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Dictionary-based anisotropic diffusion for noise reduction ☆

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ABSTRACT

This paper presents an anisotropic diffusion-based approach to noise reduction, which utilizes a pre-trained dictionary for diffusivity determination. The proposed method involves off-line and on-line processing steps. For off-line processing, a multiscale region analysis that effectively separates the structure information from image noise is proposed. Using multiscale region analysis, the proposed approach classifies local regions and constructs a dictionary of several patch classes. Further, this paper presents a dictionary-based diffusivity determination that exhibits enhanced performance of anisotropic diffusion. In addition, we propose a single-pass adaptive smoothing that uses a diffusion path-based kernel, which is derived from iterative anisotropic diffusion operations. By using single-pass adaptive smoothing for both off-line and on-line processing, the proposed method is able to avoid the use of expensive iterative region analysis. In on-line processing, the proposed approach classifies input image patches using multiscale region analysis. It subsequently selects the diffusion threshold with the highest matching ratio from the dictionary for each region. Finally, single-pass adaptive smoothing is performed with the selected diffusion threshold. Simulations show that the proposed method outperforms benchmark methods by significantly enhancing the peak signal-to-noise ratio and structural similarity indexes.

1. Introduction

Image denoising is the process of eliminating noise from a noisy image in order to improve the image quality. It is a fundamental pre-processing step in various image processing applications such as image segmentation, video coding, and medical imaging. Conventional image denoising methods often result in the loss of structure information such as edges and textures. To address this problem, researchers have attempted to develop image denoising methods that preserve structure information when smoothing is applied to suppress image noise [10].

The representative methods for structure-preserving image denoising are bilateral filtering [21], adaptive filtering [19], non-local means filtering [3], total variation diffusion [8,20], and partial differential equation (PDE)-based smoothing [2,6,7,16–18,22,26,27]. Among these, PDE-based smoothing is widely used for image denoising because of its superior performance in preserving structure information. The Perona and Malik (PM) model [18], also called the anisotropic diffusion (AD) model, is the most widely used approach to PDE-based smoothing. The AD model, inspired by the heat diffusion process, iteratively performs nonlinear diffusion filtering; a time- and space-varying diffusivity is adopted to preserve structure information while eliminating the image noise. In the AD model, the diffusivity is adjusted on the basis of region characteristics extracted from the gray level gradients. Accordingly, the diffusivity is reduced in regions with high gradients of gray levels in order to reduce the smoothing strength, thereby ensuring that the structure information in these regions is preserved or even enhanced. Although this approach is effective for image denoising, further improvements are possible from the viewpoints of structure preservation and noise elimination by revising the diffusivity-selection method. Therefore, various approaches have been proposed to determine a new diffusivity function and a diffusion threshold based on local region characteristics, in addition to the gray level gradients.

Weickert [26] defined the PM model as pseudo-anisotropy because it uses a scalar-valued diffusion coefficient that is based only on the magnitude of the gray level gradient. As a result, noise components located near strong edges could not be successfully removed using this method. To mitigate this problem, a diffusion tensor is introduced to replace the conventional scalar-valued diffusion coefficient. Application of this diffusion tensor produces diffusion along the direction of the edge while prohibiting perpendicular diffusion. Therefore, noise components located in close

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proximity to strong edges can be removed more effectively as compared to the typical AD model. Black et al. [2] proposed a new diffusivity function that uses Tukey's biweight for enhanced edge sharpness preservation. In [27], a kernel-based method is adopted to improve the accuracy of the separation between the image signal and image noise. Further, the diffusivity is adaptively determined as a function of the median absolute deviation of the gradient magnitudes [2]. Chao and Tsai [7] proposed a new AD model for edge-preserving smoothing that utilizes a local variance to determine the diffusion threshold. Using this local variance, they attempted to reduce the blurring effect around image boundaries and texture regions. Similar to [7], Li et al. [16] utilized contextual information extracted from the local variance while determining the diffusion threshold for a region. In their methods, the noise variance and diffusion threshold are calculated in each iteration using the Canny edge detector [5].

Although these AD-based image-denoising methods, which adaptively adjust the diffusion threshold depending on the region characteristics, facilitate enhanced structure information preservation, they still have some drawbacks. First, conventional region-analysis methods do not effectively distinguish between weak structure information and image noise because they generally use only the local variance of a given noisy image. Second, the conventional algorithms do not extract the optimal diffusivity for a local region because they simply adjust the diffusivity proportionally, based on the results of the region analysis. Finally, the conventional image-denoising methods require the region-analysis process to be performed iteratively before each AD filtering, thereby imposing high computational costs.

In this paper, we propose a single-pass AD model that improves the quality of a denoised image using a dictionary-based diffusivity determination method. Specifically, we first propose a multiscale region analysis to improve the accuracy of the separation between the structure information and image noise. Second, a dictionary-based diffusivity determination method is proposed to regionally select the optimal diffusion threshold using a training process. Finally, we propose single-pass adaptive smoothing using a diffusion path-based kernel (DPK) designed by approximating the iterative AD operations. This enables the proposed method to bypass an iterative region analysis. Moreover, the application of dictionary-based diffusivity determination results in significantly enhanced noise reduction performance over the typical AD. This is achieved by utilizing its enhanced maximum smoothing strength.

The remainder of this paper is organized as follows. In Section 2, we explain the principle of the typical AD model, which forms the theoretical basis of the proposed method. In Section 3, we describe the proposed method, which involves both on-line and off-line processing. In Section 4, we evaluate the image quality using benchmark methods as well as the proposed method. Finally, our conclusions are presented in Section 5.

2. Anisotropic diffusion based noise reduction

AD is a PDE-based noise reduction method that uses a nonlinear diffusion process for noise elimination by modifying the heat equation. Theoretically, AD distinguishes an image signal from image noise using the gray level gradient in a given noisy image. Then, AD iteratively eliminates the gray level variations caused by the image noise while preserving the gray level variations induced by the original image signal. This is accomplished by applying the following PDE for noise elimination:

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

where div and ∇ denote the divergence and the gradient operator, respectively, and $g(\nabla I(x,y,t))$ and $I(x,y,t)$ denote the diffusion coefficient and gray level of a pixel (x,y) at time t, respectively. If $g(\cdot)$ is a constant for all pixels, Eq. (1) is reduced to an isotropic diffusion. Isotropic diffusion-based noise elimination leads to blurring of the structure information because it applies the same smoothing strength to all the pixels regardless of their region characteristics. To preserve the structure information of a given image, the AD model introduces a diffusivity function ($g(\cdot)$) that generates a time and spatially varying diffusion coefficient. As proposed in Perona and Malik [18], the diffusivity function is defined as:

$$g(\nabla I) = 1/\left(1 + (\nabla I/K)^2\right) \text{ or } g(\nabla I) = e^{-(\nabla I/K)^2}, \tag{2}$$

where K denotes the diffusion threshold. The diffusivity function is a monotonically decreasing function satisfying $g(x) \to 0$ as $x \to \infty$. Depending on the determination of the diffusivity function and the K value, the performance of the AD model can be altered significantly. In particular, K can determine the backward and forward diffusion modes. To explain diffusion modes, we introduce the following flux function [18]:

$$\phi(\nabla I) = g(\nabla I) \cdot \nabla I. \tag{3}$$

As shown in Fig. 1, the sign of the gradient of the flux function, ($\phi'(\nabla I)$), reverses at the K value. If $\phi'(\nabla I) > 0$, the forward mode is activated to smooth the gray level variation. Otherwise, the backward mode is activated to inhibit smoothing and to increase the slope of the edges, resulting in an enhancement in their sharpness. In the forward mode, if the value of K is large, it leads to over-smoothing and results in the blurring of the structure information. Conversely, if the value of K is small, the smoothing strength is inadequate to successfully eliminate the image noise. This leads to a requirement for numerous iterative operations to remove image noise. Hence, it is important to select an optimal value of K to maximize the quality of the denoised image.

To apply the PDE obtained in a continuous domain (Eq. (1)) to a discrete two-dimensional image domain, and thereby, to find its solution, the following numerical approximation is used:

$$I^{t+1}(x,y) = I^t(x,y) + \Delta t \sum_{d=1}^{D} \left[g(\nabla I_d^t(x,y)) \cdot \nabla I_d^t(x,y) \right], \tag{4}$$

where $I^t(x,y)$ denotes the gray level of a pixel (x,y) at time t. Δt is a time step and D and d are the total number of diffusion directions and direction indexes, respectively. In the case of two-dimensional (2D) image domains, D is set to four, considering the neighboring pixels on the north, south, west, and east sides. ∇I_d^t represents the gradient between the original and neighboring pixels in each direction at time t. If D is set to eight, the gradients of the diagonal neighbors, north–west, northeast, south–west, and southeast can be calculated in a similar manner.

In Eq. (4), it is important to select a proper Δt value when determining the diffusion rate. If the selected value of Δt is small, several numerical iterations may be required to determine the solution. Conversely, although selecting a large Δt value may

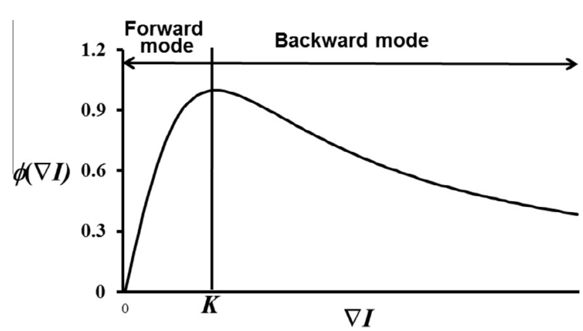

Fig. 1. Normalized flux function, $\phi(\nabla I)$.