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An improved anisotropic diffusion filter with semi-adaptive threshold for edge preservation

Jiangtao Xu*, Yuanyuan Jia, Zaifeng Shi, Ke Pang

School of Electronic Information Engineering, Tianjin University, Tianjin, PR China

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ABSTRACT

This paper presents a noise removal method based on a semi-adaptive threshold in anisotropic diffusion filter to get better detail information protection and stronger noise suppressing ability. In this model, a method of local difference value is applied to distinguish corrupted pixels and noise-free pixels, and parts of the corrupted pixels are replaced by the pixels which have been pre-denoised through a Gaussian filter. Then an anisotropic diffusion model with a semi-adaptive threshold in diffusion coefficient function is applied to get a restored image. In order to implement the semi-adaptive threshold for each diffusion, the gradient value of the corrupted pixels is introduced in the threshold, which results in more diffusion in smooth areas and less diffusion in boundary regions. Compared with the traditional anisotropic diffusion models, the experimental results show that the proposed method can improve the *PSNR* by 30% and *SSIM* by 5%. The filtered images and experimental data indicate that the proposed method performs efficiently in both edge preservation and noise removing.

1. Introduction

Digital image is an important source for human to access complex information in an information age. However, images are easily and unavoidably corrupted by noise in the process of transmission or storage, which makes post-processing difficult. Therefore image denoising with details adequately preserved is a fundamental problem in digital image processing field. In recent years, the anisotropic diffusion filter has received much attention since it was first proposed by Perona and Malik in 1990, which is called Perona–Malik model (PM model) [1]. The PM model uses the gradient value in the direction of east, west, south and north to distinguish variations which are caused by noise and edge in the corrupted image [2]. Unlike conventional spatial filters that blur boundaries or edge structures, anisotropic diffusion filter can eliminate noise and preserve or even enhance edges simultaneously [3].

The PM model can be viewed as a gradient descent of a suitable heat conduction function [4,5]. When there is a unique global minimum in the heat conduction function, it is considered as well posed. However, it is ill posed if the heat conduction function has an infinite number of global minimums, which leads to staircasing phenomenon in flat regions and noise amplification in edge regions [6]. To avoid this, a lot of effort has been made to overcome the challenges [7–9]. In [10], Catte proposed a method (Catte model) that performs a pre-denoising using a Gaussian filter before each iteration. This method can effectively remove noise, but how to choose a right σ of Gaussian kernel is an open problem [11]. In [12], a classical total variation scheme (TV model) for removing noise from polluted images is presented by Rudin, Osher and Fatemi. A better effect with tiny staircases is obtained to a certain degree through the using of gradients alone. In [13], Barcelos built a well-balanced model inspired by the idea

* Corresponding author. Tel.: +86 13752356309.
E-mail address: xujiangtao@tju.edu.cn (J. Xu).

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of mean curvature motion [14]. This method utilized both diffusion and the forcing term to preserve the detail information and avoid staircasing. In [15], Yu exploited an instantaneous coefficient of variation in order to make the process of diffusion edge-sensitive. In [16], edge detector based on anisotropic diffusion scheme (EAD model) is proposed by Prasath and Singh who introduced a spatially adaptive term α in an anisotropic model. This method can achieve good effect by an adaptive edge detector-based indicator function. In [17], Chao and Tsai utilized local variance (CTD model) to preserve the edge information in the diffusion process. This model can effectively preserve information with the application of local variance. However, its ability of noise removing is a little weak when the noise density is high. In [18], Wang proposed a modified Perona–Malik (MPM) model based on directional Laplacian, which diffuses image along the edge direction of the original image. The MPM model directly generalizes the PM model using directional Laplacian with an inhomogeneous weight. In [19], Khan, Arya and Pattanaik introduced a model (UNKD model) which uses a pre-denoising process by applying Laplacian based on second order pixel difference operation to effectively restore the edges when performing the anisotropic diffusion.

In this paper, the aim is also to alleviate the staircasing effect and preserve edge information simultaneously based on PM model. A method with local difference value is applied at first to distinguish the corrupted pixels and free-noise pixels in a polluted image, and then a pre-reduction of noise is utilized to remove the high-pitched noises. Finally, a semi-adaptive threshold function based on local gradient is applied in the diffusion coefficient. Unlike previous anisotropic diffusion filters, which use a constant threshold parameter to control the smoothing level during all the iterations, the proposed filter in this paper uses a semi-adaptive threshold function in accordance with the flat regions or edge regions where the pixels are located to adjust the extent of smoothing level.

2. Basics of anisotropic diffusion filter

2.1. Perona–Malik model

In 1990, Perona and Malik proposed an anisotropic diffusion based on traditional heat conduction equation:

$$\begin{cases} \frac{\partial I}{\partial t} = div[c(||\nabla I||) \cdot \nabla I] \\ I_{t=0} = I_0 \end{cases} \tag{1}$$

where I_0 is the original image at time t, div is a divergence operator, ∇I is the gradient of the image and $c(\|\nabla I\|)$ is diffusion coefficient. Two widely used diffusion coefficient functions are given by Perona as Eqs. (2) and (3):

$$c(||\nabla I||) = \exp\left[-(\frac{||\nabla I||}{K})^2\right] \tag{2}$$

$$c(||\nabla I||) = \frac{1}{1+(\frac{||\nabla I||}{K})^2} \tag{3}$$

where K is a constant threshold value to control the smoothing level. Eq. (2) expresses high contrast values and Eq. (3) involves wide regions [20].

The advantage of Eq. (1) is that the diffusion coefficient $c(\|\nabla I\|)$ can be set adaptively in every iteration, which makes it possible to distinguish the boundary of image and decrease the diffusion along the edge direction. However, this PM model is ill posed, since the process of diffusion is not stable, and the artifacts such as staircasing or blocky effects are much more likely to happen.

2.2. Improved Perona–Malik models

2.2.1. Catte model

To avoid the artifacts, Catte proposed a method that performs a pre-processing using Gaussian filter before the iteration:

$$\begin{cases} \frac{\partial I}{\partial t} = div[c(||\nabla G_\sigma * I||) \cdot \nabla I] \\ I_{t=0} = I_0 \end{cases} \tag{4}$$

where $G_\sigma * I$ denotes a convolution of the image at time t with a Gaussian kernel of scale σ. This method can remove noise effectively, but it is difficult to select scale σ suitably.

2.2.2. TV model

If the diffusion function is $c(s)=(\varepsilon+s^2)^{-1/2}$, then the model of total variation (TV) is recovered.

$$\begin{cases} \frac{\partial I}{\partial t} = div[c(||\nabla I||, \varepsilon) \cdot \nabla I] \\ c(||\nabla I||, \varepsilon) = \frac{1}{\sqrt{\varepsilon + ||\nabla I||^2}} \end{cases} \tag{5}$$

where $\varepsilon=10^{-6}$. The numerical algorithm is simple and relatively fast, and the total variation of the image is minimized subject to constraints involving the statistics of the noise in the TV model [12].

2.2.3. EAD model

Edge detector based on anisotropic diffusion (EAD) performs better in noise removing and edge preservation than those conventional models in the field of anisotropic diffusion filter. In this method, diffusion coefficient is also dependent on the spatially adaptive term α. The formula is given by Eq. (6)

$$\begin{cases} \frac{\partial I}{\partial t} = div[\alpha \cdot c(||\nabla I||) \cdot \nabla I] \\ \alpha = 1 - \nabla G_\sigma * C(I) \end{cases} \tag{6}$$

where G_σ represents a Gaussian kernel and C is a Canny edge detector.

2.2.4. CTD model

An improved anisotropic diffusion model called CTD for detail preserving is proposed by Chao and Tsai. Both local gradient and local variance are incorporated by the CTD model to preserve edge regions and detail information while removing noise. The equations are written as

$$\begin{cases} \frac{\partial I}{\partial t} = div\left[c(||\nabla I||, \sigma_{t,N}^2) \cdot \nabla I\right] \\ c(||\nabla I||, \sigma_{t,N}^2) = 1/\left[1+(\frac{||\nabla I|| \cdot \sigma_{t,N}^2}{K_0})^2\right] \\ \sigma_{t,N}^2 = 1 + \frac{\sigma_t^2 - Min\sigma_t^2}{Max\sigma_t^2 - Min\sigma_t^2} \cdot 254 \end{cases} \tag{7}$$