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Anisotropic diffusion noise filtering using region adaptive smoothing strength

Sanghun Kim [a], Suk-Ju Kang [b], Young Hwan Kim [a,*]

[a] Department of Electrical Engineering, Pohang University of Science and Technology (POSTECH), Pohang 37673, Republic of Korea
[b] Department of Electronic Engineering, Sogang University, Seoul 04107, Republic of Korea

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ABSTRACT

This paper presents an improved anisotropic diffusion method using region adaptive smoothing strength. Unlike existing methods, the proposed method uses an adaptive classifier to find a good estimate of the optimal smoothing strength for each iteration to consider the varying noise characteristics. Further, when training the classifiers, the usefulness of the training data is verified and less useful data are excluded to avoid degraded training results, thereby generating robust and improved denoising performance. For reduction of the computational complexity, this paper also proposes a simple region analysis technique. Consequently, the proposed method is appropriate for the devices that have relatively small computing power. Experimental results confirm that the proposed method outperforms AD-based benchmark methods by increased peak signal-to-noise ratio up to 2.37 dB and structural similarity up to 0.0557 for 10% noise level.

1. Introduction

Noise can be combined with the original signal during the image acquisition and transmission processes. It not only corrupts the displayed image but also degrades the performance of image-processing algorithms. For example, noise causes an over-segmentation for image segmentation and a flicker-type error for stereo matching. Therefore, denoising algorithms have been widely studied as basic image processing and preprocessing for other image-processing methods.

Anisotropic diffusion (AD) is one of the most widely used denoising methods because of its cost-effective results. It is motivated by the heat diffusion process and implemented as a nonlinear smoothing. To imitate the process of solving for the heat diffusion, AD filtering is constructed as an iterative approach. Diffusivity is proportional to the gradient magnitude of the intensity as follows:

$$\frac{\partial I(x,y,t)}{\partial t} = div(g(\nabla I(x,y,t)) \cdot \nabla I(x,y,t)), \tag{1}$$

where $I(x,y,t)$ is the gray level of pixel (x,y) at time t and div and ∇ indicate the divergence and gradient operators, respectively. The diffusion coefficient $g(\nabla I(x,y,t))$ is spatially and temporally varying for an anisotropic diffusion, whereas it is a constant for an isotropic diffusion.

Eq. (1) must be converted to a discrete version for application to the image plane as follows:

$$I^{t+1}(x,y) = I^t(x,y) + \Delta t \sum_{d=1}^{D} \left[g(\nabla I_d^t(x,y)) \cdot \nabla I_d^t(x,y) \right], \tag{2}$$

where $I^{t+1}(x,y)$ is the gray level of pixel (x,y) at time t and Δt is a time step. A small Δt demands a high number of iterations; however, an overly large Δt can lead to unexpected behavior. d is an index that indicates a diffusion direction and D is the total number of diffusion directions. D is usually set to four or eight. ∇I_d^t is the gradient between the center pixel and an adjacent pixel in the d-th direction. Diffusivity function $g(\cdot)$, which generates the diffusion coefficient, must monotonically decrease and satisfy two conditions: $g(x)$ goes to one as x goes to zero and goes to zero as x goes to infinity. When AD was introduced for denoising, two diffusivity functions were proposed as follows:

$$g(\nabla I) = \exp\left(-\left(\frac{\nabla I}{k} \right)^2 \right), \tag{3}$$

$$g(\nabla I) = 1 \Big/ \left(1 + \left(\frac{\nabla I}{k} \right)^2 \right), \tag{4}$$

* Corresponding author.
E-mail address: youngk@postech.ac.kr (Y.H. Kim).

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where k is the smoothing strength used to regulate the diffusion. Noise is suppressed minimally if k is excessively small; an overly large k could induce a blurring effect.

Further, when AD was first proposed for denoising, a unified k was used for the entire image [1]. Therefore, diffusion was performed based solely on the gradient without considering region characteristics. However, low gradient does not always indicate noise and high gradient does not always guarantee edges that should be preserved. Consequently, many methods have since been proposed to improve the denoising quality by utilizing region characteristics. Chao's AD (CAD) set k inversely proportional to the variance of the intensity [2]. They focused on the fact that texture regions, which should be preserved, have comparably high variance, whereas smooth regions, which should be well mixed, have low variance. However, CAD fails to preserve weak edges and texture information while comparably preserving the strong edges well because CAD uses the normalized variance. Li's AD (LAD) also exploited contextual information extracted from the variance [3]. Although LAD provides a somewhat improved denoising quality, it requires high computational complexity to determine k and a considerable number of iterations are required to achieve an optimal denoising quality. Cho's dictionary-based AD (DAD) generated and exploited a look-up table based on the multiscale variances to determine k and utilized a single-pass AD to avoid iterative AD filtering [4]. DAD achieves superior denoising quality compared to the existing AD-based methods; however, it loses the advantages of AD-based methods, such as low computational complexity and controllability between the denoising quality and computations. Meaningful improvement in denoising quality has been realized by methods using a region adaptive k [2–4]. However, existing methods exploit the same criterion to determine the k value for each iteration. In reality, noise distribution and noise power are changed during iterative AD filtering. Moreover, existing learning-based methods perform training without any refinement to the training data. Improved training result accuracy can be obtained if training data are filtered by verifying the usefulness of the training data.

The proposed method uses different criteria for each iteration using decision trees to consider the varying noise characteristics. Furthermore, unlike existing denoising methods using a learning-based region adaptive k, insensitive data to k are filtered prior to training. This is because the majority of the training data is usually insensitive to k and degrades the quality of the classifier. Moreover, the proposed method can be performed with low computational complexity owing to a proposed region analysis metric.

This paper is organized as follows. Section 2 describes the proposed denoising method. Section 3 demonstrates the experimental results for denoising quality and computational complexity. Finally, Section 4 concludes the paper.

2. Proposed method

2.1. Overview of the proposed method

The proposed denoising method is based on iterative AD filtering. It employs a learning-based approach to determine the region adaptive k. The proposed method is organized with training (off-line phase) and testing (on-line phase) processes as illustrated in Fig. 1.

Training configurations of k's for the given number of iterations N requires $O(c^N)$ tests where c is the number of candidate k's. This amount of complexity is impractically large even for the training process. The basic idea of reducing the complexity, we adopted, is training k of the intermediate image iteratively so that the complexity can be reduced to $O(N{\cdot}c)$.

It is expected that the noise is similarly reduced during the testing process as it is in the training process. In the training process, AD filtering is iteratively performed on the input noisy image. Classifiers are constructed using the intermediate noisy images, which are generated from the iterative AD filtering. In the testing process, we used a classifier corresponding to the current iteration in order to consider varying noise condition.

2.1.1. Training (off-line phase)

The classifier Tr^t for the current iteration and the denoised image $I^{t+1}_{N;train}$ are generated using the noisy image for the current iteration $I^{t}_{N;train}$ and the reference image $I_{Ref;train}$. To generate the classifier Tr^t, the pairs of feature vectors and ground truth are required. The classifier is trained to estimate a suitable output value for arbitrary input feature vectors using the prepared pairs. Feature vectors, which are extracted from the current denoised image, are used to estimate the appropriate smoothing strength k in the on-line phase. (A detailed description of feature vectors is presented in Section 2.2.) The ground truth for each pixel is obtained through exhaustive search. For this, AD filtering was firstly performed on selected training images using the various k values in the predefined range. Then, the best k for each pixel is selected by comparing the pixels of the denoised image and the noise-free reference image, one by one. To prevent the interference of the meaningless data in training, the proposed method verifies the sensitiveness to smoothing strength k. In the implementation, a decision tree [5] is used as a classifier. The decision tree is one of the widely used learning approaches [6]. (A detailed description of the decision tree is presented in Section 2.3.) It is noticeable that the noisy image $I^{t}_{N;train}$ is required as an input for the t-th training process. Thus, not only classifier Tr^t but also denoised image after AD filtering, $I^{t+1}_{N;train}$, should be generated in the t-th training process. $I^{t+1}_{N;train}$ is obtained by performing AD filtering on $I^{t}_{N;train}$ using the ground truth.

2.1.2. Testing (on-line phase)

The denoised image and the classifier at the current iteration are used to obtain the denoised image in the next iteration. To begin, feature vectors are extracted from the current denoised image. Then, the k value for a pixel is estimated by the classifier in the current iteration using the feature vectors of the pixel as an input. If, unfortunately, the classifier provides a larger k than the optimal value, denoising quality will be degraded. On the other hand, if the estimated value of k is smaller than the optimal, more iterations will be necessary to achieve the same denoising effect. The output image is obtained by performing AD filtering using the estimated k values from the classifier. The output image obtained from the current iteration is used as an input image for the next iteration. The output image becomes the final denoised image when the testing process is terminated.

2.2. Feature vector extraction (region analysis)

The variance of the intensity is the preferred feature to specify the regional characteristics. The variance is clearly high for texture regions and low for homogeneous regions. In the denoising process, it is preferred to mix the color information with the neighborhood pixels to reduce the noise in homogeneous regions. Conversely, it is better to preserve the original signal for texture regions. Therefore, high k and low k are required for homogeneous regions and texture regions, respectively. The conventional CAD and DAD used the local variance for a region analysis to estimate a proper k value. However, the major drawback of the variance is high computational complexity. To solve this problem, a pseudo