An Improved Directional Weighted Median Filter for Restoration of Images Corrupted with High Density Impulse Noise

Awanish Kumar Shukla, Vikrant Bhatia1, Member, IEEE  
Department of Electronics and Communication Engineering, SRMGPC, Lucknow (U.P.), India

R. L. Verma, Mohd. Sanawer Alam  
Department of Electronics, Instrumentation and Control Engineering, AIET, Lucknow (U.P.), India

Abstract—This paper presents an approach to improve the performance of Directional Weighted Median (DWM) Filter based restoration of images corrupted with fixed-valued impulse noise. The proposed approach involves minimum absolute difference criteria to distinguish among the edge and non-edge pixels. The identified corrupted pixels are then replaced by weighted median or mean value computed within the local window employing the proposed decision criteria. Further, to filter the residual noise at high density corruption; the proposed approach converges in less than five iterations. Simulation results show improvement in visual quality of restored images both in terms of noise filtering as well as preservation of edges and structural content.

Keywords—absolute difference; Directional weighted median (DWM); high density impulse; Noise Suppression Index (NSI); structural content;

I. INTRODUCTION

Impulse noise may be introduced during a series of stages like image acquisition, transmission or registration stages. This noise can degrade the quality of image. Salt-and-pepper noise and random-valued noise are two types of impulse noise. Salt-and-pepper noise is basically a bipolar fixed valued impulse noise also known as Data-drop-out or spike noise [1]-[5]. During the time of image digitization, the degree of distortion is larger in comparison to the image signal; hence noise intensity gets saturated as extreme values resulting in an image corrupted with white and black spots. It is necessary to suppress the noise present in images before further processing the image like edge detection, segmentation and recognition [6]-[12]. Spatial filtering approaches using order-statistics filters are popular for restoration of images corrupted with impulse noise. Median filtering approaches find effective usage for filtering of impulse noise compared to linear smoothing filters [13]. Other variants of median filtering approach developed in continuation are Centre Weighted Median Filter (CWMF) [14], Decision-based Median Filter (DBMF) [15], Recursive Weighted Median Filter (RWMF) [16] and Adaptive Median Filter (AMF) [17]-[18]. AMF is more effective than median filters in noise suppression but it deteriorates the image details. In order to prevent these deteriorations Fuzzy Adaptive Median Filters (FAMF) and switch mode fuzzy adaptive median filter (SMFAMF) was proposed by T. Abdullah et al [19]. These variants of filtering approaches were limited by variable and large sized spatial windows. The performance of these filters degraded at higher noise densities due to the improper differentiation between edges and impulses which results in blurring of restored image. Other non-linear filtering approaches for denoising employed wavelets [20]-[22], morphological filters [23]-[28], volterra filters [29]-[34] and Directional Weighted Median filters (DWM) [35]-[37]. DWM approaches incorporated spatial processing in four to twelve directions (depending upon window size) to differentiate edge and non-edge pixels with fixed weights and thresholds [38]-[39]. However, these variants of DWM do not yield satisfactory performance to suppress impulses of high density (more than 90¾). Large numbers of iterations are required to suppress high impulse levels; thereby enhancing the computational load. In this paper a new filtering approach is proposed which works effectively with high density noise as well as simultaneously preserves structural content of the restored image. In this approach, a window of fixed size (5×5) is considered which reduces the implementation complexity. Before computing weighted median for a local window, the pixel of interest is classified to be edge or non-edge pixel. The rest of the paper is organized as follows: Section II presents the details of proposed noise filtering approach. This is followed by the results & discussions in section III and finally section IV concludes the work.

II. PROPOSED NOISE FILTERING APPROACH

The contribution in the present work can be highlighted in terms of following features: Directional Weighted Median filtering with fixed size sliding window and rapid convergence of iterative reconstruction at high noise densities. The proposed approach of DWM filtering processes a noisy image using a 5×5 spatial sliding window (w). The central pixel of this local window is classified as edge pixel, noisy pixel and noise free pixel. Different weights are then used in differentiating edge & non-edge pixels and noisy & noise free pixels.
A. Directional Approach for Noise Detection

The present work proposes a selective decision criterion to separate noisy pixels from the edge pixels (as both lie within the high frequency region). The procedure initiates to distinguish between the edge and the noisy pixels prior to noise suppression. In this, the decision to segregate edges (from noisy pixels) is performed by considering 8 directions (in total) within a 5x5 window (w). The sum of absolute differences of centre pixel (i.e. w (3, 3)) from its neighbouring pixels is then computed in each direction as indicated in Eq. (1).

\[
\Delta_{ij}(k) = \sum_{i,n} \phi \cdot |X_{ij} - X_{(i,j),n}| \\
\Delta = \min[|\Delta_{ij}|,...,(8)]
\]

where: \(\Delta_{ij}(k)\) is absolute difference summation for the pixel located at \((i,j)\), \(\phi\) is the weight of the corresponding pixel to be decided experimentally, \(k\) represents directions (ranging from 1 to 8), \(m\) horizontal and vertical indices from centre pixel and \(i, j\) specify the pixel position. The minimum value of absolute difference summation \(\Delta\) computed in Eq. (2) indicates that the centre pixel \((w(3,3))\) is not an edge pixel. A pre-defined threshold \(T\) is then used to determine whether the obtained non-edge pixel is noisy or not. If the value of this minimum absolute difference, is less than the threshold it indicates that the \(w(3,3)\) is noise-free and will remain unprocessed. Otherwise, it is noisy and should be processed to remove impulse noise according to the procedure explained in following section

B. Improved DWM Filtering Approach

In the proposed approach, the decision to separate the edges from noisy pixels is already performed in the previous subsection. The impulse intensities of local window are truncated prior to the filtering and are re-arranged to form a new window (Wnew). The weighted median (med) and mean values are then computed for this new window (Wnew). Once, the weighted median and mean are determined the proposed approach involves a bi-level decision criteria to process Wnew proposed in work of A. K. Shukla et al. [40]. Hence, the entire image is then spatially processed by sliding the window (w) serially and restoring the centre pixels as per the proposed approach. The proposed approach employs a dynamic process to update the threshold value in a linear manner depending upon the available noise density. The threshold \(T\) is therefore modified iteratively starting with larger threshold (T0) and decreasing linearly to suppress high density noise using Eq. (3).

\[
\text{NSI} = \text{Noise Suppression Index of noisy image}[41].
\]

where: \(\text{represents number of iterations of proposed filter and NSI is Noise Suppression Index of noisy image}[41].\)

The proposed approach is being performed iteratively to suppress impulse noise.

III. RESULTS AND DISCUSSIONS

A. Quantitative Computation of Restored Image Quality

The performance of the proposed approach is estimated subjectively and objectively for visual inspection and quantitative evaluation respectively[42]-[43]. The quality of restored image is measured quantitatively using two quality measures: Peak Signal-to-noise ratio (PSNR) [44]-[46] and Structural Similarity Index (SSIM)[47]-[48]. Higher the value

\[
\text{PSNR} = 10 \log_{10}\frac{\text{Peak}^2}{\text{MSE}}
\]

where: Peak is largest intensity value of gray-level image and MSE is mean squared error given in Eq. (5).

\[
\text{MSE} = \frac{1}{M \times N} \sum_{i,j=1}^{M \times N} \left| s(i,j) - r(i,j) \right|^2
\]

where: \(s(i,j)\) and \(r(i,j)\) denotes standard test and restored image respectively. Other quality metric SSIM (ranging from 0 to 1) is used to indicate the structural symmetry between the restored image and reference image. The SSIM closer to unity means more structural content are preserved during restoration; hence, better quality of denoised-image. SSIM is given Eq. (6).+

\[
\text{SSIM} = \frac{1}{M \times N} \sum_{i,j=1}^{M \times N} \left( \frac{2 \mu_s \mu_r + C_1}{\mu_s^2 + \mu_r^2 + C_2} \right) \left( \frac{2 \sigma_{sr} + C_3}{\sigma_s^2 + \sigma_r^2 + C_4} \right)
\]

where: \(\mu_s, \mu_r, \sigma_s, \sigma_r\) are the mean and standard deviation of the standard and restored image, and \(\sigma_{sr}\) is the covariance between both images. C1 and C2 are constants used to provide stability.

B. Simulation Results

Proposed filtering operation is applied on standard grayscale MRI image of size 256x256 pixels corrupted with salt and pepper noise of varying density (from 10% to 98%). Figure 1 shows the noisy (figure 1(b) & 1(c)) and restored images (figure 1(d) & 1(e)) along with original standard test image (figure 1(a)) of MRI for low, medium and high noise levels for visual demonstration. PSNR (in dB) of restored images is calculated for various noise densities in Table I. From Table I and Fig. 1(d) & 1(e), it is completely removed yielding high PSNR values. At the same clear that for the noise density varying from 10% to 40% noise time, the value of SSIM is close to unity (0.9931-0.9719) indicating better structural similarity between restored image and the reference image. Even, for noise density between 50 to 80% impulses are suppressed and a good control has been exercised.

Table I. Values of PSNR (dB) and SSIM for Different Densities of Impulse Noise.

<table>
<thead>
<tr>
<th>Noise Density (%)</th>
<th>PSNR (dB)</th>
<th>SSIM</th>
</tr>
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<tbody>
<tr>
<td>10</td>
<td>73.0289</td>
<td>0.9931</td>
</tr>
<tr>
<td>20</td>
<td>69.607</td>
<td>0.9849</td>
</tr>
<tr>
<td>30</td>
<td>67.823</td>
<td>0.9765</td>
</tr>
<tr>
<td>40</td>
<td>67.0450</td>
<td>0.9719</td>
</tr>
<tr>
<td>50</td>
<td>65.7010</td>
<td>0.9616</td>
</tr>
<tr>
<td>60</td>
<td>64.4216</td>
<td>0.9483</td>
</tr>
<tr>
<td>70</td>
<td>63.0092</td>
<td>0.9282</td>
</tr>
<tr>
<td>80</td>
<td>61.7141</td>
<td>0.9026</td>
</tr>
<tr>
<td>90</td>
<td>59.4618</td>
<td>0.8629</td>
</tr>
</tbody>
</table>
to limit over-smoothening and the obtained values of SSIM range between 0.9616-0.9026. The results for very low and medium density salt and pepper noise are shown in Figure 1. For impulse contamination levels of 90 to 98% the proposed method yields reasonably good restoration with complete removal of noise as shown in Fig. 2.

C. Comparison of Results

For the purpose of comparisons, simulations are carried out on MR image (corrupted with fixed valued impulse noise with different noise densities) for other denoising approaches like:

Table II. Comparison of Restoration result in terms of PSNR (dB) Values for Different Denoising Approaches.

<table>
<thead>
<tr>
<th>Noise Density (%)</th>
<th>Various Denoising Approaches</th>
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<tbody>
<tr>
<td></td>
<td>SMFAMF [49]</td>
</tr>
<tr>
<td></td>
<td>BFOCAF [50]</td>
</tr>
<tr>
<td></td>
<td>PA</td>
</tr>
<tr>
<td>20</td>
<td>33.5</td>
</tr>
<tr>
<td>30</td>
<td>31.5</td>
</tr>
<tr>
<td>40</td>
<td>35.2</td>
</tr>
<tr>
<td>50</td>
<td>40.5</td>
</tr>
<tr>
<td>60</td>
<td>50.0</td>
</tr>
</tbody>
</table>

SMFAMF [49] and BFOCAF (a combination of an adaptive median filter and the bacterial foraging optimization (BFO) technique) [50]. These comparisons are made with proposed approach (PA) in Table II (in terms of PSNR); from where it is clear that SMFAMF [49] and BFOCAF [50] filters leave residual noise in restored image even at 50% noise level. When the noise density is greater than 50%, PSNR of other filtering approaches drops unlike the proposed approach which gives acceptable level of PSNR values. Although, it can be seen that the proposed approach (PA) yields higher values of the PSNR among other denoising approaches. The above performance analysis depicts that the proposed approach outperform other denoising approaches even at high noise densities with great improvement in PSNR. The proposed filtering approach can also suppress noise densities of 95% and above yielding a PSNR of the order of 49.36 dB; which is a reasonably high value attained in comparison to other denoising approaches as shown in Fig. 2.

IV. CONCLUSION

An improvement in performance of directional weighted-median filter is proposed in this paper. The directional filtering approach is employed to separate edge & non-edge pixels and noisy & noise free pixels using an automated threshold mechanism. Further, the impulse filtering is effectively performed by incorporating bi-level decision criteria after excluding saturated values while updating the pixel being processed. The proposed filtering approach therefore provides reasonably good results for higher noise levels with a fixed window size. It has been observed experimentally that the proposed approach converges in less than five iterations for noise densities above 80%; ensuring rapid convergence and minimal computational load. The applicability of the proposed denoising approach can be well extended for removal of noises in other modalities like SAR images for environment monitoring [51]-[52] and for computer-aided diagnosis of life threatening diseases [53]-[57].
Figure 2. (a), (b), (c) are noisy image for 90, 94 & 98% noise and (d), (e), (f) are corresponding restored images respectively.

REFERENCES

