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Random-valued impulse noise removal by the adaptive switching median detectors and detail-preserving regularization

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ABSTRACT

This paper firstly proposes an adaptive non-local switching median filter. Then, a two-phase scheme is presented to remove the random-valued impulse noise. In the first phase, the adaptive switching median filter or the adaptive non-local switching median filter is used to identify the pixels which are likely to be the noise candidates. In the second phase, only the noise candidates' values are restored by a detail-preserving regularization method. Simulation results show that the proposed method is significantly superior to some of the state-of-the-art methods.

1. Introduction

Digital images are apt to deteriorate during their acquisition, storage or transmission in noise environment. Classically, this degradation is the result of two phenomena. The first one is deterministic and is related to the image acquisition manner. The other one is random and corresponds to the noise coming from any signal transmission or signal storage [1]. Little useful information can be acquired from the corrupted image without their being restored, and the corrupted images severely impede subsequent image processing tasks, such as image segmentation, edge detection or object recognition. Therefore, it is absolutely necessary to restore the original image from the corrupted image [2].

Image denoising, being a pre-processing of removing unwanted noise imposed in images, is widely studied in image and video applications. During the past decade, numerous and diverse denoising methods have been proposed to remove the two common types of noise distributions: additive Gaussian noise and impulse noise. In this paper, we only consider the random-valued impulse noise.

The median filter (MED) [3] is the most popular choice for removing the impulse noise from images because of its effectiveness and high computational efficiency. However, it is invalid at high noise densities [4]. When the noise level is over 30%, the edge details of the original image will not be preserved and some patches will be appeared. To avoid the damage of edge pixels, a lot of solutions have been proposed to trade off detail preservation against noise reduction, such as the multistate median filter [5], the center weighted median filter [6], the Tri-State median filter (TSM) [7], the rand-order mean filter [8] and the stack filter [9]. However, these filters are still implemented uniformly across the image without considering whether the current pixel is a noise free or not. As a result, this would inevitably alter the intensities and remove the image details contributed from uncorrupted pixels, and cause image quality degradation. In order to overcome this drawback, the switching scheme or the two-stage method [10] is introduced. The basic idea is that the noisy pixels are detected first and filtered afterward, whereas the uncorrupted pixels are left unchanged [11]. Recently, many impulse noise removal methods based on two-stage idea have been reported, including the two-pass median filter [12], progressive switching median (PSM) filter [13], the adaptive weighted median filter [14], the peak-and-valley filter [15], the conditional signal-adaptive median filter [16], a directional weighted median filter (DWM) [17], Luo-iterative median filter (Luo) [18], the pixel-wise MAD filter [19], the adaptive switching median filter (ASWM) [20], the contrast enhancement-based filter [21], etc. Among these filters, the adaptive switching median filter has shown good performance for identifying the pixels which are likely to be the noise candidates, but the replacement method in the second phase cannot preserve the features of the images, in particular, the edges are smeared.

Recently, using the non-smooth data-fitting term (e.g., ℓ_1), an edge-preserving regularization method has been proposed to remove the impulse noise [22]. Sequentially, a two-stage method in [23] and [24] was proposed to improve this variational method in

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removing impulse noise. However, its capability is mainly limited by the accuracy of the noise detector in the first phase.

This paper firstly proposes an adaptive non-local switching median filter, and then a two-stage scheme which combines the adaptive switching median filter or the adaptive non-local switching median filter with the variational method proposed in [22] is presented to remove the impulse noise. More precisely, in the first phase, the adaptive switching median filter or the adaptive non-local switching median filter is used to identify the noise pixels. In the second phase, these noise candidates are restored by an edge-preserving regularization method. The performance of the proposed two-stage scheme, denoted by ASWM-EPR and ANSW-EPR, is much better than some of the state-of-the-art impulse noise removal methods.

This paper is organized as follows. In Section 2, the adaptive switching median filter is reviewed and the adaptive non-local switching median filter is presented. The proposed two-stage impulse noise removal method is presented in Section 3. Section 4 gives simulated experiments. Finally, a brief conclusion is presented in Section 5.

2. Adaptive non-local SWM filter

2.1. Review of the impulse noise model

When an image is corrupted by random-valued impulse noise, only part of the pixels is changed. To be precise, let $x_{i,j}$ and $y_{i,j}$ denote the luminance value of the original image and the noisy image at the location $(i, j) \in A \equiv \{1, 2, ..., M\} \times \{1, 2, ..., N\}$, respectively. An image containing impulse noise with probability p can be described as follows:

$$y_{i,j} = \begin{cases} x_{i,j}, & \text{with probability } \ 1-p \\ n_{i,j}, & \text{with probability } \ p \end{cases}. \tag{1}$$

where $n_{i,j}$ denotes uniformly distributed random number in $[n_{\min}, n_{\max}]$, which is the dynamic range of the image. For 8-bit images, $n_{\min} = 0$ and $n_{\max} = 255$.

2.2. Review of the adaptive switching median (ASWM) filter

The switching median (SWM) filter is a two-step scheme. In the first phase, each pixel is judged whether it is a noise pixel or not by the way – the absolute difference between the median value in its neighborhood and the value of the current pixel itself is whether greater than a given threshold. If satisfy, a classic median filter is applied in the second phase; if not, the current pixel is noise free and will be not changed. However, it is not wise to execute the operation of noise detection by the same threshold without considering the local characteristic, such as the local mean and the local standard deviation. The adaptive switching median (ASWM) filter, proposed in [20], is an adaptive SWM filter that does not require a priori knowledge and automatically defines a local threshold based on the local standard deviation. More precisely, let $y_{i,j}$ denotes the value of the noisy image at pixel location (i, j). The restored image $z_{i,j}$ by the ASWM filter is given as follows:

$$z_{i,j} = \begin{cases} m_{i,j} & \text{if } \ |y_{i,j} - M_{i,j}| > \alpha \times \delta_{i,j}, \\ y_{i,j} & \text{otherwise} \end{cases} \tag{2}$$

where $M_{i,j}$, $\delta_{i,j}$ and $m_{i,j}$ represent the weighted mean, the weighted standard deviation and the median in its neighborhood, respectively. $|\,|$ denotes the absolute value operator. α is a given parameter and $\alpha \times \delta_{i,j}$ represents the local threshold.

2.3. The proposed adaptive non-local switching median (ANSM) detector

The ASWM filter has already been a good noise detector. However, at high noise densities, some noise values may be far from their neighbors' values, in which case, the weighted standard deviation could be large so that the absolute difference between the weighted median value in its neighborhood and the value of the current pixel itself is less than the local threshold even if the α is very small. Thus, it needs to find a way to overcome this drawback. In this paper, a better noise detector is presented to detect the noise candidates at high noise densities. First, the proposed strategy is illustrated through an example.

From Fig. 1, we know that the processing pixel (i, j) (i.e. whose value $y_{i,j}$ is 115) is in nine sub-windows of size 3×3. These sets can be expressed as follows:

$$\Omega Q_{1,i,j} = \{y_{i+s,j+t} : -2 \le s \le 0, -2 \le s \le 0\}, \tag{3}$$

$$\Omega Q_{2,i,j} = \{y_{i+s,j+t} : -2 \le s \le 0, -1 \le s \le 1\}, \tag{4}$$

$$\Omega Q_{3,i,j} = \{y_{i+s,j+t} : -2 \le s \le 0, 0 \le s \le 2\}, \tag{5}$$

$$\Omega Q_{4,i,j} = \{y_{i+s,j+t} : -1 \le s \le 1, -2 \le s \le 0\}, \tag{6}$$

$$\Omega Q_{5,i,j} = \{y_{i+s,j+t} : -1 \le s \le 1, -1 \le s \le 1\}, \tag{7}$$

$$\Omega Q_{6,i,j} = \{y_{i+s,j+t} : -1 \le s \le 1, 0 \le s \le 2\}, \tag{8}$$

$$\Omega Q_{7,i,j} = \{y_{i+s,j+t} : 0 \le s \le 2, -2 \le s \le 0\}, \tag{9}$$

$$\Omega Q_{8,i,j} = \{y_{i+s,j+t} : 0 \le s \le 2, -1 \le s \le 1\}, \tag{10}$$

$$\Omega Q_{9,i,j} = \{y_{i+s,j+t} : 0 \le s \le 2, 0 \le s \le 2\}. \tag{11}$$

Each sub-window or set has a weighted mean $M_{k,i,j}$ and a weighted standard deviation $\delta_{k,i,j}$ defined in [20] expressed as:

$$M_{k,i,j} = \text{mean}(\Omega Q_{k,i,j}), \quad k = 1, 2, ..., 9 \tag{12}$$

$$\delta_{k,i,j} = \text{deviation}(\Omega Q_{k,i,j}), \quad k = 1, 2, ..., 9 \tag{13}$$

Then, computing the absolute difference between the processing pixel value and the each weighted mean $M_{k,i,j}$, if the absolute difference is greater than the corresponding local threshold $\alpha \times \delta_{k,i,j}$, the processing pixel may be a noise one in the sub-window $\Omega Q_{k,i,j}$. It is reasonable that, the more the processing pixel is considered as a noise in the nine sub-windows, the more

Fig. 1. A noisy Lena image.