Research Journal of Applied Sciences 8 (10-12): 501-506, 2013
ISSN: 1815-932X

Performance Analysis of Impulse Noise Reduction using Pseudo Random Methodology

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Abstract: In medical imaging, object enhancement and segmentation, the impulse noise is occurred by affecting the original pixel values. The effective denoising techniques are required for the image processing applications to remove the impulse noise. Researchers have proposed a Pseudo Random algorithm for detection and removal of impulse noises in images. In this research, Edge Preserving methodology is proposed to detect the impulse noise affected pixels in a simplified manner and those detected pixels are removed using cloud algorithm. The extensive experimental results show that the proposed technique preserves the edge pixels and achieves better performances in terms of quantitative evaluation and visual quality. The proposed simulation results prove that the methodology has better performance than the existing methodology for impulse noise detection and removal.

Key words: Pseudo random, cloud, denoising, impulse noise, edge preserving

INTRODUCTION

A digital image transmitted through any communication channel is randomly corrupted by impulse noise (Chen and Wu, 2001a, b). It is more essential to eliminate this impulse noise from the image before subsequent processing such as image segmentation, object recognition and edge detection. Images are frequently corrupted by impulse noise due to noisy sensors or channel transmission errors. There are many types of impulse noises. Numerous algorithms have been proposed to remove impulse noise while preserving the image details. The mostly adopted technique for the removal of impulse noise is to use median-based filters (Chen *et al*., 1999; Wang and Zhang, 1999).

Noise filtering and image enhancement are the two main aspects of image processing. These tasks are an essential part of any image processor whether the final image is utilized for visual interpretation or for automatic analysis. The aim of noise filtering is to eliminate noise and its effects on the original image, without corrupting the image. For this purpose, non-linear techniques such as the median and order statistics filters have been proved to provide more appropriate results compared to linear methods. However, the median-based method fails to distinguish thin lines from impulses. Accordingly, the thin lines are misinterpreted as impulses and are removed. In this study, researchers propose a cost-effective and detail preserving approach for noise reduction based on Cloud Model, focussing on random-valued impulse noises. Eliminating such random-valued noise is more difficult than cleaning fixed-valued impulse noise, since the differences in grey levels between a noisy pixel and its noise-free neighbours are mostly significant in the latter. The proposed method involves two steps which are applied alternatively; impulse noise detection using Simple Edge-Preserved Denoising (SEPD) and noise filtering using Cloud Model (CM). CM filtering gives a high performance, especially when the noise ratio is high.

Literature review: Karakos and Trahanias (1995) introduced a new class of filters, the Directional-Distance Filters (DDF) which combine both Vector Directional Filter (VDF) and Vector Median Filter (VMF) in a novel way of approach. The results show that DDF can eliminate the noise much more effectively than the VMF and that they possess the property of chromaticity preservation. Wang and Zhang (1999) proposed a new median-based filter, i.e., Progressive Switching Median (PSM) filter to restore images corrupted by salt-pepper impulse noise. The algorithm was developed by the following two main points; switching scheme-an impulse detection algorithm is used before filtering thus only a proportion of all the pixels will be filtered and progressive methods-both the

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impulse detection and the noise filtering procedures are progressively applied through several iterations. The simulation results demonstrate that the proposed algorithm is better than conventional median based filters and is particularly effective for the cases where the images are very highly corrupted.

Chen and Wu (2001a) in their letter gave a new ranking based estimates based average median filters with varied centre weights. The experimental results showed that their proposed scheme consistently works well in suppressing both types of impulses with different noise ratios.

Chen and Wu (2001b) proposed a generalized framework of median based switching schemes called Multi-State Median (MSM) filter. By using simple thresholding logic, the output of the MSM filter is adaptively switched among those of a group of Centre Weighted Median (CWM) filters that have different centre weights. Their result showed that the MSM filter is equivalent to an adaptive CWM filter with a space varying centre weight which is dependent on local signal statistics. The efficiency of the proposed filter has been evaluated by extensive simulations. Crnojevic *et al.* (2004) has proposed a median absolute algorithm for detection of impulse noises. But this method gave the less PSNR as low image denoising quality and also this algorithm has complex architecture and low performance in terms of latency and correlation properties.

Chan *et al.* (2004) has proposed an adaptive centre median filtering algorithm for impulse noise detection and removal. Even though this method provides good image denoising quality, the edges in the noise affected areas are degraded during the noise detection process. This method is also provides a linear results for better performance. Yu *et al.* (2008) has proposed a new technique for the detection of various kinds of noises in medical and satellite images. This method was based on rank relative differences on the original and corrupted pixels.

Chan *et al.* (2004) presented an iterative procedure for removing impulse noises from the images or videos. But this procedure was not suitable for low resolution noise affected images and also it achieved low PSNR such as 26 dB only for high resolution images. Yu *et al.* (2008) proposed edge preserve based impulse noise detection and removing algorithm. This method highly concentrated on pixels in edge regions only and did not concentrate on the pixels in other regions. Estrada *et al.* (2009) used Stochastic image denoising model for detection of impulse noises.

This Stochastic modelling produced complex design methodologies and mathematical formulation. Cai *et al.* (2010) proposed fast two-phase image deblurring under impulse noise algorithm. This method provided low image quality in decoding section. Trahanias and Venetsanopoulos (1993) proposed an vector directional filters for removal of random impulse noise detection and removal process.

MATERIALS AND METHODS

Proposed denoising algorithm description: The proposed pseudo denoising methodology includes impulse noise detection and removal process. Researchers propose a simple edge preserving filter for the detection of impulse noise from various standard images and cloud algorithm for removal of detected impulse noise from images or videos.

Proposed edge preserving (noise detection) algorithm: The proposed Simple Edge-Preserved Denoising (SEPD) comprises of 3 components: optimum information detector, edge noise filter and impulse detector. The optimum information identifier detects the maximum and minimum luminance values. By observing its luminance values, the designed filter identifies the superior edges and generates an new pixel.

Optimum information identifier: The optimum information identifier is used to identify whether the pixel under investigation are affected by impulse noise or not. For this reason, it follows unique identification methodology for the detection process. This study or module is very important because the whole impulse noise detection and removal process will be successful if and only if it follows or satisfies this module. The optimum information identifier finds the maximum and minimum luminance values (MINinM and MAXinM) in the Mask (M) as shown in Fig. 1.

Consider an example, a pixel ($P_{i,j}$) being corrupted by a fixed impulse noise ($f_{i,j}$) then the luminance value will be the maximum or minimum value in grey scale. If $f_{i,j}$ is equal to MINinM or MAXinM, researchers set φ to 1 and also verify its 5 neighbouring pixels are equal to the optimum data and save these results in I_B. If $f_{i,j}$ does not equal MINinM/MAXinM then pixel $P_{i,j}$ is free from noise and the subsequent stages for denoising the pixel $P_{i,j}$ are omitted.

Edge-preserving filter: An edge-preserving filter technique is implemented to detect the edges present in the mask M. To locate the edge, 12 directional differences are taken into account (D_1-D_{12}). Only directions which contain noise-free pixels are considered so as to reduce mis-detection. If a flit in I_B equals to 1 then that pixel is

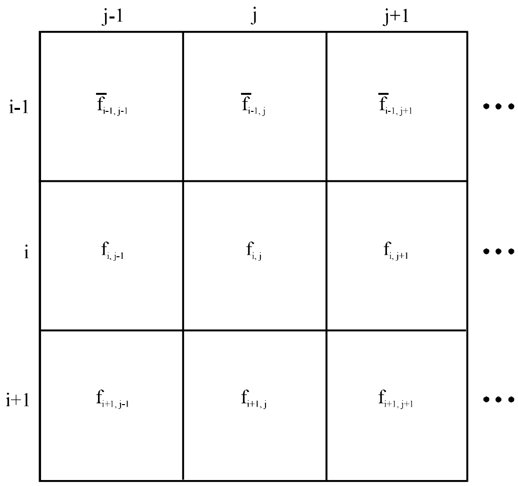

Fig. 1: The 3×3 mask (M) centred on $P_{i,j}$

Table 1: Mapping of I_B to its corresponding directions

I_B	Selected directions	I_B	Selected directions
00000	D_2, D_5, D_8, D_{10}	10000	D_2, D_5, D_8, D_{12}
00001	D_3, D_5, D_8, D_{10}	10001	D_1, D_5, D_8, D_{12}
00010	D_2, D_8, D_{10}, D_{12}	10010	D_2, D_4, D_8, D_{12}
00011	D_1, D_6, D_8, D_{10}	10011	D_1, D_6, D_8, D_{12}
00100	D_2, D_5, D_7, D_{10}	10100	D_1, D_2, D_5, D_7
00101	D_3, D_5, D_7, D_{10}	10101	D_1, D_5, D_7
00110	D_2, D_4, D_9, D_{10}	10110	D_1, D_2, D_4
00111	D_1, D_9, D_{10}	10111	D_1
01000	D_2, D_5, D_8, D_{11}	11000	D_2, D_5, D_6, D_8
01001	D_3, D_5, D_7, D_9	11001	D_3, D_5, D_6, D_8
01010	D_2, D_6, D_8, D_{11}	11010	D_2, D_4, D_6, D_8
01011	D_6, D_8, D_9	11011	D_6, D_8
01100	D_2, D_5, D_9, D_{11}	11100	D_2, D_4, D_5, D_7
01101	D_3, D_5, D_9	11101	D_3, D_5, D_7
01110	D_2, D_4, D_9, D_{11}	11110	D_2, D_4
01111	D_9	11111	Not available

considered as a noise affected pixel. The directions contained in such noisy pixels are discarded to avoid mis-detection. At every state, only a maximum of 4 directions are selected to reduce the cost of hardware implementation. Suppose, if there are >4 directions, only 4 of them are selected according to the difference in its angle. Table 1 shows the mapping of I_B to its corresponding directions being selected.

If all the pixels $P_{i,j+1}$, $P_{i,j-1}$, $P_{i+1,j+1}$, $P_{i+1,j-1}$ and $P_{i+1,j}$ are supposed to be affected by noise, i.e., I_B= 11111, the edge can not be detected hence the approximate value of $P_{i,j}$ i.e., $\hat{f}_{i,j}$ will be the weighted average of 3 previously denoised pixels' luminance value and can be denoted as:

$$\frac{\hat{f}_{i-1,j-1}+2\times\hat{f}_{i-1,j}+\hat{f}_{i-1,j+1}}{4}$$

But if $I_B \neq 11111$, in all other cases the edge-preserving filter selects 4 directions and calculates the directional differences between them and finds the direction with least difference (D_{min}). If the directional difference is small, it should be known that an edge is present in that direction.

Impulse detector: Normally, if a pixel is affected by a fixed value impulse noise, its value will be the minimum/maximum value in grey scale. Consider for example, if $P_{i,j}$ is affected by fixed impulse noise then $f_{i,j}$ equals to MINinM or MAXinM. Conversely, if $f_{i,j}$ is equal to MINinM or MAXinM then $P_{i,j}$ may or may not be affected by impulse noise. Simply, researchers can say, a pixel with value equal to MINinM or MAXinM may be wrongly detected as a noisy pixel. In order to avoid this misdetection, researchers put forth a condition, i.e., if $P_{i,j}$ is a noise-free pixel then $f_{i,j}$ should be close to $\hat{f}_{i,j}$ and $|f_{i,j}-\hat{f}_{i,j}|$ should be less compared with a threshold T_h.

Obviously, T_h is a predefined value which affects the execution of the proposed model. In the experiment, the value of threshold T_h is 20. Even though it is not possible to calculate an optimum value of threshold by manual calculations, a more accurate threshold can provide a better result.

Cloud algorithm

Noise model: Generally, some errors occur during data transmission due to noisy sensors and communication channels and often cause corruption of the digital image. As a result, the noisy pixels have values equal to the minimum or maximum grey level in a random manner. Consider an image I at pixel location i, j and $[DR_{min}, DR_{max}]$ be the dynamic range of I, i.e., for all i, j$\epsilon\rho$. Let $g_{i,j}$ for i, j$\epsilon\rho$ be the grey value of I. Assume N_y as a noise corrupted image and the observed grey level at location i, j is given by:

$$N_y = \begin{cases} DR_{min} & \text{with probability } p \\ DR_{max} & \text{with probability } q \\ g_{i,j} & \text{with probability } 1-p-q \end{cases} \quad (2)$$

where, the noise level = p+q

Weighted cloud filter: At high noise levels, median filters do not operate well, i.e., some image details are not preserved. The cloud filter classifies a pixel into "good" or "bad" pixels. If the pixel is a good one, it retains its original value and the corrupted pixels are replaced. The cloud filter immediately removes the corrupted pixel after it has been detected thus reducing memory space and increasing the computational efficiency.

Thus, in the cloud filter, the noise-detector and the post-filter share a common window, i.e., the window size of the post-filter is that the window used by the noise-detector previously. But, if the cloud filter is unable to identify whether a pixel is "good" or "bad" for example, in a 3×3 window then the filter increases the window size adaptively.

Consider a 7×7 window. In this, if a pixel is identified as 'corrupted', the cloud filter removes that pixel immediately in the same 7×7 window and the noise pixel is replaced with the median value or its variants. Assume a pixel $P_{i,j}$ located at i, j is noisy and $P_{i,j}$ is identified by the noise detector as noisy pixel and $g_{i,j}$ is its grey value. Let $W_{i,j}^{2N+1}$ be the window of size (2N+1)×(2N+1) located at i, j which has been already used by the noise detector to identify $P_{i,j}$ previously, i.e.:

$$W_{i,j}^{2N+1}=\{(i+s, j+t) \quad -N \leq s,\ t \leq N \tag{3}$$

The cloud filter replaces the noisy pixel with the weighted mean of the other pixels and their weights are the certainty degrees of them. Yet, the certainty degree of each drop in the cloud is a random value.

RESULTS AND DISCUSSION

To study the behaviour and operational performances of different denoising techniques, various simulations were performed on the well known images: Lena, Airplane, Peppers, Boat, Gold hill and Couple. These 6 test grey-images have a size of 512×512 and resolution of 8-bits. For the experiment, researchers first corrupt these images by impulse noise for example, salt and pepper noise. The "salt" and "pepper" noise are assumed to be equi-probable. Noise is included artificially to the original image using the MATLAB command "imnoise". The impulse noise used in the simulations are random valued and is uniformly distributed in the range of [0, 255]. A 9×9 window has been adopted throughout the experiment. The proposed denoising method (SEPD with Pseudo Random Method) is quantitatively evaluated and compared in terms of subjective testing, i.e., visual quality where recommended parameters and thresholds are used. For the quantitative testing of the reconstructed images, researchers make use of the Peak Signal to Noise Ratio (PSNR). From the results, it is observed that the proposed denoising methodology performs very well, even at high noise ratio of 90%. To prove the visual quality, the reconstructed image of proposed method is compared with that of images obtained by other denoising methods employing "Lena" image which is 60% corrupted. It has been proven that the denoised image obtained by the proposed method has a better visual quality than others and is shown in Fig. 2.

Table 2 and 3 illustrate the performances of the proposed method and other existing denoising methods in terms of PSNR and MSE. In both Table 1 and 2, the proposed method gives comparable results at low noise levels but it attains a superior performance than the other methods at high noise ratios. This is mainly due to the accurate selection of the optimal direction which leads to

Fig. 2: Lena image obtained by various denoising methods; a) original image, b) noise corrupted image, c) de-noised image obtained by PSW Method, d) de-noised image obtained by EPRIN Method and e) de-noised image obtained by the proposed method

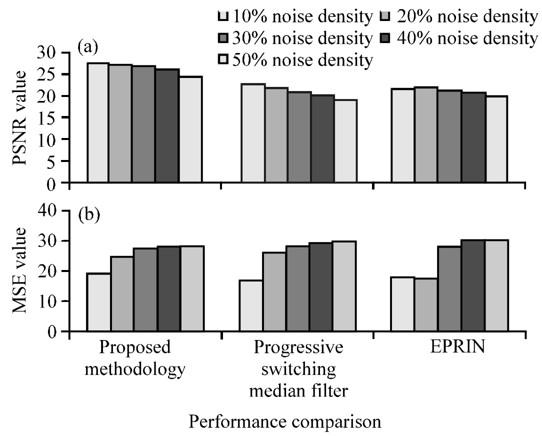

Fig. 3: Graphical representation of the performance comparisons in terms of a) PSNR and b) MSE

Table 2: Performance comparison of proposed method in terms of PSNR

Methodology	Noise density (%) 10	20	30	40	50
Proposed methodology	27.45	27.10	26.76	26.19	24.16
Progressive switching median filter	22.68	21.77	20.95	20.16	19.14
EPRIN (Yu *et al*., 2008)	21.47	21.91	21.31	20.76	20.14

Table 3: Performance comparison of proposed method in terms of MSE

Methodology	Noise density (%) 10	20	30	40	50
Proposed methodology	19.12	24.65	27.12	27.97	28.10
Progressive switching median filter	17.25	26.12	28.19	29.12	29.67
EPRIN (Yu *et al*., 2008)	18.29	17.87	27.98	29.87	29.95

Table 4: Performance comparison of proposed method in terms of denoising latency

Methodology	Elapsed denoising latency (sec)
Proposed methodology	12
Progressive switching median filter (PSW)	15
EPRIN (Yu *et al*., 2008)	16

the suppression of the pixels that are not similar to the ones in the optimal direction and vice-versa. For further improvement, researchers implement a second iteration on the first restored image obtained by the first iteration. The results prove that the proposed technique preserves the thin lines and fine-details of the image (Lena) efficiently.

Moreover, the residual noise can be visibly observed in the images restored by other methods. The same results are graphically illustrated in Fig. 3. The performance of the proposed denoising technique is compared with other denoising methods in terms of the denoising latency as tabulated in Table 4 and it is graphically represented in Fig. 4.

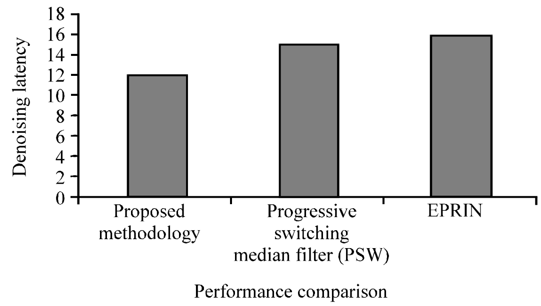

Fig. 4: Graphical illustration of performance comparison in terms of latency

CONCLUSION

In this research work, a new Pseudo Random technique is design and implemented on various set of images for the detection and removal of impulse noise. The proposed technique makes use of edge preserving for the detection of impulse noise and cloud algorithm for the removal of noisy pixels from an image or video. Extensive simulations prove that the proposed technique gives a better performance in terms of quality related parameters such as PSNR and MSE when compared to existing methodology for impulse noise detection and removal. Even if the noise ratio reaches 95%, the details, the image texture and the edges of the images are preserved using the proposed pseudo random algorithm.

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