Optik 126 (2015) 956–961

Contents lists available at ScienceDirect

Optik

journal homepage: www.elsevier.de/ijleo

A switching median–mean filter for removal of high-density impulse noise from digital images

Chengbin Zhang, Kaifu Wang*

College of Aerospace Engineering, Nanjing University of Aeronautics and Astronautics, Nanjing 210016, China

ARTICLE INFO

Article history:
Received 1 February 2014
Accepted 12 February 2015

Keywords:
Impulse noise
Switching median filter
Mean filter

ABSTRACT

A new, efficient switching median–mean filter is proposed to remove high density impulse noise from digital images. The proposed method consists of detection and filtering stages. The pixels that are labeled noise-free in the detection stage remain unchanged and the noisy-pixels are replaced by the reference image based the proposed filter with 3 × 3 window. The simulation results show that the proposed filter outperforms some existing methods, both in vision and quantitative measurements. Moreover, our method is not only efficient to remove high density impulse noise and preserve the details in the image, but also possess a short processing time.

1. Introduction

During digital images acquisition or transmission, these digital images are sometimes corrupted by impulse noise. The impulse noise is also known as salt and pepper noise is quantized in two extreme values, which are minimum or maximum values in a digital image [1]. Impulse noise, even with low noise density, can change the appearance of the image significantly. Therefore, how to efficiently remove impulse noise is an important research task.

It is well known that if the noise is non-additive, linear filtering fails, so most of the algorithms use a nonlinear approach to achieve better results [2]. Median filters are the most prominent non-linear rank ordered filters that provide excellent results in the removal of impulse noise than other spatial averaging filters due to their perfectness, computational efficiency and simplicity. However, the standard median filter was defined to process all pixels in the image equally, including the "noise-free pixels". This will result in the elimination of fine details. So the standard median filter is only effective to work at low noise density. Thus, some variations and improvements of median filter have been proposed, such as weighted median filter [3] and center-weighted median filter [4].

One of the branches for the improvement of median filter is adaptive median filter, such as the work by [5]. In this framework, the size of the median filter is made adaptable to the local noise content. Small filter size is applied at pixel locations with low noise density in order to keep the image details. Larger filter size is applied at pixel locations with higher noise density in order to remove the noise successfully. These filters started with a smaller window size first, and increased the size until certain conditions are met.

Another type of the median based methods is the switching method, which consists of two stages. The first stage is to detect the "noise pixels". And the second stage is to remove the noise. In the switching method, only "noise pixels" are changed, and the "noise-free pixels" are kept unchanged. This condition enables the method to preserve most of the image details. Among the recently proposed switching-based filters are difference-type noise detection based cost function-type filter [6], second-order difference analysis based median filter [7], a new directional weighted median filter [3], switching median filter with boundary discriminative noise detection [8], opening closing sequence filter [9], fast switching median filter [10], efficient edge-preserving filter [11] and switching-based filter using non-monotone adaptive gradient method [12]. One of the switching median methods is known as adaptive switching median filter, such as an efficient adaptive switching median filter for salt and pepper impulse noise removal (ASMF) [13], adaptive switching median filter [14], improved switching median filter based on local outlier factor [15] and noise adaptive fuzzy switching median filter [16].

Although these switching-based filters perform better than the standard median filter due to the noise detection stage, they only use the local statistics within a small neighborhood of pixels for removing impulse noise and thus tend to damage image details at high density impulse noise [17]. Therefore, some different methods are proposed, such as decision-based non-local means filter (DNLM) [17], improved median filter (IMF) by a fixed 3 × 3

* Corresponding author.
E-mail address: kfwang@nuaa.edu.cn (K. Wang).

http://dx.doi.org/10.1016/j.ijleo.2015.02.085
0030-4026/© 2015 Published by Elsevier GmbH.

window [18], linear mean–median filter (LMMF) [19], a switching non-local means filter [20]. Unfortunately, these non-local filters require more complex algorithms and longer processing time at high density impulse noise.

In this paper, we propose an efficient switching median–mean filter (SMMF) to remove high-density impulse noise from digital images. The proposed method is simple and efficient to remove impulse noise from images, and can preserve the details inside the image. This paper is organized as follows. Section 2 describes the proposed method. Section 3 presents our results and discussions. Section 4 concludes the paper.

2. The proposed method

We divide our method into two stages, which are the noise detection stage, and the filtering stage. These two stages are described in the following sections.

2.1. Stage 1: detection stage

During this stage, the image pixels are grouped into two classes, which are "noise-free pixels" and "noise pixels". Based on [2], we assume that the intensity value of noise pixel is 0 or $L-1$, for image with L intensity levels. Therefore, at each pixel location (i,j), a noise mask a is marked as follows:

$$a^f(x,y)=\begin{cases}0 & f(x,y)=0\,\text{or}\,f(x,y)=L-1\\ 1 & \text{otherwise}\end{cases} \tag{1}$$

where f is an image, the value 1 denotes the "noise-free pixel" and value 0 denotes the "noise pixel".

2.2. Stage 2: filtering stage

In this stage, we will obtain the restored image g is defined as:

$$g(x,y)=[1-a^f(x,y)]r(x,y)+a^f(x,y)f(x,y) \tag{2}$$

where $r(x, y)$ is the reference image obtained by our proposed method. Our novel filter for finding $r(x, y)$ is described by the following algorithm.

2.2.1. Switching median–mean filter (SMMF¹)

For each pixel location (i,j) with $a(i,j)=0$, do the following:

Step 1: The mask a^f is obtained by Eq. (1), and $S_{ij}=[a^f_{i-1,j-1}\;a^f_{i-1,j}\;a^f_{i-1,j+1};a^f_{i,j-1}\;a^f_{i,j}\;a^f_{i,j+1};a^f_{i+1,j-1}\;a^f_{i+1,j}\;a^f_{i+1,j+1}]$ is defined as a filtering window, and the first filtered image is obtained as follows:

$$f_1(i,j)=\begin{cases}\underset{(i,j)\in S_{ij}}{\text{median}}\{f(i,j)\} & a^f(i,j)=0\\ f(i,j) & a^f(i,j)=1\end{cases} \tag{3}$$

If the S_{ij} is a zero matrix, then $f_1(i,j)=0$.

Step 2: The mask a^{f_1} is obtained by Eq. (1), and $S_{ij}=[a^{f_1}_{i-1,j-1}\;a^{f_1}_{i-1,j}\;a^{f_1}_{i-1,j+1};a^{f_1}_{i,j-1}\;a^{f_1}_{i,j}\;a^{f_1}_{i,j+1};a^{f_1}_{i+1,j-1}\;a^{f_1}_{i+1,j}\;a^{f_1}_{i+1,j+1}]$ is obtained, and the second filtered image is obtained as follows:

$$f_2(i,j)=\begin{cases}\underset{(i,j)\in S_{ij}}{\text{median}}\{f_1(i,j)\} & a^{f_1}(i,j)=0\\ f_1(i,j) & a^{f_1}(i,j)=1\end{cases} \tag{4}$$

If the S_{ij} is a zero matrix, then $f_2(i,j)=0$.

Step 3: The mask a^{f_2} is obtained by Eq. (1), and $S_{ij}=[a^{f_2}_{i-1,j-1}\;a^{f_2}_{i-1,j}\;a^{f_2}_{i-1,j+1};a^{f_2}_{i,j-1}\;a^{f_2}_{i,j}\;a^{f_2}_{i,j+1};a^{f_2}_{i+1,j-1}\;a^{f_2}_{i+1,j}\;a^{f_2}_{i+1,j+1}]$ is obtained, and the third filtered image is obtained as follows:

$$f_3(i,j)=\begin{cases}\underset{(i,j)\in S_{ij}}{\text{median}}\{f_2(i,j)\} & a^{f_2}(i,j)=0\\ f_2(i,j) & a^{f_2}(i,j)=1\end{cases} \tag{5}$$

If the S_{ij} is a zero matrix, then $f_3(i,j)=0$.

Step 4: The mask a^{f_3} is obtained by Eq. (1), and $S_{ij}=[a^{f_3}_{i-1,j-1}\;a^{f_3}_{i-1,j}\;a^{f_3}_{i-1,j+1};a^{f_3}_{i,j-1}\;a^{f_3}_{i,j}\;a^{f_3}_{i,j+1};a^{f_3}_{i+1,j-1}\;a^{f_3}_{i+1,j}\;a^{f_3}_{i+1,j+1}]$ is obtained, and the fourth filtered image is obtained as follows:

$$f_4(i,j)=\begin{cases}\underset{(i,j)\in S_{ij}}{\text{median}}\{f_3(i,j)\} & a^{f_3}(i,j)=0\\ f_3(i,j) & a^{f_3}(i,j)=1\end{cases} \tag{6}$$

If the S_{ij} is a zero matrix, then $f_4(i,j)=0$.

Step 5: The mask a^{f_4} is obtained by Eq. (1), and $S_{ij}=[a^{f_4}_{i-1,j-1}\;a^{f_4}_{i-1,j}\;a^{f_4}_{i-1,j+1};a^{f_4}_{i,j-1}\;a^{f_4}_{i,j}\;a^{f_4}_{i,j+1};a^{f_4}_{i+1,j-1}\;a^{f_4}_{i+1,j}\;a^{f_4}_{i+1,j+1}]$ is obtained, and the fifth filtered image is obtained as follows:

$$f_5(i,j)=\begin{cases}\underset{(i,j)\in S_{ij}}{\text{median}}\{f_4(i,j)\} & a^{f_4}(i,j)=0\\ f_4(i,j) & a^{f_4}(i,j)=1\end{cases} \tag{7}$$

If the S_{ij} is a zero matrix, then $f_5(i,j)=0$.

Step 6: Set the filtering window $S_{ij}=[111;111;111]$, and the reference image is obtained as follows:

$$r(i,j)=\begin{cases}\underset{(i,j)\in S_{ij}}{\text{mean}}\{f_5(i,j)\} & a^f(i,j)=0\\ f(i,j) & a^f(i,j)=1\end{cases}. \tag{8}$$

In order to describe our method more clearly, we select an image patch f in the rectangular box from Lena image corrupted by 90% impulse noise as an example and corresponding filtered image patch g are shown in Fig. 1. Then, all pixels in the rectangular box will be processed stepwise by SMMF¹. We can find our method is efficient to remove high density impulse noise uses 3×3 window, and possesses small deviations. This is because we use the iterative small filter to select the closest uncorrupted pixel of surrounding of noise pixel, then our method can preserve the details inside the image well.

2.2.2. Switching mean–median filter (SMMF²)

The switching mean–median filter (SMMF²) is the simple modified SMMF¹ and described as follows:

Step 1: The mask a^f is obtained by Eq. (1), and $S_{ij}=[a^f_{i-1,j-1}\;a^f_{i-1,j}\;a^f_{i-1,j+1};a^f_{i,j-1}\;a^f_{i,j}\;a^f_{i,j+1};a^f_{i+1,j-1}\;a^f_{i+1,j}\;a^f_{i+1,j+1}]$ is defined as a filtering window, and the first filtered image is obtained as follows:

$$f_1(i,j)=\begin{cases}\underset{(i,j)\in S_{ij}}{\text{mean}}\{f(i,j)\} & a^f(i,j)=0\\ f(i,j) & a^f(i,j)=1\end{cases} \tag{9}$$

If the S_{ij} is a zero matrix, then $f_1(i,j)=0$.

Step 2: The mask a^{f_1} is obtained by Eq. (1), and $S_{ij}=[a^{f_1}_{i-1,j-1}\;a^{f_1}_{i-1,j}\;a^{f_1}_{i-1,j+1};a^{f_1}_{i,j-1}\;a^{f_1}_{i,j}\;a^{f_1}_{i,j+1};a^{f_1}_{i+1,j-1}\;a^{f_1}_{i+1,j}\;a^{f_1}_{i+1,j+1}]$ is obtained, and the second filtered image is obtained as follows:

$$f_2(i,j)=\begin{cases}\underset{(i,j)\in S_{ij}}{\text{mean}}\{f_1(i,j)\} & a^{f_1}(i,j)=0\\ f_1(i,j) & a^{f_1}(i,j)=1\end{cases} \tag{10}$$

If the S_{ij} is a zero matrix, then $f_2(i,j)=0$.

Step 3: The mask a^{f_2} is obtained by Eq. (1), and $S_{ij}=[a^{f_2}_{i-1,j-1}\;a^{f_2}_{i-1,j}\;a^{f_2}_{i-1,j+1};a^{f_2}_{i,j-1}\;a^{f_2}_{i,j}\;a^{f_2}_{i,j+1};a^{f_2}_{i+1,j-1}\;a^{f_2}_{i+1,j}\;a^{f_2}_{i+1,j+1}]$ is obtained, and the third filtered image is obtained as follows:

$$f_3(i,j)=\begin{cases}\underset{(i,j)\in S_{ij}}{\text{mean}}\{f_2(i,j)\} & a^{f_2}(i,j)=0\\ f_2(i,j) & a^{f_2}(i,j)=1\end{cases} \tag{11}$$

If the S_{ij} is a zero matrix, then $f_3(i,j)=0$.