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An adaptive diffusion coefficient selection for image denoising

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ABSTRACT

In the gradient dependent denoising methods based on partial differential equation, the process of denoising is controlled through the gradient operation. Hence, the edges are preserved while texture and fine details (having oscillatory nature, the same as noise) are degraded. This paper proposes an algorithm which adaptively selects diffusion coefficient using the residual local power and the amount of the gradient magnitude. Since texture regions correspond to large values of the local power of the residue, this strategy permits to simultaneously preserve the edges, textures, and fine details. To evaluate the proposed method, a variety of experiments are carried out confirming the performance of the proposed algorithm with respect to peak signal-to-noise ratio, mean structural similarity, universal quality index, visual information fidelity and visual quality.

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1. Introduction

Image denoising is an important step in machine vision and image processing. Since noise is related to high frequencies, it is too difficult to remove it while preserving the important features. This problem has attracted an extensive interest and is still a valid challenge [1,2]. One of the best techniques for image denoising is based on partial differential equation (PDE) [3]. In the linear form, the diffusion coefficient is a constant that leads to isotropic diffusion. It is equivalent to filtering the image by Gaussian kernel with a time varying standard deviation, therefore it blurs the edges to some extent [4]. To overcome this problem, anisotropic diffusion was proposed by Perona and Malik (PM) [5]. In the PM nonlinear diffusion, the diffusion coefficient is introduced as a decreasing function of gradient magnitude of the image that varies with time and space. At the edges where the gradient is large, the diffusion coefficient becomes small resulting in edge preservation. On the other hand, in the smooth regions (where the gradient is small) the large diffusion coefficient leads to strong diffusion removing noise. Sharpening occurs for the regions with a higher magnitude of gradient while blurring is observed for the rest. Hence, the PM equation preserves the edges and even enhances them in some cases while removing noise.

PM equation has stimulated a great deal of interest in many image processing applications especially for image denoising [6–12]. It is commonly employed as a tool for segmentation, denoising, edge detection, inpainting, and enhancement of images [13–16].

Most of the denoising methods assume that noise is oscillatory and the image is smooth or piecewise smooth. Therefore, these methods try to separate the smooth parts from the oscillatory ones. The problem is that textures and fine details in the image have oscillatory nature similar to noise. As a result, they are compromised during the noise removing process [17]. Gilboa et al. [18] proposed a ramp preserving complex diffusion which uses imaginary part of image as an approximation for Laplacian to control the diffusion. Barbu et al. [19] discussed a variational model based on minimization of a convex function of the gradient under minimal growth conditions. It smoothens the degraded image and preserves the edges. A directed diffusion equation using wavelet soft thresholding was introduced by Xiaoli et al. [20] to investigate the edges and details blurring issues. To avoid diffusion perpendicular to edge direction, Wang et al. [21] introduced a modified PM model using directional Laplacian. Prasath et al. [22] suggested a weighted anisotropic diffusion to reduce blurring and staircasing effects. Xu et al. [23] suggested an adaptive thresholding in PM diffusion coefficient to better handle the diffusion as time elapsed. A new diffusion coefficients proposed by Tebini et al. [24,25] for better control of the diffusion process in regions containing edge. Wang et al. [26] proposed new second and fourth order anisotropic equations for efficient denoising. Wang et al. suggested a modified ROF [27] model which diffuses along with isophotes for better edge preserving [28]. All of these methods are gradient dependent where the gradient controls the diffusion process and therefore degrades texture and fine details.

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To overcome these drawbacks, a new algorithm based on the PM model is proposed in this paper. Since the diffusion coefficient in PM process depends only on the edge detector, some texture degradation will happen. For texture preserving, we introduce a texture detection operator by applying PM process to the noisy image and calculating the local variance of residue. The residual local variance is adaptively scaled during the time and added to the diffusion coefficient argument of PM model to control it. Accordingly, the diffusion coefficient is small in textures and fine details as well as the edges and consequently these regions are preserved.

The organization of the paper is as follows: In Section 2, some traditional benchmarks and state-of-the-art methods are reviewed in brief. We use these methods to evaluate the proposed method in a comparative study later. Section 3 is devoted to the proposed algorithm. The experimental results are given in Section 4 and finally the conclusion is presented in Section 5.

2. Related works

In the following subsections some popular PDE-based methods and several state-of-the-art denoising algorithms are reviewed in brief. These methods will be used for comparing the results.

2.1. PM nonlinear diffusion

Perona and Malik (PM) [5] proposed an anisotropic diffusion for applications in image processing:

$$I_t = \operatorname{div}\big(c(x,y,t)\nabla I\big) = c(x,y,t)\Delta I + \nabla c.\nabla I, \quad I|_{t=0} = I_0 \tag{1}$$

where div, ∇, and Δ denote divergence, gradient, and Laplacian operators with respect to space variables, respectively. Also, I_0 is the input noisy image, I is the denoised image, and c stands for the diffusion coefficient. The coefficient c is a positive decreasing function of the gradient magnitude. Therefore, in the edges where the gradient magnitude is large, the diffusion coefficient is small and as a result, the blurring effect is negligible. Similarly, in the smooth regions where the gradient magnitude is small, the diffusion coefficient is large and consequently the blurring effect is significant. The following diffusion coefficient is proposed by PM [5]:

$$c\big(|\nabla I|\big) = \frac{1}{1+(\frac{|\nabla I|}{k})^2} \tag{2}$$

where k is a threshold. For $|\nabla I| > k$ sharpening occurs while $|\nabla I| < k$ results in blurring. The PM performance depends on its parameters such as stopping time and smoothing threshold [29]. Catte et al. [30] demonstrated the ill-posedness of PM equation and proposed a regularized version wherein the diffusion coefficient introduced as a function of smoothed gradient:

$$I_t = \operatorname{div}\big(c\big(|\nabla I * G_\sigma|\big)\nabla I\big) \tag{3}$$

where $*$ and G_σ are the convolution operator and Gaussian kernel with standard deviation σ, respectively. Although [30] solves a deep theoretical problems related to PM algorithm, the characteristics of this process essentially remain. The PM method preserves the edges and even enhances them in some cases, but it leads to isolated points and texture degradation [3].

2.2. ROF

Due to the oscillations caused by noise, the total variation (TV) norms of original and noisy image are significantly different. Rudin, Osher and Fatemi (ROF) [27] minimized the total variation of the noisy image subject to the constraints involving the statistics of noise. By assuming that noise is additive with zero mean and known power σ_n^2, the minimization problem becomes:

$$\min_I \int_\Omega \big(|\nabla I|\big)\mathrm{d}x\mathrm{d}y \quad \text{subject to } \frac{1}{|\Omega|}\int_\Omega (I-I_0)^2\mathrm{d}x\mathrm{d}y = \sigma_n^2 \tag{4}$$

ROF method minimizes the total variation of the image and strongly removes its oscillations, therefore, some texture information is removed in addition to noise.

2.3. GSZ

Gilboa, Sochen, and Zeevi (GSZ) [31] reformulated Eq. (4) to preserve the textures:

$$\min_I \int_\Omega \big(|\nabla I|\big)\mathrm{d}x\mathrm{d}y \quad \text{subject to } P_{\hat{R}}(x,y) = S(x,y) \tag{5}$$

where $P_{\hat{R}}$ presents the local power of $(I-I_0)$ and $S(x,y) \geq 0$ is defined as follows:

$$S(x,y) = \frac{\sigma_n^4}{P_R(x,y)} \tag{6}$$

where P_R is the local power of residue of denoised image by ROF (see [31] for more details). GSZ runs ROF twice and preserves the texture.

2.4. Xiaoli method

Xiaoli et al. [20] proposed a directed diffusion equation. In this method, an initial approximation of the original image is calculated and then the denoised image is achieved by applying the following equation:

$$I_t = \alpha_1 b\,\operatorname{div}\big(c\big(|\nabla I * G_\sigma|\big).\nabla I\big) + \alpha_2 I\,\operatorname{div}\big(c\big(|\nabla b * G_\sigma|\big).\nabla b\big) \tag{7}$$

where α_1 and α_2 are two coefficients that avoid edge smoothing and b is the initial approximation driven by wavelet soft thresholding denoising method.

2.5. MPM

Wang et al. [21] discussed a modified PM (MPM) model using directional Laplacian in which the diffusion is directed along the edge:

$$I_t = \left[\frac{\partial}{\partial x}(c_m I_x)N_1^2 + \frac{\partial}{\partial y}(c_m I_y)N_2^2\right] + \left[\frac{\partial}{\partial x}(c_m I_y) + \frac{\partial}{\partial y}(c_m I_x)\right]N_1 N_2 + \alpha c_m \Delta I \tag{8}$$

where the direction of diffusion is

$$N = (N_1, N_2) = (-\partial I_0/\partial y, \partial I_0/\partial x)/|\nabla I| \tag{9}$$

and the diffusion coefficient is $c_m = 1/\sqrt{1+(|\nabla I|)^2}$.

2.6. WWBAD

Prasath et al. [22] suggested a weighted and well-balanced anisotropic diffusion (WWBAD) as follows:

$$I_t = g\,\operatorname{div}\big(c_w\big(x, |\nabla I|\big).\nabla I\big) - \lambda(1-g)(I-I_0) \tag{10}$$

where g is an edge stopping function and c_w includes weight function.

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