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A novel diffusion system for impulse noise removal based on a robust diffusion tensor

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ABSTRACT

The removal of impulse noise is a prerequisite step in image analysis. The classic partial differential equation (PDE) has achieved a great success in suppressing Gaussian noise, but its performance in reducing impulse noise is less satisfactory. The main difficulty arises from finding a nice diffusion function. To tackle this problem, the paper develops a novel diffusion system to suppress impulse noise. The proposed diffusion system consists of two phases. In the first phase, an effective image filter called Clean Pixel Excluder (CPE) is designed to identify clean pixels from the noisy ones. In the second phase, a robust diffusion model is reformulated by developing a novel diffusion tensor to control the smoothing on both direction and strength adaptively. A numerical scheme based on the multi-scale technique is provided. Extensive experiments on both synthetic and real images show that the proposed system achieves a superior performance over several standard methods in terms of noise suppression and detail preservation.

1. Introduction

Impulse noise, caused by the malfunctioning pixel in a camera sensor or transmission in the noisy channel, is widely seen in modern industry. It can be classified either as salt and pepper noise with the noise pixel taking only the maximum or minimum, or as random-value impulse noise in the dynamic range. The restoration of the noisy image corrupted by impulse noise has been extensively studied. Median filtering was one of the most well-known methods due to its simplicity [1,2], but it was prone to overlooking local feature such as the possible presence of edges [3,4]. Recently, a model named weighted-linking pulse coupled neural network (PCNN) was proposed to construct a two-channel parallel noise filter. This model firstly detected noise pixel by neuron pulses and then removed the noise pixel iteratively by evaluating signal variations of the neuron pulses [5]. Alajlan et al. [6] proposed a method to achieve detail preservation and noise smoothing concurrently. A decision-based algorithm was shown to obtain encouraging results except when the noise ratio was high [7]. In [8], the authors proposed a new impulse detector, which was based on the differences between the current pixel and its neighbors aligned with four main directions. A recent work proposed by Cai et al. decoupled denoising problem into two phases to smooth Gaussian noise and impulse noise [9]. However, when the image was only corrupted by impulse noise, the model turned out to be a well-known detail preserving model [10–12]. Diffusion techniques, successfully applied in removing Gaussian noise [13–15], have been also developed to smooth impulse noise [16]. In [16], the authors smoothed random-value impulse noise by designing a speed control function and a fidelity function. However, the divergence operation used therein may deteriorate diffusion process and result in an unsatisfactory result.

Inspired by the work [16], this paper proposes an effective diffusion system by developing a Clean Pixel Excluder (CPE) filter and a robust diffusion model for the removal of impulse noise. In the first phase, the CPE filter is formulated to discriminate clean pixels from the corrupted ones. Then, a robust diffusion model is reformulated by designing a diffusion tensor $\boldsymbol{E}$ to control the smoothing on both direction and strength adaptively. Numerically, the multi-scale method [17] is used to estimate noise geometry structure. The performance of the proposed method is also validated by extensive experiments.

The outline of the paper is as follows. In Section 2, we describe the classic diffusion models briefly. The proposed CPE filter and the multi-scale diffusion model with a robust diffusion tensor are described in Section 3. Section 4 conducts extensive experiments and makes a discussion in detail on the experimental results, and the conclusion is followed in Section 5.

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2. A brief review

Nonlinear diffusion filtering is basically an evolutionary process. A generic evolutionary equation can be modeled as

$$\begin{cases} \dfrac{\partial I}{\partial t} = div(\boldsymbol{D}\nabla I) \\ I_{(t=0)} = I_0 \end{cases}, \tag{1}$$

where I_0 is the noisy image, $div(\cdot)$ denotes the divergence operation and $\boldsymbol{D}$ is a diffusion tensor, which is defined by

$$\boldsymbol{D} = \lambda_+ \theta_+ \theta_+^T + \lambda_- \theta_- \theta_-^T,$$

where λ_+, λ_- and θ_+, θ_- are the spectral elements of the tensor $\boldsymbol{D}$, respectively. Naturally, the local geometry structure of an image I possesses some common features:

- The two orthogonal directions θ_+ and θ_-, representing the local maximum and minimum variations of image gray level, respectively.
- The two eigenvalues λ_+ and λ_-, measuring variations of the image gray level along θ_+ and θ_-, respectively.

Different settings of elements λ_+ and λ_- result in different diffusion schemes. For instance, by defining

$$\begin{cases} \lambda_+ = 1 \\ \lambda_- = 0 \end{cases},$$

one will have the well-known curvature flow equation [18]:

$$\frac{\partial I}{\partial t} = I_{\theta_- \theta_-}.$$

The divergence-based equation in Eq. (1) may not be able to fully smooth the noise, since the divergence operator degrades geometry attributes of the tensor $\boldsymbol{D}$. Recently, an algorithm called oriented Laplacian-based equation has been proposed to achieve a significant improvement in diffusion tensor preservation [17], which is formulated as

$$\frac{\partial I}{\partial t} = \mathrm{tr}(\boldsymbol{DH}), \tag{2}$$

where $\boldsymbol{H}$ is a Hessian matrix.

Although the aforementioned algorithms achieve encouraging results in removing Gaussian noise, they are incapable of smoothing impulse noise. The goal of this paper is to formulate a specialized diffusion system to remove impulse noise.

3. The proposed multi-scale diffusion system

In this section, we will describe our diffusion system, which consists of two phases. In the first phase of noise detection, we design a filter aiming to discriminate clean pixels from the noisy ones. In the second phase, a robust trace-based diffusion model is reformulated to correct and restore the noise pixels.

3.1. Definition of the CPE filter of an image

Salt and pepper noise as a type of impulse noise can be well recognized by detecting the maximum and minimum in the image. However, such schemes may fail when image pixel shares the same value with the noise one. To overcome this drawback, we define a new filter named Clean Pixel Excluder (CPE) to discriminate the image pixel whose gray level is the same as that of the noise one.

Let I be an image of size $r \times c$, and $N_{(x,y)}$ be a neighboring area centering in pixel (x, y) with the window size of $w \times w$:

$$N_{(x,y)} = \{(k,l) : |k-x| \le (w-1)/2, |l-y| \le (w-1)/2\}, \tag{3}$$

where (k, l) denotes the pixel position in the window.

The CPE filter is defined by

$$CPE(I_{(x,y)}, z) = \begin{cases} I_{(x,y)} & \text{if } F(I_{(x,y)}, z) > \varepsilon \\ a, a \notin Z & \text{if } F(I_{(x,y)}, z) \le \varepsilon \end{cases} \tag{4}$$

with $F(\cdot)$ defined by

$$F(I_{(x,y)}, z) = \sin\left(\sum_{k=-(w-1)/2}^{(w-1)/2} \sum_{l=-(w-1)/2}^{(w-1)/2} \left(\frac{\| z - I_{(x+k, y+l)} \|}{z * w^2} \right) \pi \right), \tag{5}$$

where z is a noise gray level belonging to noise gray level set Z, $z \in Z$. ε is a small tuning threshold and a is a real number, satisfying $a \notin Z$. The main idea of the proposed filter assumes that the neighboring pixels of each pixel possess similar gray levels, and thus a singular gray level is seldom observed. Therefore, the clean pixel can be easily excluded by inspecting its neighbors by the CPE operation.

Following the CPE operation, one will have a noise candidate set S, defined by

$$S_{(x,y)} = \begin{cases} 1 & CPE(I_{(x,y)}, z) \in Z \\ 0 & CPE(I_{(x,y)}, z) \notin Z \end{cases}. \tag{6}$$

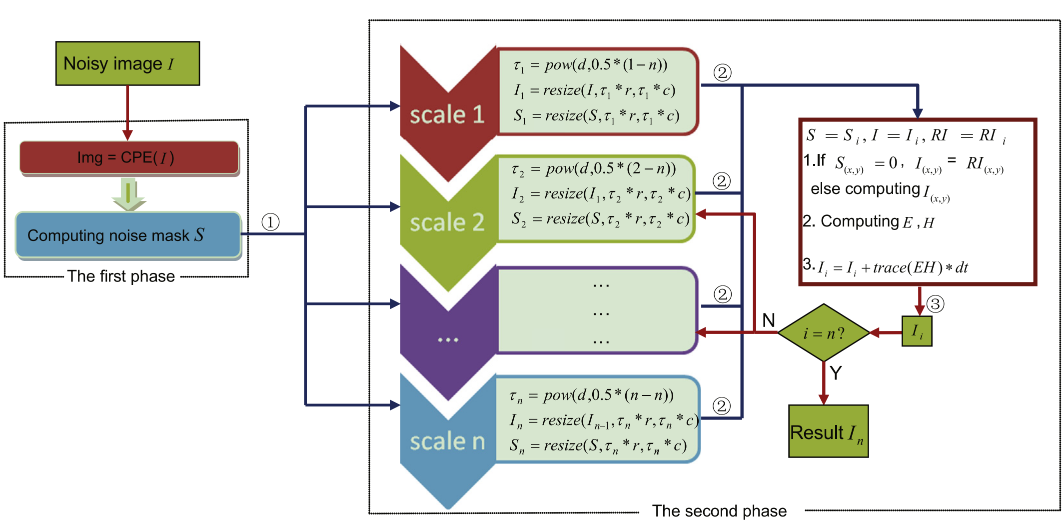

Fig. 1. Flowchart of the proposed diffusion system.

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