacian gradient edge detector. Finally, experiments were conducted on ten images selected from the ImageNet dataset, comparing the proposed Gaussian gradient edge detector with traditional edge detectors. Evaluation results demonstrate that the proposed method achieves higher Peak Signal-to-Noise Ratio (PSNR) and lower Mean Square Error (MSE) than comparison algorithms. Experimental results indicate that the proposed method can effectively improve the quality of edge detection for noisy images in practical applications.

Keywords: edge detection; Gauss-Laplace; Gauss filter; noise image; peak signal-to-noise ratio (PSNR); mean square error (MSE)

0 Introduction

Images consist of pixels with varying gray levels. While point and line detection are important in detecting gray-level discontinuities, edge detection remains the most general approach. Edge detection in images is achieved by utilizing either the extrema of first-order derivatives (gradient operators) or zero-crossings of second-order derivatives (Laplacian operators). It is the process of identifying and locating sharp discontinuities in an image and plays a crucial role in image analysis as one of the traditional segmentation techniques. Gaussian filters serve a vital function in edge detectors and are used for one-dimensional signal smoothing. When moving from fine to coarse scales, zero-crossings disappear in the scale-space representation of its second-order derivative. For two-dimensional signal applications, zero-crossings do not emerge as the scale increases.

Several studies have explored edge detection methodologies. Reference [6] proposed an image segmentation model incorporating edge detection via Canny and normalized cut feature vectors, with preprocessing using median, Gaussian, or Frost filters based on noise type. Reference [7] developed an edge detection technique for medical images that traces anatomical organ boundaries using intensity and texture gradient features, yielding effective results compared to traditional active contour models. Reference [8] applied various gradient-based edge detectors to images, noting that while the Canny operator produces good results, parameter adjustment is sometimes necessary. Reference [9] demonstrated that morphological edge detectors produce effective results on noisy images compared to Laplacian and Sobel edge detectors. Reference [10] presented edge detection based on morphological operations, determining edges through the difference between dilated and eroded images. Reference [11] analyzed various edge detectors on the Berkeley dataset [12], showing that preprocessing with Gaussian filters before edge detection yields excellent results.

However, the aforementioned methods still suffer from varying degrees of noise sensitivity. To address this limitation, this paper proposes an improved Gaussian-Laplacian operator for image edge detection. The algorithm improves the traditional Laplacian edge detection operator and combines it with a Gaussian filter. Experiments were conducted on ten images selected from the ImageNet dataset, and compared with commonly used gradient operators, the proposed method achieved satisfactory results, validating its reliability.

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1 Common Gradient Operators

Most edge detection algorithms are based on image derivatives or gradients. Images are typically corrupted by Gaussian noise or speckle noise, making edge detection in noisy images critically important. The purpose of an edge detector is to trace the boundaries or contours of desired regions of interest in an image.

1.1 Sobel Operator

The Sobel operator consists of a pair of 3×3 convolution kernels. The kernels produce maximum responses for edges running vertically and horizontally. The kernels are applied separately to the input image to produce different measurements of gradient components in each direction (G_x and G_y), which are then combined to find the absolute magnitude of the gradient at each point and its direction [12].

The gradient magnitude is given by:

$$|\nabla g| = \sqrt{g_x^2 + g_y^2}$$

The gradient direction is determined by:

$$\theta = \tan^{-1}\left(\frac{g_y}{g_x}\right)$$

[Figure 1: see original paper] shows the Sobel edge detection masks for determining gradients in the vertical and horizontal directions. [Figure 2: see original paper] presents the results of Sobel operator edge detection on the Lena image [13].

1.2 Roberts Cross Gradient Operator

The Roberts cross gradient operator is primarily used to compute the two-dimensional spatial gradient of an image. This method is simple and fast. Edge detection is the process of identifying and locating sharp discontinuities in an image. The Roberts cross gradient operator is a first-order differential operator. In the presence of noise and non-uniform illumination, it cannot completely outline object edges and thus cannot suppress noise. The kernels in the Roberts operator produce maximum responses for edges at 45°. [Figure 3: see original paper] shows the mask for the Roberts operator, while [Figure 4: see original paper] displays the edge detection results of the Roberts cross gradient operator on the Lena image.

1.3 Prewitt Operator

Similar to the Sobel operator, the Prewitt operator detects vertical and horizontal edges in images. Unlike the Sobel operator, it does not emphasize pixels near the mask center. Like the Roberts cross gradient operator, the Prewitt operator is also a first-order differential operator and is similarly sensitive to noise, being susceptible to corruption by Gaussian noise or speckle noise. The edge detection masks for the Prewitt gradient operator are shown in [Figure 5: see original paper], and [Figure 6: see original paper] presents the edge detection results on the Lena image.

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2 Improved Gaussian-Laplacian Operator

2.1 Laplacian Operator

Unlike the gradient operators described above, the Laplacian operator finds edges based on the second derivative of the image, searching for zero-crossings. The Laplacian transform $L(x, y)$ of an image with pixel intensity values $I(x, y)$ is given by:

$$\nabla^2 I = \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2}$$

Traditional Laplacian operators often produce double-pixel-wide edges. [Figure 7: see original paper] shows commonly used Laplacian operator templates. It is evident that when detecting edges of bright spots in darker regions, Laplacian operations make them even brighter. Therefore, like gradient operators, Laplacian operators cannot suppress image noise. This paper improves upon this by determining whether an edge pixel lies in a dark or bright region after identifying it as an edge pixel. [Figure 8: see original paper] shows the extended template for the improved Laplacian operator, and [Figure 9: see original paper] presents the edge detection results on the Lena image based on the improved Laplacian operator.

2.2 Gaussian-Laplacian Operator

As discussed in Section 2.1, the Laplacian operator cannot suppress noise. An operator that combines Gaussian smoothing filter with the Laplacian operator —smoothing noise before edge detection—would certainly achieve good results. Based on this principle, the Gaussian-Laplacian operator is proposed. [Figure 10: see original paper] shows commonly used 5×5 Gaussian-Laplacian templates, and [Figure 11: see original paper] displays the edge detection output on the Lena image using the Gaussian-Laplacian operator.

2.3 Gaussian Smoothing Filter

Laplacian edge detection involves two stages: edge enhancement and tracking [14]. A Gaussian filter is applied to smooth the image, and its larger kernel size reduces noise sensitivity. After determining the edge direction, non-maximum suppression is applied to trace the edge path while ignoring pixels that are not part of edges. Finally, hysteresis thresholding is applied to eliminate streaking using two thresholds (t_1 and t_2) on the gradient magnitude of the image. Pixels with values greater than t_1 are considered edge pixels, and pixels connected to edge pixels with values greater than t_2 are also presumed to be edge pixels.

Gaussian gradient uses derivatives of the Gaussian method to determine gradients/derivatives of scalar 2D images and 3D volumes. The two-dimensional representation of the Gaussian kernel is:

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

The σ term in the Gaussian filter is called the smoothing scale, which significantly affects the filter' s response. Larger σ values result in more blurred images and reduced noise sensitivity. [Figure 12: see original paper] shows the Gaussian blur effect on the Lena image.

Generally, a function $f(x, y)$ can be expressed in terms of tensor product as $f(x, y) = g(x) \otimes h(y)$. Instead of applying a 2D kernel, a separable filtering approach is used to compute one-dimensional kernels along the x and y directions. The Gaussian function is separable and can be decomposed into the product of two 1D Gaussian functions. An important property of the Gaussian filter is that it is the only filter that satisfies the uncertainty relation:

$$\Delta x \cdot \Delta w \geq \frac{1}{2}$$

where Δx and Δw are the variances in spatial and frequency domains, respectively. This unique property provides the optimal trade-off between the conflicting objectives of localization in spatial and frequency domains. For the filter, the Gaussian kernel response is non-zero over an infinite domain and most of the region, but it becomes very small due to its exponential form.

2.4 Edge Detection Using Improved Gaussian-Laplacian Operator

The steps of the proposed improved Gaussian-Laplacian gradient edge detection are summarized as follows:

a) The input image can be grayscale or color. The variable sigma is used to determine the Gaussian kernel in both directions. An appropriate sigma value is selected in the Gaussian gradient edge detection method. [Figure 13: see original paper] shows the input Lena image, and [Figure 14: see original paper] displays the grayscale-processed image and the Gaussian-filtered image.

b) Gaussian kernels are generated along the x and y directions. The generated Gaussian kernels involve convolution of the Gaussian function with the first derivative of the Gaussian function.

Some differentials of the Gaussian function are as follows:

$$g(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2}{2\sigma^2}}$$

$$g'(x) = \frac{\partial}{\partial x} g(x) = -\frac{x}{\sigma^2} \cdot \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2}{2\sigma^2}}$$

c) Gaussian smoothing is performed on the image using the generated kernels. The Gaussian kernels in the x and y directions are given by equation (15):

$$H_x = g(x) \otimes g'(x), \quad H_y = g'(x) \otimes g(x)$$

The results are shown in [Figure 15: see original paper].

d) Edge detection is performed on the generated Gaussian-smoothed image. Let f be the Gaussian-smoothed version of the image. When $\sigma = 1$, the output has a segmentation effect; when $\sigma = 2$, segmentation occurs; and the most effective results are produced when $\sigma = 1.5$. The image obtained from edge detection is shown in [Figure 16: see original paper].

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3 Experiments and Results

3.1 Experimental Setup

To evaluate the performance of the proposed improved Gaussian-Laplacian gradient algorithm, experiments were conducted on ten images selected from the ImageNet dataset [15]. The proposed Gaussian gradient edge detector was compared with traditional edge detectors. [Figure 17: see original paper] shows the edge detection results on one sample image, where (a) is the original image; (b) is the result from Sobel operator; (c) from Roberts operator; (d) from Prewitt operator; (e) from Gaussian-Laplacian operator; and (f) from the improved Gaussian-Laplacian operator. The simulation was completed using MATLAB

2012a software on a PC with an Intel Core i3 @ 3.30 GHz processor, 4 GB RAM, running Windows 10 operating system on a 64-bit processor.

3.2 Experimental Results

Several edge detection algorithms were compared with the proposed method using ten images from the ImageNet dataset, and the results were summarized statistically. , , and summarize the PSNR values, MSE values, and computation times of several edge detection algorithms, respectively, with corresponding line charts for intuitive comparison. [Figure 18: see original paper] shows the PSNR value comparison, [Figure 19: see original paper] shows the MSE value comparison, and [Figure 20: see original paper] shows the computation time comparison.

The performance metrics in [Figure 18: see original paper] and [Figure 19: see original paper] demonstrate that the proposed improved Gaussian-Laplacian method achieves high PSNR and low MSE. While the computation time of the proposed method is slightly higher than other methods ([Figure 20: see original paper]), it outperforms conventional techniques in terms of edge tracking quality. The Sobel, Roberts, and Prewitt operators are first-order differential operators that cannot completely outline object edges in the presence of noise and non-uniform illumination. The Gaussian-Laplacian operator also provides unsatisfactory noise smoothing. The proposed improved Gaussian-Laplacian method effectively solves both problems. For PSNR and MSE calculations, ground truth images were provided in the ImageNet dataset.

4 Conclusion

This paper proposes an improved Gaussian-Laplacian gradient algorithm for edge detection, which achieves satisfactory results compared with commonly used gradient operators. The algorithm improves the traditional Laplacian edge detection operator and combines it with a Gaussian filter. To evaluate performance, experiments were conducted on ten images from the ImageNet dataset using PSNR and MSE as evaluation metrics. Experimental results demonstrate the superiority of the proposed method over conventional edge tracking algorithms, significantly improving edge detection quality. Segmentation plays a crucial role in analyzing regions of interest in telemedicine applications, and it is hoped that the proposed method will effectively assist medical applications in the future.

References

[1] Liu Chen, Chi Tao, Li Bingchun, et al. Level set image segmentation method by global and local information [J]. Application Research of Computers, 2017, 34 (12): 3889-3894.

[2] Yang Tingting, Gu Meihua, Zhang Weichuan, et al. Review of color image edge detection algorithms [J]. Application Research of Computers, 2015, 31 (9): 2566-2571.

[3] Chintalapudi K K, Govindan R. Localized edge detection in sensor fields [C]// Proc of the 1st IEEE International Workshop on Sensor Network Protocols and Applications. 2016: 59-70.

[4] Aslam A, Khan E, Beg M M S. Improved edge detection algorithm for brain tumor segmentation [C]// Proc of International Symposium on Computer Vision and the Internet. 2015: 430-437.

[5] Chen Xi, Zhang Ge. Non-Gaussian gabor filters for biometric feature extraction [J]. Computer Engineering & Applications, 2017, 53 (18): 170-175.

[6] Pujar J H, Gurjal P S, Shambhavi D S, et al. Medical image segmentation based on vigorous smoothing and edge detection ideology [J]. World Academy of Science Engineering & Technology, 2010, 19 (68): 444.

[7] Somkantha K, Theera-Umpon N, Auephanwiriyakul S. Boundary detection in medical images using edge following algorithm based on intensity gradient and texture gradient features [J]. IEEE Trans on Bio-Medical Engineering, 2011, 58 (3): 567.

[8] Saif J A M, Hammad M H, Alqubati I A A. Gradient based image edge detection [J]. IACSIT International Journal of Engineering and Technology, 2016, 8 (3): 153-156.

[9] Ren Honge, Liu Mian, Dong Benzhi. Edge detection algorithm of woodflour based on modified morphological operator [J]. Computer Engineering & Applications, 2015, 51 (5): 183-186.

[10] Cao Fengyun, Li Donglin, Zhang Huaqiang, et al. An algorithm of image edge detection based on adaptive multi-directions gray scale morphology [J]. Optical Technique, 2016, 42 (3): 234-238.

[11] Zhang Gunmei, Sun Xiaoxu, Chen Binbin, et al. Edge detection algorithm combining fractional order derivative and Canny operator [J]. Journal of Image & Graphics, 2016, 21 (8): 1028-1038.

[12] Mahmood N, Shah A, Waqas A, et al. Image segmentation methods and edge detection: an application to knee joint articular cartilage edge detection [J]. Journal of Theoretical and Applied Infomation Technology, 2015, 71 (1): 87-93.

[13] Lyu Fuqi, Li Xiaomin. Hybrid image fusion and denoising algorithm using MLT and SRS [J]. Natural Science Journal of Xiangtan University: Natural Science Edition, 2018, 40 (1): 111-114.

[14] Hazarika D, Nath V K, Bhuyan M. SAR image despeckling based on combination of Laplace mixture distribution with local parameters and multiscale

edge detection in lapped transform domain [J]. Procedia Computer Science, 2016, 87 (11): 140-147.

[15] Du Youtian, Li Qian, Zhou Yadong, et al. Semi-supervised learning method of network images based on heterogeneous information fusion [J]. Acta Automatica Sinica, 2012, 38 (12): 1923-1932.

[16] Dong B, Byna S, Wu K. Spatially clustered join on heterogeneous scientific data sets [C]// Proc of IEEE International Conference on Big Data. 2015: 799-808.

[17] Manjanaik N, Manjunath R. Intra frame coding for advanced video coding standard H. 264 to control PSNR and reduce bit rate using Gaussian pulse [C]// Proc of IEEE International Conference on Electrical, Electronics, and Optimization Techniques. 2016: 4326-4331.

[18] Rahman M J, Lampe L. Robust MSE-based transceiver optimization for downlink cellular interference alignment [C]// Proc of IEEE International Conference on Communications. 2015: 4624-4629.

[19] Wang Xiaohua, Xu Xue, Wang Weijiang, et al. A sparse fitting image adaptive compressive sensing algorithm [J]. Journal of Beijing Institute of Technology, 2017, 37 (1): 88-92.

[20] Wang Jun, Liang Fengmei. Non-rigid medical image registration based on P-spline and local mutual information [J]. Application Research of Computers, 2017, 34 (8): 2538-2541.

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