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Rapid and efficient image restoration technique based on new adaptive anisotropic diffusion function

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ABSTRACT

The anisotropic diffusion is an efficient smoothing process. It is widely used in noise removing and edges preserving via different schemes. In this paper based on a mathematical background and the existing efficient anisotropic function in the literature we developed a new mathematical anisotropic diffusion function which is able to overcome the drawbacks of the traditional process such as the details loss and the image blur. The simulations results and the comparative study with other recent techniques are conducted and showed that the proposed schema generates a wide improvement in the quality of the restored images. This improvement has been shown subjectively in terms of visual quality, and objectively with reference to the computation of some criteria. The simulated images are well de-noised but the most important is that details and structural information are kept intact. In addition to that, the proposed new function was found very interesting and presents numerous advantages like its similarity to the conventional model and the importance of the speed hence it converges faster which allows an opportunity to be well implemented in our de-noising process.

1. Introduction

Improving the image quality is the most important goal in image processing. So, we are looking for an efficient method of noise removal, which is able to de-noise efficiently the image. Linear smoothing technique allows good results but it causes the loss of the details and the image becomes inexploitable for further processing information extraction. They are potentially more powerful than linear filters because they are able to reduce noise levels without simultaneously blurring edges however they can be computationally expensive to use as well as they can generate spurious features and distort existing features in images. Scale space representation is based on the convolution with a chosen kernel in the smoothing operation. The most important parameter supervising an anisotropic filtering function is its convergence speed. This parameter is able alone to characterize the filtering process to be real time running and it allows it to be electronically implemented. The higher the convergence speed is, the more interesting the filtering process is especially when the image is composed by many details and edges or textures. For this reason we are highly interested in the development of a new anisotropic function which is faster than the existing recent models in the literature. Then, the new model is chosen such as it behaves in the range of [0 1]. In addition the proposed model satisfies the convergences requirements and reversibility.

Witkin [1] proposed to generate coarser resolution images by convolving the original image with a Gaussian kernel. This description was developed by Koenderink [2] who motivates the diffusion equation formulation by announcing two criteria, the first is that of causality and the second is about the homogeneity and isotropy. These criteria lead to the diffusion equation formulation. In an analogous way, anisotropic diffusion is considered as an important solution for better image de-noising and edges preserving. Therefore, variational methods for image smoothing have been proposed to reduce noise and restore the quality of an image for better observation. The anisotropic diffusion is a nonlinear iterative process which aims to process separately noise and details by calculating the gradient of each pixel. The first model of anisotropic diffusion has been proposed by Perona and Malik [3]. This model is based on a new definition of the scale space representation via anisotropic diffusion, in which P and M proposed to replace the heat equation by a nonlinear equation. Many studies based on a modified anisotropic diffusion have been proposed for an efficient de-noising technique and edge preserving [4–8]. Anisotropic diffusion algorithms are a powerful tool in image processing. These processes are based on two constraints such as good edge enhancement and fast convergence speed. By this way, this function

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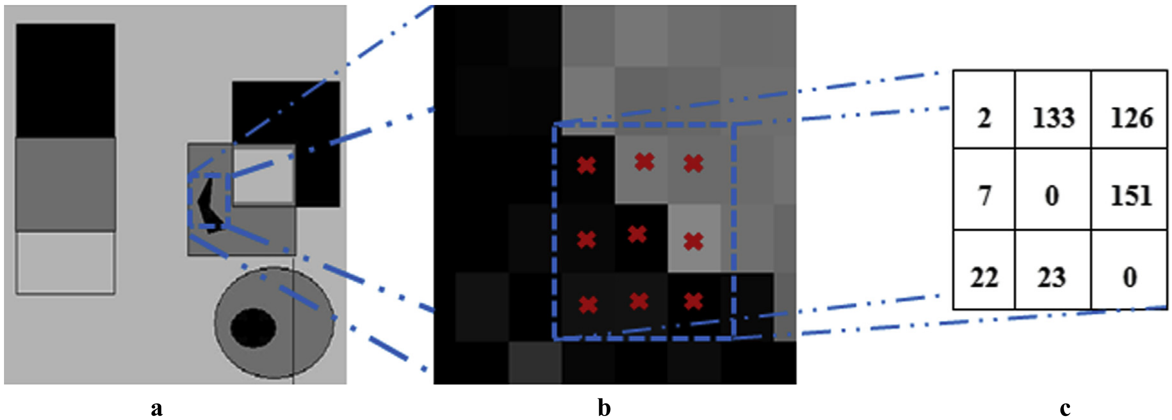

Fig. 1. Spatial neighbors of a selected pixel: (a) input image, (b) zoomed section, (c) first derivative.

will be easier and faster for real time implementation. In this paper, a new anisotropic adaptive schema which smooths the noisy zones at the same time, enhances the edges and preserves the content is presented.

The remainder of this paper is organized as follows: the basic information about Perona & Malik anisotropic diffusion (AD) and its regularized models will be given in Section 2. Section 3 describes our contribution to denoised images without hitting edges and contents. The implementation technique of the new function in the denoising process will be held in Section 4. Section 5 exposes different evaluation metrics and the comparative study of the new algorithm with diverse recent works [3,15–17,23–30]. Conclusion appears in the last section.

2. State of the art and techniques evolution

2.1. Perona and Malik model

The first model of the nonlinear PDE approaches has been proposed in [3] by Perona and Malik, as illustrated by the following equation:

$$\begin{cases} \dfrac{\partial I(x,y,t)}{\partial t} = div\big(g(\|\nabla I(x,y,t)\|).\nabla I(x,y,t)\big) \\ I(x,y,0) = I\_0 \end{cases} \tag{1}$$

where t is the time parameter, $I(x,y,t)$ is the image at time t; div represents the divergence operator; $\nabla I(x,y,t)$ is the gradient of the image, $g(.)$ is the diffusion function and I_0 is the original image (at $t=0$).

The choice of the diffusion coefficient g is very important for an efficient filtering. In fact, the diffusion is higher when a small gradient is detected, consecutively, conversely for higher gradient magnitude. The diffusivity function is chosen to be a non-negative decreasing conductance function which satisfies these conditions:

$$\begin{cases} \lim\limits_{x\to 0} g(x) = 1 \\ \text{and} \\ \lim\limits_{x\to\infty} g(x) = 0 \end{cases} \tag{2}$$

Two different diffusion coefficients are suggested by P&M, in the literature described by Eqs. (3) and (4):

$$g_1\big(\|\nabla I\|\big) = \frac{1}{1+(\frac{\|\nabla I\|}{k})^2} \tag{3}$$

and

$$g_2\big(\|\nabla I\|\big) = \exp\left[-\left(\frac{\|\nabla I\|}{k}\right)^2\right] \tag{4}$$

k is the threshold parameter used to adjust the diffusion process. The gradient $\|\nabla I\|$ serves as the edge detector. Consequently, the diffusion is stopped across edges when the gradient is significant than k $(g=0)$ on the other hand it is encouraged the diffusion is maximal in the uniform regions $(g=1)$ when the gradient magnitude is smaller than k. Perona and Malik sampled the anisotropic diffusion equation to:

$$I_{t+1}(s) = I_t(s) + \frac{\lambda}{|\eta_s|}\sum_{p\in\eta_s} g_k\big(|\nabla I_{s,p}|\big)\nabla I_{s,p} \tag{5}$$

where I is a discretely sampled image, s denotes the pixel position in the discrete 2-D grid, t denotes the iteration step, g is the conductance function and k is the gradient threshold parameter. Constant $\lambda \in [0,1]$ determines the rate of diffusion and η_s represents the 8 neighbors of the pixel s: $\eta_s = \{N, S, E, W, NE, SE, SW, NW\}$ where N, S, E and W are the North, South, East and West neighbors of pixel s, respectively. ∇ represents the difference between two adjacent pixels in the different directions.

$$\nabla I_{s,p} = I_t(p) - I_t(s), \quad p \in \eta_s = \{N, S, E, W, NE, SE, SW, NW\} \tag{6}$$

Edges are significant local changes of intensity in an image. Often, points that lie on an edge are identified by detecting the local maxima or minima of the first derivative or detecting the zero-crossings of the second derivative. The first derivative has a peak at the edge while the second derivative has a zero crossing. The first derivative is computed based on a finite difference such as:

$$f'(x,y) = \lim_{h\to 0}\frac{f(x+h,y)-f(x,y)}{h} \tag{7}$$

$$f''(x,y) = \lim_{h\to 0}\frac{f'(x+h,y)-f'(x,y)}{h} \tag{8}$$

Fig. 1 illustrates the 8 neighborhood of a selected pixel in an area of the original image, and the first derivative.

The differences with the closest neighbors and the conduction coefficients are computed as follows: