Adaptive Rank-ordered Mean Filter for Removal of Impulse Noise from Images

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Abstract

This paper presents a new algorithm for detection of fixed-valued and random-valued impulses from images based on locally obtained statistics. By incorporating the rank-conditioned median (RCM) and center-weighted median (CWM) filters into an impulse noise detection framework, an adaptive mechanism is formed for effectively reducing impulse noise while preserving image details. The rank-conditioned mechanism checks whether the central pixel is well-within the ordered data set, while the center-weighted mechanism is to select more appropriate local thresholds. Simulations show that the proposed scheme works well in suppressing both types of impulses at different noise ratios.

1. Introduction

Most of the classical linear digital image filters, such as averaging lowpass filters have low pass characteristics and they tend to blur edges and to destroy lines, edges and other fine image details. One solution to this problem is the use of the median (MED) filter, which is the most popular order statistics filter [1,2] under the nonlinear filter classes. This filter has been recognized as a useful filter due to its edge preserving characteristics and its simplicity in implementation. The median filter, especially with larger window size destroys the fine image details due to its rank ordering process. Applications of the median filter require caution because median filtering tends to remove image details such as thin lines and corners while reducing noise. One way to improve this situation is the weighted median WM filter [3,4,5,6], which is an extension of the median filter that gives more weight to some values within the window. It emphasizes or de-emphasizes specific input samples, because in most applications, not all samples are equally important. The special case of the median filter is the center-weighted median (CWM) filter [7], which gives more weight only to the central value of the window. It is also reasonable to give emphasis to the central sample, because it is one that is the most correlated with the desired estimate.

The median filter, as well as its modifications and generalizations [8] are typically implemented invariantly across an image. They tend to alter pixels undisturbed by noise. Additionally, they are prone to edge jitter in cases where the noise ratio is high. As a result, their effectiveness in noise suppression is often at the expense of blurred and distorted image features. Another way to circumvent this situation is to incorporate some decision making process in the filtering framework. At each pixel location, it is to detect whether the current pixel is contaminated. One of the very simple but effective impulse detection filter is the rank-conditioned median (RCM) filter [9,10], in which the data sample is ranked according to their magnitudes and the central sample is considered to be corrupted if it lies outside the trimming rank [9,10]. The corrupted pixels are replaced by the median values, while the noise-free pixels are left unaltered. Since not every pixel is filtered, undue distortion can be avoided. Recently, impulse detection based median filtering techniques realized by threshold operations have been investigated [11,12,13]. In those approaches, the output is switched between those of the identity and some median based filters. However, one disadvantage is that the decision rules are typically based on a single threshold for locally obtained statistics. Those strategies tend to work well for large, fixed-valued impulses but poorly for random-valued impulses, or vice versa. Differently, the median filter is replaced with a rank-ordered mean (ROM) filter [14,15,16] that excludes the current pixel from the operation window. In the ROM-based switching scheme [14,15,16], multiple thresholds are used in impulse detection that operates on the differences between the current pixel and the remaining rank-ordered elements in the filter window. It has been shown to work well in removing both types of impulses.

In this work, we propose a novel adaptive rank-ordered mean (AROM) filter that employs the switching scheme based on the two-stage impulse detection mechanism. The objective is to utilize the rank-conditioned median (RCM) filter [9,10] and center-weighted median (CWM) filter [7] to define more general operators. In the first stage impulse detection scheme, the RCM mechanism sees if the central sample lies outside the trimming range and how much small or big the central pixel is in comparison with other pixels that lie within the trimming range in the window. In the second stage impulse detection scheme ,the CWM mechanism with variable center weights is used to decide the values of local thresholds in the sliding window. The ultimate output is switched between the current pixel itself and the rank-ordered mean of two central ranks of the surrounding pixels in the window.

The rest of the paper is organized as follows. The new impulse detector is formulated in Section 2. Section 3 reports a number of experimental results to demonstrate the performance of the new filter. Finally, conclusions are drawn in Section 4.

2. Formulations

Let $C = \{\boldsymbol{c} = (c_1, c_2) \mid 1 \le c_1 \le H, 1 \le c_2 \le W\}$ be the pixel coordinates of an image, where H and W denote the height and width, respectively. At each location $\boldsymbol{c} \in C$, a filter window is defined in terms of the coordinates symmetrically surrounding the current pixel, where the size is $N = 2n + 1$, and n is a nonnegative integer.

Let $\boldsymbol{x}(c)$ denote the sample vector of all pixels including the central pixel $x(c) = x_N(c)$ in the filter window, which is then given by

$$\boldsymbol{x}(c) = [x_1(c), x_2(c), \ldots, x_N(c)]^T \quad (1)$$

where $x_1(c)$ is the upper left pixel value in the window, $x_{N-1}(c)$, the lower right value and pixels are scanned from left to right and top to bottom as $x_1(c), x_2(c), \ldots, x_{N-1}(c)$ The ordered data set of all the pixels including the central sample $x(c)$ is then given by

$$\boldsymbol{x}_r(c) = [x_{(1)}(c), x_{(2)}(c), \ldots, x_{(N-1)}(c), x_{(N)}(c)]^T \quad (2)$$

where $x_{(1)}(c), x_{(2)}(c), \ldots, x_{(N)}(c)$ are the elements of the window arranged in ascending order such that $x_{(1)}(c) \le x_{(2)}(c) \le \ldots \le x_{(N)}(c)$.

For the current pixel $x(c)$ under consideration, we first define the rank-difference D as follow:

$$D = \max\{ x_{(i)}(c) - x(c),\ x(c) - x_{(N+1-i)}(c)\} \quad (3)$$

where $i = 1, 2, \ldots,$ or N.

The Equ. (3) is used to separate uncorrupted pixels from impulses in the first stage impulse detection scheme. Normally, the impulse is much smaller or bigger than most of the pixel values in the window and this property is exploited to discriminate impulses from the rest of other pixels in the window. Normally, impulses appear at the extremes after ranking. This condition may be true for the feature pixels. A threshold θ is employed, such that the central sample will undergo further testing for the detection of impulses in the second stage detection scheme if $D > \theta$ is true and the central pixel is not well-within the ordered data set.

The output of the CWM filter, in which a weight adjustment is applied to the central sample $x(c)$ within the sliding window, is described as

$$Y^w = \text{median}(\mathbf{x}^w) \quad (4)$$

$$\text{where } \boldsymbol{x}^w = \{\boldsymbol{x}(c), (w-1) \Diamond x(c)\} \quad (5)$$

In the above equation, $w = 2k + 1$, where k is a nonnegative integer, denotes the center weight, and the operator $\Diamond$ represents the repetition operation. Throughout the following discussion, unless otherwise stated, the window size is assumed to be $2L + 1$ ($L > 0$). Clearly, the output of the median (MED) filter is Y^1 (i.e. $k = 0$), whereas the identity filter is equivalent to Y^{2k+1}, where $k \ge L$. For the current pixel $x(c)$, we define differences

$$d_k = |Y^w - x(c)| = |Y^{2k+1} - x(c)| \quad (6)$$

where $k = 0, 1, \ldots, L - 1$ and $d_k \le d_{k-1}$ ($k \ge 1$), based upon the derivation shown by Chen and et. al. [13]

The differences in Equ. (6) provide information about the likelihood of corruption for the current pixel. If the central sample does not contain an impulse, it would be desirable to make the center weight large, such that no smoothing takes place (identity filter). On the other hand, if an impulse were present in the center of the window, no emphasis should be given to the center sample and the center weight should be the smallest weight, that is, reducing the CWM filter structure to a simple median. A set of thresholds T_k ($k = 0, 1, \ldots, L - 1$), where $T_{k-1} > T_k$ is employed. The proposed filter is realized as follows:

$$\hat{x}(c) = \begin{cases} m, & (r(c) < 2 \text{ or } r(c) > N - 1)\ \&\ D > \theta\ \&\ d_k > T_k, \\ x(c), & \text{otherwise.} \end{cases} \quad (7)$$

where $\hat{x}(c)$ is the final estimate of the current pixel $x(c)$, $r(c)$ is the rank of the center pixel, $k = 0, 1, 2,$ or 3 and m is given as follow:

$$m = median(x_1(c), x_2(c), \ldots, x_{N-1}(c)) \,. \quad (8)$$

Chen et al. [17]. devised a method for the selection of thresholds and we use those thresholds in our experimentation.

In the Equ. (7), the corrupted center pixel is replaced by the median of the all the pixels in the window that excludes the center pixel, if it is detected as an impulse by the impulse detection mechanisms. Inclusion of the center pixel to obtain the median value will not affect the performance of the proposed filter in filtering out the corrupted pixel in the homogeneous window that contains more or less similar pixels, but the performance of the filter will be worsen in the window that contains image features, because the corrupted pixel naturally occurs at one of the extremes after ranking, which may give the filtered output biasing towards the undesired pixel value.

The proposed algorithm checks whether the central sample lies in one of the extremes. In the case of the multiple occurrence of similar pixels in the same window, the proposed algorithm tracks the corrupted pixel successfully. If one of the corrupted pixels lies outside the trimming range, the next step is to find the rank-difference between the corrupted sample and one of the pixels that lies inside the trimming range, but on the other side of the median value, opposite to the corrupted pixel in the ordered data set. It is done to give a much higher value for the rank-difference in the Equ. (3). It may so happen that the central sample is a healthy pixel that lies at one of the extremes and there are multiple and similar corrupted pixels in the same window. In such cases, the proposed algorithm will signal the central sample as a corrupted pixel in the first stage of impulse detection, but it is the second stage of impulse detection that has to detect that the central sample is not a corrupted one.

3. Simulations

The proposed algorithm was tested using various types of 8-bits gray scale images of 512×512 size. The images are Lena, Pepper, Mandrill, Airplane, Lake and Goldhill. Fixed-valued and random-valued impulses were artificially injected in these images at various noise ratios. The noise intensity of fixed-valued impulses corresponds to 0 or 255, while for random-valued impulses, the noise values are uniformly distributed in the range of [0, 255]. The performance of the proposed algorithm was compared with the median (MED) filter, center-weighted median (CWM) filter [7], rank-conditioned median (RCM) filter [9], tri-state median (TSM) filter, rank-ordered mean (ROM) filter [14] and Chen et. al. [17] median filter. There are many performance measures available and peak-peak signal to noise ratio (PSNR) has been adopted as the objective criterion to evaluate the performance of the filters in our experiment. In all cases, a filtering window of 3×3 size slides from pixel to pixel in raster scanning fashion. Thresholds used in different filtering schemes were tuned respectively for different degraded images. Finally, all the algorithms were implemented recursively, that is, the estimate of the current pixel is dependent on the new values instead of the old ones, of previously processed pixels.

The first experiment is conducted to gauge the efficiency of the proposed technique for filtering images corrupted at different noise ratios. The results for Lena image are shown in Fig. 1, where the noise ratios for the two types of impulses range from 5% to 40%. It is seen vividly from these graphical figures that the proposed technique provides superior results to the other methods mentioned in our paper in removing both types of impulses at different noise ratios.

To assess the effectiveness of the proposed filter in processing different images, Tables I and II present the comparison results for images degraded by both kinds of impulses, where 20% of the pixels are contaminated in each image. It is seen the better performance of the proposed method from these tables that PSNR values of the proposed method are bigger than those of the other filtering methods under study.

4. Conclusions

In this work, a new filter, called adaptive rank-ordered mean (AROM) filter, is introduced. By incorporating the RCM filter and the CWM filter into an impulse noise detection framework, an adaptive mechanism is formed for effectively reducing impulse noise while preserving image details. Our proposed filtering framework outperforms the MED, CWM, RCRS, TSM, ROM and Chen et. al. filters and it is clearly seen in terms of PSNR. In addition, the proposed filter presents a quite stable performance over a wide variety of images.

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TABLE I

COMPARATIVE RESULTS IN PSNR (dB) OF FILTERING DIFFERENT IMAGES CORRUPTED BY 20% FIXED-VALUED IMPULSES

Filter types	*Lena*	*Pep per*	*Mand rill*	*Air plane*	*Lake*	*Gold hill*
MED	30.71	31.63	21.85	29.04	27.07	29.20
CWM	30.81	30.55	23.05	29.37	27.66	29.33
RCM	31.21	31.45	21.86	29.72	27.48	29.70
TSM	32.61	31.93	23.02	30.99	28.54	30.43
ROM	36.08	33.63	24.59	32.19	31.00	34.11
Chen et. al.	36.47	33.55	24.66	32.27	30.92	34.28
Proposed	37.80	35.07	25.50	33.78	32.22	34.35

TABLE II

COMPARATIVE RESULTS IN PSNR (dB) OF FILTERING DIFFERENT IMAGES CORRUPTED BY 20% RANDOM-VALUED IMPULSES

Filter types	*Lena*	*Pep per*	*Mand rill*	*Air plane*	*Lake*	*Gold hill*
MED	30.88	31.38	21.83	29.32	27.01	29.66
CWM	32.14	32.16	23.57	30.37	28.59	30.24
RCM	32.00	31.47	21.91	29.69	27.45	29.54
TSM	33.95	33.83	23.30	31.66	29.90	31.93
ROM	34.08	33.00	23.38	31.43	29.86	32.28
Chen et. al.	34.16	33.20	23.43	31.35	29.00	32.28
Proposed	34.64	33.85	23.60	32.01	30.25	32.37

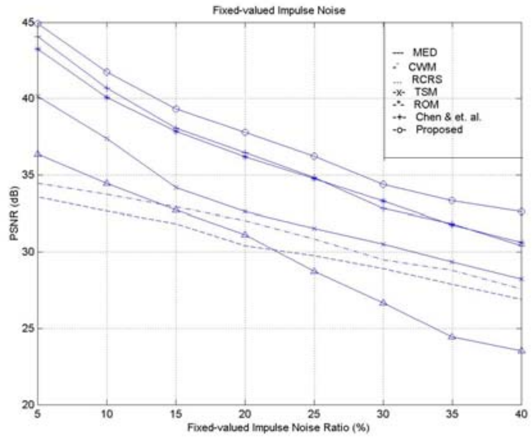

Fig. 1(a). Performance comparison of proposed filters with other filters in removal of fixed-valued impulses.

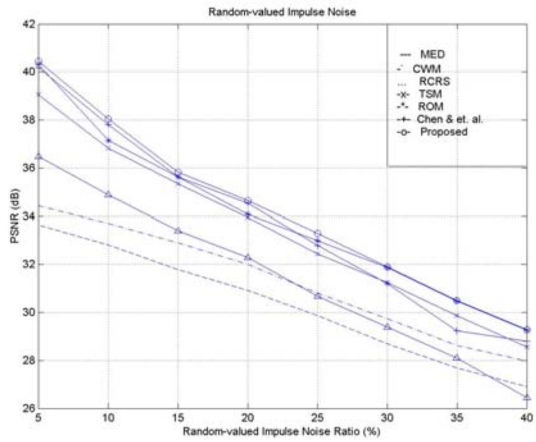

Fig. 1(b). Performance comparison of proposed filters with other filters in removal of random-valued impulses.