Optik 126 (2015) 1598–1601

Contents lists available at ScienceDirect

Optik

journal homepage: www.elsevier.de/ijleo

Switching median and morphological filter for impulse noise removal from digital images

Cao Yuan, Yaqin Li *

School of Mathematics & Computer Science in Wuhan Polytechnic University, No. 68, Xuefu South Road, Changqing Garden, Wuhan City, Hubei Province, China

ARTICLE INFO

Article history:
Received 24 March 2014
Accepted 11 May 2015

Keywords:
Impulse noise
Noise detector
Median filter
Morphological filter

ABSTRACT

A switching median and morphological filter is presented for removing impulse noise. In the proposed filter, the noise detector is first adopted to identify noise pixels by combining the morphological gradient based on the erosion and dilation operators with the top-hat transform. Then the detected impulses are removed by the hybrid filter, which combines the improved median filter using only the noise-free pixels with the conditional morphological filter using the improved morphological operations. Extensive simulations demonstrate that the proposed filter can realize accurate noise detection and it has significantly better restoration performance than a number of decision-based filters at the various noise ratios.

1. Introduction

In the process of recording or transmission, digital images are often contaminated by impulse noise arising from faulty sensors, channel transmission errors and timing errors in analog-to-digital conversion [1,2]. To improve the quality of degraded digital images, it is of great significance to adopt effective approaches to remove impulse noise from digital images.

Various filters have been proposed for the removal of impulse noise. Among them, the median filter [3] and the morphological filter [4–6] have been well known for their superior performance in noise suppression and edge preservation in comparison with linear filters. However, the standard median filter and the morphological filter are implemented on the entire image and modify both noise pixels and noise-free ones, therefore resulting in damage to image details. To address this problem, numerous switching-based filters have been proposed by firstly utilizing a noise detector to identify the noise pixels and then removing them using the local statistics based filter. Examples include progressive switching median (PSM) filter [7], adaptive center weighted median (ACWM) filter [8], directional difference based switching median filter (DDSM) [9], Laplace detector-based switching median (LDSM) filter [10], pixel-wise MAD-based (PWMAD) filter [11], switching median filter with boundary discriminative noise detection (BDND) [12], opening closing sequence (OCS) filter [13], fast switching median (FSM) filter [14], efficient edge-preserving (EEP) filter [15], convolution noise detection-based switching median (CNDSM) filter [16] and noise adaptive fuzzy switching median (NAFSM) filter [17]. Although these filters usually perform better than the median filter and the morphological filter, they tend to remove many important features or retain numerous impulses in the filtered images at high noise ratios.

To effectively restore the images corrupted by impulse noise especially at high noise ratios, we propose a switching morphological and median (SMM) filter. In the proposed SMM filter, noise pixels are identified by the morphological noise detector based on such morphological operator as erosion, dilation, opening and closing. The detected noise pixels are restored by combining the improved median filter with the conditional morphological filter. The advantage of the proposed filter in noise detection and noise removal has been demonstrated by extensive comparisons with numerous well-known decision-based filters operating on standard test images.

2. Morphological noise detector

It has been well known that the pixels corrupted by impulse noise will display intensity extremes in their neighborhood. Accordingly, the erosion operator and the dilation operator are adopted to identify all the corrupted pixels in that the two operators correspond to finding the minimum and maximum of the pixel values within a specified neighborhood, respectively.

* Corresponding author. Tel.: +86 18971666920.
E-mail addresses: yuancao1980@mail.com (C. Yuan), leeyaqin@gmail.com (Y. Li).

http://dx.doi.org/10.1016/j.ijleo.2015.05.032
0030-4026/

Let the input image f and the structuring element b denote two discrete-valued functions defined on a two-dimensional discrete space. The erosion and the dilation can be defined as:

$$(f\Theta b)(i,j)=\min\left\{f(i+s,j+t)-b(s,t)\,\middle|\,(i+s,j+t)\in D_f,(s,t)\in D_b\right\} \tag{1}$$

$$(f\oplus b)(i,j)=\max\left\{f(i-s,j-t)+b(s,t)\,\middle|\,(i-s,j-t)\in D_f,(s,t)\in D_b\right\} \tag{2}$$

where Θ and $\oplus$ denote the erosion operator and the dilation operator, respectively. D_f and D_b denote the domain of the gray-scale image f and the domain of the structuring element b, respectively.

With the above erosion and dilation operators, two morphological gradients are determined as:

$$g_e(i,j)=f(i,j)-(f\Theta b)(i,j) \tag{3}$$

$$g_d(i,j)=(f\oplus b)(i,j)-f(i,j) \tag{4}$$

Based on the two morphological gradients $g_e(i, j)$ and $g_d(i, j)$, the hybrid gradient $g_h(i,j)$ is defined as $g_h(i,j)=g_d(i,j)\bullet g_e(i,j)$. It is easy to understand that the considered pixel at (i,j) will be noise candidate with the noise flag $\eta(i,j)=1$ if $g_h(i,j)=0$ or noise-free pixel with $\eta(i,j)=0$ if $g_h(i,j)\neq 0$.

The above noise detection strategy based on the hybrid morphological gradient can identify the corrupted pixels very effectively. However, it will misclassify some uncorrupted pixels as the noise pixels. For example, a noise-free pixel located at the edge region in the corrupted image will be misidentified as the noise candidate if it takes the minimum intensity value or maximum one in the detection window. Similarly, a pixel located in the smooth edge where all the pixels have the same intensity values will be also misclassified as the noise candidate. To address this problem, the opening operator $(f\circ b')(i,j)$ and the closing operator $(f\bullet b')(i,j)$ will be adopted to dismiss some misidentified noise-free pixels from the noise candidates.

For any detected noise candidate at (i,j), $(f\circ b')(i,j)$ and $(f\bullet b')(i,j)$ are the cascades of erosion–dilation and erosion–dilation defined as:

$$(f\circ b')(i,j)=((f\Theta b')\oplus b')(i,j) \tag{5}$$

$$(f\bullet b')(i,j)=((f\oplus b')\Theta b')(i,j) \tag{6}$$

With the opening and closing operators, the white top-hat transform $WTT(i,j)$ and the black top-hat transform $BTT(i,j)$ are expressed as:

$$WTT(i,j)=f(i,j)-(f\circ b')(i,j) \tag{7}$$

$$BTT(i,j)=(f\bullet b')(i,j)-f(i,j) \tag{8}$$

The above two transforms, $WTT(i, j)$ and $BTT(i, j)$, will extract bright features and dark features smaller than the structuring element b', respectively. Let the new local morphological measure $M(i, j)$ denote the bigger one between $WTT(i,j)$ and $BTT(i,j)$. It is clear that $M(i, j)$ characterizes both bright features and dark features in the images. Thus, the noise candidate at (i,j) will be a true noise pixel if $M(i, j)$ exceeds a predefined detection threshold T_{d} or a noise-free pixel if $M(i,j)\leq T_d$.

Based on the noise detection results, the noise ratio R can be roughly estimated as:

$$R=\frac{S}{M\times N} \tag{9}$$

where S denotes the number of the detected noise pixels in the image while M and N denote the total number of pixels in the horizontal and vertical dimensions of the image.

3. Morphological and median filter

The hybrid filter combining the conditional morphological filter with the improved median filter will be adopted to remove the detected impulses. For any noise pixel (i, j) with $\eta(i, j)=1$ in the image, the conditional erosion and conditional dilation can be defined as:

$$(f\Theta b'')^c(i,j)=\min\left\{f(i+s,j+t)-b''(s,t)/\eta(i+s,j+t)=0,\ (i+s,j+t)\in D_f,(s,t)\in D_{b^*}\right\} \tag{10}$$

$$(f\oplus b'')^c(i,j)=\max\left\{f(i-s,j-t)+b''(s,t)/\eta(i-s,j-t)=0,\ (i-s,j-t)\in D_f,(s,t)\in D_{b\bullet}\right\} \tag{11}$$

Based on the above two operators, the conditional opening and conditional closing can be expressed as:

$$(f\circ b'')^c(i,j)=((f\Theta b_1)^c\oplus b_2)(i,j) \tag{12}$$

$$(f\bullet b'')^c(i,j)=((f\oplus b_1)^c\Theta b_2)(i,j) \tag{13}$$

where $b1$ denotes the structuring element used for the conditional erosion or the conditional dilation while $b2$ means the structuring element used for the erosion or the dilation. The conditional opening and the conditional closing can remove the impulses with high amplitude and the impulses with low amplitude, respectively. Accordingly, the two combined operators, $(f\circ b'')^c(i,j)$ and $(f\bullet b'')^c(i,j)$, can suppress impulse noise in the image very effectively. However, the outputs of the two operators are likely to deviate from the true value of the corrupted pixel to some extent. Therefore, the improved median filter is combined with the two operators to accurately estimate the noise pixel value.

Let the median value of the increasingly ordered samples of noise-free pixels in the $(2L_f+1)\times(2L_f+1)$ filtering window $W(i, j)$ centered at (i,j) be $m(i,j)$. The true value $r(i,j)$ of the noise pixel can be estimated by combining the output of the conditional morphological filter with that of the improved median filter, i.e.,

$$r(i,j)=\frac{(f\circ b'')^c(i,j)+w(i,j)\cdot m(i,j)+(f\bullet b'')^c(i,j)}{w(i,j)+2} \tag{14}$$

where $w(i,j)$ denotes the weighted coefficient of the median value $m(i,j)$. Extensive simulations show that the decreasing value should be assigned to $w(i,j)$ with the increasing noise ratio to yield good restoration results. Therefore, $w(i,j)$ is formulated as:

$$w(i,j)=\frac{1-R}{2R} \tag{15}$$

It should be noted that for the structuring element $b1$ and the filtering window W, their sizes will be adaptively determined in the same way. Take W for example. Starting with $L_f=1$, the filtering window is iteratively extended outwards by one pixel in its four sides until the number of noise-free pixels within this window is 1 at least. For the SMM filter, the final output of any pixel at (i,j) will be $r(i,j)$ if $\eta(i,j)=1$ or $f(i,j)$.

4. Experimental results

To demonstrate the effectiveness of the proposed SMM filter, comparisons about noise detection performance and restoration performance are made among the BDND filter, the OCS filter, the FSM filter, CNDSM filter, NAFSM filter and the SMM filter. The 512×512 gray-level images such as Bridge, Boat, Barbara and Pepper are chosen as the test images. These images are corrupted by the salt-pepper impulses with the equal probability. Simulations