Int. J. Electron. Commun. (AEÜ) 68 (2014) 1129–1135

Contents lists available at ScienceDirect

International Journal of Electronics and Communications (AEÜ)

journal homepage: www.elsevier.com/locate/aeue

A sparsity-ranking edge-preservation filter for removal of high-density impulse noises

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ARTICLE INFO

Article history:
Received 20 December 2013
Accepted 5 June 2014

Keywords:
Image processing
Impulsive noise
Edge preservation
Sparsity ranking

ABSTRACT

In this study, a novel sparsity-ranking edge-preservation filter (SREPF) is proposed for removal of high-density impulse noise in images. Using the sparse matrix representation, the first stage of SREPF is not only to identify the noisy candidates but also to decide the processing order of them via a rank of noise-pixel sparsity in the working window. Then the second stage of SREPF utilizes a modified double Laplacian convolution to confirm the truly noisy pixels and yield a directional mean to recover them. This new approach has achieved more remarkable success rate of the edge detection than other edge-preservation methods especially in high noise ratio over 0.5. As a result, SREPF has significant improvements in terms of edge preservation and noise suppression exhibited by the peak signal-to-noise ratio (PSNR) and the structural similarity index metric (SSIM). Simulation results show that this method is capable of producing better performance compared to several representative filters.

1. Introduction

The corruption of digital image by impulse noise (also known as salt and pepper noise) is mainly caused by error in image acquisition, transmission and/or recording. Therefore, a large number of algorithms have been proposed to eliminate impulse noise in the condition of improving image quality. Among them, the standard median filter (MF) and its modifications can provide efficient noise reduction capability and has been widely used to remove impulsive noise in image processing. Two dimension MF (2-D MF) is realized by passing a window over the input image, and taking the median value of the pixels inside the window as the output associated with the center of the window [1]. More sophisticated median filter includes: weighted median filtering [2–5] that assigns different weights to different pixels within the median filter's mask and adaptive median filter (AMF) [6] that increases window size to provide more uncorrupted pixels for sorting are introduced to remove salt and pepper noise due to their good denoising power. However, the major drawback of these MF-based filters is that they are effective only at low noise densities. One of the major reasons is some desirable and important details are also removed since those filters modify both the noise and noise-free pixels [7].

To overcome the above drawback, Wang and Zhang [8] proposed progressive switching median filter (PSMF) detects impulse noise pixels before filtering and replaces them with estimated values while leaving the remaining pixels unchanged. It can help to preserve thin line and other detail features in the original image. The switching scheme (SMF) has attracted more attention [9–15] because it can avoid the damage of good pixels by employing an impulse detector to determine which pixel should be filtered. Inherited advantage of the SMF, the decision based algorithm (DBA) [16] and modified decision based algorithm (MDBA) [7,17] were proposed. In these algorithms, image is denoised by using a $(2n+1)\times(2n+1)$ size of window where the neighboring pixels are used for replacing the central noise by various methods. In addition, the correlation between corrupted pixel and its neighborhood pixels leads to better edge preservation. However, they still perform defectively in noise detection and damage the fine details in the image at a higher noise ratio above 50%.

In the other way, some special filters that take into account the local features as a result of which details and edges can be recovered satisfactorily were suggested [4,18–26]. Instead of simply replacing noisy pixels by outputs of median filter, those filters use the information of the differences between the current pixel and its neighbors aligned with four main or more directions in the window. It is shown that such kind of approaches can preserve some edges while it is removing noise. However, the detector requires that at least one pair of pixels in desired direction is noise free simultaneously. This condition is quite hard to meet with the increasing

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http://dx.doi.org/10.1016/j.aeue.2014.06.001
1434-8411/

noise level and the filter can only use a default value or mean for restoring the noise pixels. Take the approach in the efficient edge-preserving algorithm (EEPA) [19,27] for example, it uses the mean of two neighbor pixels as the default value when its directional detection fails at an increasingly noisier image. Therefore, the border of restored images is usually damaged seriously as they do not have enough neighbor pixels for reference.

In this study, we present a novel method to solve the above obstacle. The core idea of our approach is to decrease the number of error pixels of noise detection for image processing via a simple modification. Based on a similar idea of SMF, SREPF is also composed of a detector stage and a filter stage. However, by using of the sparse matrix representation, it is not only to identify the noisy candidates but also to decide the processing order of them via a rank of noise-free pixel sparsity in working window in the detector stage. In the filter stage of SREPF, a modified double Laplacian convolution is used to confirm the truly noisy pixels and the directional mean to recover them. The proposed method successfully resolved the problem of lack of referring neighbors in border or the first row of an image that is most hard to reconstruct. Simulation results show that this new approach has significant improvements in terms of edge preservation and noise suppression than a lot of existing filters. Since the proposed technique is primarily a rearrangement of processing sequence, it retains the computational efficiency and can be simply apply to other existing filters.

The rest of the paper is organized as follows: Section 2 briefly describes the design of the sparsity-ranking edge-preservation filter; Section 3 presents some simulation results; Conclusion and potential future work are presented in Section 4.

2. The design of the sparsity-ranking edge-preservation filter

2.1. Sparsity-ranking

Consider the actual situation, salt-and-pepper is only a special case of "Noise Model 4" in [28]. So we choose the model 4 as the study object to make our algorithm more realistic and more general. The model is described in detail in [28]. Instead of two fixed values, impulse noise could be more realistically modeled by two fixed ranges that appear at both ends with length m_1, m_2 respectively, except that the densities of low-intensity impulse noise and high-intensity impulse noise are unequal. That is, for each image pixel at location (i,j) with intensity value $o_{i,j}$, the intensity of corresponding pixel of the noisy image is given by $x_{i,j}$, in which the probability density function of $x_{i,j}$ is

$$f(x_{i,j}) = \begin{cases} \dfrac{p_1}{m_1}, & \text{for} \quad 0 \le x_{i,j} < m_1 \\ 1-p, & \text{for} \quad x_{i,j} = 0_{i,j} \\ \dfrac{p_2}{m_2}, & \text{for} \quad 255 - m_2 < x_{i,j} \le 255 \end{cases} \tag{1}$$

where p is the noise density, p_1 is the noise density for $x_{i,j} < m_1$, p_2 is the noise density for $x_{i,j} > 255 - m_2$, $p = p_1 + p_2$ and $p_1 \neq p_2$ in general.

We used the effective BDND method [27–29] for detection of impulse noise in the stage of noise detection. Based on the same idea as [27–29], the first step of detect operation is to find the impulse noise boundaries m_1 and m_2 used to establish the model of salt and pepper noise. Then, in order to identify whether the pixel is corrupted, we build a binary matrix T with the same size $(M \times N)$ of the input image X. That is, at each pixel location (i,j), the corresponding element of mark matrix T will be created by using the following equation:

(A)

0	156	156	255	158
255	157	157	255	0
158	158	0	158	255
158	158	255	158	0
159	255	159	159	159

(B)

0	156	156	255	158
255	157	157	255	0
158	158	158	158	255
158	158	255	158	0
159	255	159	159	159

Fig. 1. (A) Two local regions before the filter and (B) Two local regions after the filter.

$$t_{i,j} = \begin{cases} 1, & 0 \le x_{i,j} < m_1 \\ 1, & 255 - m_2 < x_{i,j} \le 255 \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

where $x_{i,j}$ is the pixel intensity value at location (i,j) and $1 \le i \le M$, $1 \le j \le N$. $t_{i,j} = 1$ represents a corrupted candidate pixel, while $t_{i,j} = 0$ represents an uncorrupted pixel to be retained.

Differ from other switching methodology [9–15], an additional function is performed in detect stage for consequent filtering operation. As we mentioned in Section 1, the major obstacle of the edge-preservation design is hard to ensure a pair of noise free pixels in detected direction at high noise level. Based on the uncertainty of the noise distribution, we can easily observe a few lower noise density regions even in a highly corrupted image. In image processing, it is effortless to reconstruct the image and preserve picture quality in a local region with lower corrupted pixels. Intuitively, if we filter out those low-noise regions first, then the number of noisy pixels of their neighboring regions may be decreased and may make the job of edge detection simpler. This can be shown in Fig. 1. There are two 3×3 sized windows, one in picture center (gray region), and the other in the upper right corner (the region with double lines border). Two regions have their own three and five noise pixels (the intensity with 0 or 255) respectively before the filter process. If the center region is filtered first, the upper right region has reduced to four noise pixels. Also, it creates a pair of pixels aligned along in skew diagonal that had not been found before filtering of the center region. Therefore, it is evident that a suitable processing sequence will be helpful for increasing the success rate of the edge detection and improving the quality of restored images.

In order to set up a better filter sequence ξ of SREPF, we first count the number of surrounding corrupted pixels in each region with $(2n+1) \times (2n+1)$ window $X_{i,j}$. For each location with $t_{i,j} = 1$, a mark sub-matrix $T_{i,j}$ with the same size of window $X_{i,j}$ is used for counting the amount of "1" in $T_{i,j}$. All the window counts are registered to build up a matrix C for the image. Each element of matrix C can be expressed as

$$c_{i,j} = \sum_{s=i-n}^{i+n} \sum_{k=j-n}^{j+n} t_{s,k} \tag{3}$$

where $c_{i,j}$ represents the number of noisy pixels in $T_{i,j}$, $c_{i,j} \in [0, (2n+1)^2]$. The less of noisy pixels within the window $X_{i,j}$ (lower $c_{i,j}$ value), the more useful reference information could help to recover the corrupted pixel.

In the subfield of numerical analysis, sparse matrix representation is a populated tool for saving the space of a matrix primarily with zero elements. The count matrix C can be regarded as a sparse