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Decision-based adaptive morphological filter for fixed-value impulse noise removal

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ABSTRACT

A novel adaptive switching morphological filter for removing fixed-value impulse noise is proposed. The proposed filter firstly identifies noise pixels using the two-stage morphological noise detector, in which the initial noise detection is used to identify the noise candidates based on the morphological gradients and the refined noise detection based on the combined conditional morphological operators is adopted to further classify the noise candidates as the noise pixels or noise-free pixels. Then the detected noise pixels are removed by the adaptive morphological filter using the conditional rank-order morphological operators while the noise-free pixels are left unaltered. Extensive simulations show that the proposed filter outperforms a number of existing switching-based filters because of its excellent performance in terms of noise detection and image restoration.

1. Introduction

In the process of image formation, image recording, image transmission via sensors or communication channels, image will be inevitably corrupted by impulse noise due to sensor malfunction, transmission errors, storage faults, and difficult acquisition conditions [1–3]. Characterized by short, abrupt alterations of the intensity values in the images, impulse noise will cause image degradation by producing the significant intensity difference between the corrupted pixel and its local neighborhood. It is imperative, and even indispensable, to remove impulse noise to improve the quality of degraded images, thereby facilitating subsequent image processing operations such as edge detection, image segmentation and object recognition, to name a few [4]. A most widely used method to remove impulse noise is the median filter [5]. This filter exhibits good noise suppression ability and high computational efficiency [6]. However, the standard median (MED) filter operates uniformly for both the corrupted pixels and the uncorrupted ones, thereby causing the damage to the details contributed from the uncorrupted pixels [7]. One improved method is to incorporate the switching median or mean filter, which involves the preliminary identification of corrupted pixels using the noise detectors prior to image filtering. Examples include progressive switching median (PSM) filter [8], adaptive center weighted median (ACWM) filter [9], convolution noise detection based switching median (CNDSM) filter [10], pixel-wise MAD-based (PWMAD) filter [11], boundary discriminative noise detection (BDND) filter [12], fast decision-based algorithm (FDA) filter [13], switching-based adaptive directional method (SADM) filter [14], Laplacian detector-based switching median (LDSM) filter [15] and modified decision based unsymmetric trimmed median (MDBUTM) filter [16]. The disadvantages of these methods lie in two aspects. On the one hand, noise detectors adopted in these filters cannot produce both low false detection ratios and low miss detection ratios at various noise ratios. For example, the extremum-based detector in the FDA filter will misidentify many uncorrupted pixels as noise pixels at low noise ratios. The noise detector in the BDND filter cannot provide accurate noise detection results for the images with heavy-tailed histograms. The Laplacian detector used for the LDSM filter will result in increasing misclassifications of corrupted pixels with the increasing noise ratios. On the other hand, these filters cannot preserve image details well at high noise ratios.

Another commonly used algorithm to remove impulse noise is morphological filter using such operations as dilation, erosion, opening and closing based on the set theory of mathematical morphology. The traditional morphological filter will distort significant details and create artificial patterns resulting from the utilization of the above basic morphological operations and the structuring elements with the fixed size or shape. Various schemes have been proposed to improve the traditional morphological filter by

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using the combined morphological operations such as opening-closing sequence (OCS) filter [17] or using the weighted structuring elements [18], multi-directional structuring elements [19], multi-scale structuring elements [20] and adaptive structuring elements [21]. The OCS filter performs better than the ACWM, PWMAD and CNDSM filters when the images are corrupted with more than 40% impulse noise, but it tends to remove important features from the images owing to misclassification of numerous uncorrupted pixels as noise pixels when the noise ratio is lower than 40%.

To remove fixed-value impulse noise at the various noise ratios, we propose the adaptive switching morphological (ASM) filter by combining the two-stage morphological noise detector with the adaptive conditional rank-order morphological filters. The proposed noise detector can realize the accurate noise detection at the various noise ratios. The adaptive switching morphological filter can suppress impulse noise while preserving the details very well. Experimental results show that the combination of the novel noise detector with the distinctive morphological filter provides the ASM filter with significantly better noise detection performance and image restoration performance than numerous existing switching-based filters.

The rest of this paper is organized as follows. In Section 2, a detailed description of two-stage impulse noise detection is given. In Section 3, the adaptive morphological filter for impulse noise removal is presented. In Section 4, analysis and comparisons of computer simulation results, in terms of noise detection accuracy and image restoration performance, are provided. Finally, the conclusions are made in Section 5.

2. Two-stage morphological noise detection

2.1. Initial noise detection

Generally, the pixel corrupted by fixed-value impulse noise will take an intensity value substantially larger than or smaller than that of its neighbors. Therefore, a noise pixel (an impulse) will be located near one of the two ends of the intensity value ranking in its neighborhood. In view of the above characteristics of impulse noise, the morphological gradients based on the erosion and dilation operators are adopted to identify noise candidates in the images.

Let the input image f and the square structuring element b denote two discrete-valued functions defined on a two-dimensional discrete space. The basic erosion operator $(f\Theta b)(i,j)$ and dilation operator $(f\oplus b)(i,j)$ for the pixel at (i,j) will be defined as:

$$(f\Theta b)(i,j)=\mathrm{Min}\{f(i+s,j+t)-b(s,t)|(i+s,j+t)\in D_f,(s,t)\in D_b\} \tag{1}$$

$$(f\oplus b)i,j=\mathrm{Max}\{f(i-s,j-t)+b(s,t)|(i-s,j-t)\in D_f,(s,t)\in D_b\} \tag{2}$$

where Max{ } and Min{ } denote the minimum operator and the maximum operator, respectively; D_f and D_b denote the domain of the image f and that of the $(2L_b+1)\times(2L_b+1)$ square structuring element b, respectively.

Likewise, the repetitive erosion and dilation operators implemented n times can be expressed as:

$$(f\Theta b)^{(n)}(i,j)=\begin{cases}((f\Theta b)^{(n-1)}\Theta b)(i,j) & 2\le n\le N\\ (f\Theta b)(i,j) & n=1\end{cases} \tag{3}$$

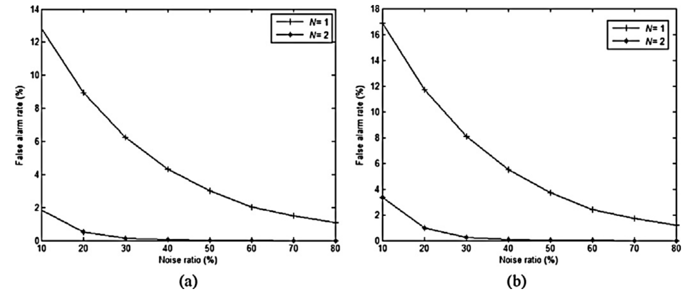

Fig. 1. Initial noise detection results with $N=1, 2$ for two corrupted images: (a) detection results for the corrupted Pepper and (b) detection results for the corrupted Bridge.

$$(f\oplus b)^{(n)}(i,j)=\begin{cases}((f\oplus b)^{(n-1)}\oplus b)(i,j) & 2\le n\le N\\ (f\oplus b)(i,j) & n=1\end{cases} \tag{4}$$

where N denotes the maximum implementation times.

Based on the repetitive erosion and dilation operators, the internal and external morphological gradients, i.e., $g_e^{(n)}(i,j)$ and $g_d^{(n)}(i,j)$, are presented as $g_e^{(n)}(i,j)=f(i,j)-(f\Theta b)^{(n)}(i,j)$ and $g_d^{(n)}(i,j)=(f\oplus b)^{(n)}(i,j)-f(i,j)$. Let $g_s^{(n)}(i,j)$ be the smaller one between the two morphological gradients. The hybrid morphological gradient $g_h(i,j)$ is defined as $g_h(i,j)=g_s^{(N)}(i,j)$. With this hybrid gradient, the pixel at (i,j) will be classified as 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 $g_h(i,j)\neq 0$.

Here the simple theoretical analysis of the effectiveness of the initial noise detection in identifying corrupted pixels is made. According to the characteristics of erosion and dilation operators, $g_e^{(n)}(i,j)=0$ or $g_d^{(n)}(i,j)=0$ $(1\le n\le N)$ holds for the corrupted pixels because these pixels have extreme intensities in their neighborhood. But for the uncorrupted pixels, we have $g_e^{(n)}(i,j)\ge g_e^{(n-1)}(i,j)$ and $g_d^{(n)}(i,j)\ge g_d^{(n-1)}(i,j)(2\le n\le N)$. It follows that all the corrupted pixels will meet the condition of $g_s^{(n)}(i,j)=0(1\le n\le N)$ while generally there will be a decrease in the number of uncorrupted pixels meeting the condition of $g_s^{(n)}(i,j)=0(1\le n\le N)$ with the increasing n values. Obviously, it is more effective to differentiate between the noise pixels and the noise-free ones using $g_s^{(n)}(i,j)$ instead of $g_s^{(n-1)}(i,j)$. Therefore, $g_s^{(N)}(i,j)$ can be used as an effective measure for the initial noise detection.

To further verify the above conclusion, Fig. 1 gives the noise detection results for two test images Bridge and Pepper corrupted by 10–80% salt-and-pepper noise using the initial noise detection with $N=1$, 2 and $L_b=1$. Here the noise detection results are evaluated by the false alarm (FA) rate defined as the ratio of the number of falsely identified uncorrupted pixels to the total number of uncorrupted pixels, and the miss detection (MD) rate defined as the number of undetected corrupted pixels to the total number of corrupted pixels in the image. Because the initial noise detection produces zero MD rate for two test images, only the FA rate is shown in Fig. 1. Clearly, the uncorrupted pixels can be classified with decreasing errors when N increases.

The above analysis indicates that the corrupted pixels in the image can be identified with no errors using the initial noise detection. However, there still exist misclassifications of uncorrupted pixels as noise ones at low noise ratios. To address this problem, the refined noise detection will be adopted to dismiss the misidentified noise-free pixels from noise candidates.