Directional 3D Peer-Group Filter for Color Image with Random Impulse Noise

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Abstract. Peer-group filtering is the most basic approach to image denoising in the spatial domain; however, the effectiveness of this method degrades rapidly with an increase in the amount of noise. In this paper, we propose a novel 3D (3 dimensions) directional peer-group filter (referred to as 3DPGF) for the restoration of color images through the removal of random impulse noise. As with other switching methods, 3DPGF proceeds through two steps. Noise detection stage is first performed using a directional peer-group method, whereupon a 3D peer-group weighted-mean technique is used to remove the noise. Simulation results demonstrate that 3DPGF is able to enhance the accuracy in the identification and removal of noise.

Introduction

Impulse noise is usually divided into two types: salt and pepper noise (S&P) and random noise. S&P noise is a fixed extreme value with values of either 0 or 255 in the red, green and blue channels of color images. In contrast, the intensity of random impulse noise is uniformly distributed across the entire luminance range [0, 255] in all three channels of a color image. Random noise and S&P noise are both produced via the mutation of a single pixel, and can seriously degrade the quality of images through the loss of information related to image detail.

Over the last decade, several filtering algorithms have been proposed to overcome the problem of random impulse noise in color images. The vector median filter (VMF)[1] is one of the most effective with regard to noise suppression and computing efficiency. Unfortunately, when the noise ratio is high, some edges and other details can be destroyed by a traditional vector median filter. Various modifications to median filters have been proposed over the last three decades to deal with this problem. Trahanias and Venetsanopoulos [2] proposed a basic vector directional filter (BVDF) and Karakos and Trahanias [3] presented a directional-distance filter (DDF). BVDF and DDF enable the separate processing of vector-valued signals via directional processing in order to maintain image sharpness. This approach has proven successful in dealing with noise of high density.

Most classical median type vector-based filters introduce too much smoothing, regardless of whether the pixels in the image are corrupted by impulse noise or not. Other well-known vector filters, such as adaptive vector median filter (AVMF)[4], robust switching VMF (RSVMF)[5], edge detection based switching VMF...
(EDSVMF)[6], have been shown to preserve the edges and fine image details by switching between non-filtering (identification) operations and filtering operations.

Peer group filtering is the simplest approach to discriminating between noise and detail in the spatial domain, due to the fact that it does not require any sorting procedures [7]. The peer-group of a pixel in an image includes all neighboring pixels that appear similar, wherein similarity is defined by the intensity of two pixels and/or the distance between them. In cases where the size of a peer group exceeds a specified threshold, the testing pixel is treated as the original. The peer-group method is able to detect noise by assuming that no objects visible within an image can be represented using a single pixel. Unfortunately, the efficiency of this method degrades rapidly with an increase in noise, such that few uncorrupted pixels remain within the window. Recent peer-group filters, such as the fast peer group filter for VMF (FPGFvmf) [7] and the fast averaging peer group filter (FAPGF) [8], have been extended to deal with color images; however, situations involving strong noise have seldom been investigated.

Quaternion techniques have also been developed to allow the filtering of color images [10]. A quaternion framework deals with the natural coupling between color components. This approach provides sufficient scope to process color images without the need to separate them into the three channels. Jin et al. [9] proposed a solution that uses quaternion rotation operations to compute color differences. Similar methods, such as quaternion switching VMF (QSVMF) [9], quaternion directional switching VMF (QDSVMF) [10], and two-stage quaternion switching vector filter (TQSVF) [11] measure differences in color based on Euclidean distance. Unfortunately, these methods commonly employ complex transformations.

In this paper, we propose a novel filter for impulse noise based on the concept of directional weighted peer-group to overcome the difficulties described above. As with other switching methods, the proposed filter proceeds through two steps. The noise detection stage employs directional weighted peer-group detection based on the spatial correlation of pixels to improve accuracy in the identification of noise. A 3D directional peer-group weighted-mean technique is then used for the removal of noise. Simulation results demonstrate that 3DPGF is able to reconstruct even images that have been greatly compromised by the effects of noise.

**Directional Weighted Peer-Group Based Image Filter**

Many of the digital images on mobile phones, digital television, monitoring systems for traffic and safety, and e-books are corrupted by noise. Images can be blurred during acquisition due to imperfections in the sensor or during transmission due to faulty memory locations, timing errors in digitization, and bit errors. In such cases, noise suppression is crucial to achieving images of high quality. Furthermore, the miniaturization of image sensors and increases in data transfer capacity are driving the need for fast, efficient denoising algorithms.

**A. Noise Models**

The proposed filter is intended for color images corrupted by random impulse noise. We used 24-bit color images; i.e., each pixel has red, green and blue channel of 8-bits (intensity values of 0 to 255). The impulse noise model assumed noise probability \( p \).

For a single pixel \( X \) located at \((i,j)\), the observed pixel \( S_{i,j} \) can be described as random impulse noise:
\[ X_{i,j} = \begin{cases} S_{i,j}, & \text{with probability } p \\ X_{i,j}, & \text{with probability } 1-p \end{cases} \quad (1) \]

**B. Noise Detection**

A peer group is a set of pixels with intensity values close to the central pixel within a \((2W + 1)\times(2W + 1)\) sliding window. Thus, most of the pixels in the window would be similar to the central pixel if the image were noise free. This is a simple, straightforward approach to the identification of noise. Unfortunately, the noise sensitivity of peer-group detectors decreases with an increase in the noise level. This is because the size of peer-group may be not significant. To overcome this difficulty, we propose that members of a peer group that are aligned in a specified direction should be given a higher weighting. There are four main directions in a \(5\times5\) detection window that could be used to formulate directional weighted peer-groups.

\[
d_1 = \{B_{i-2,j}, B_{i-1,j}, B_{i+1,j}, B_{i+2,j}\} \\
d_2 = \{B_{i,j-2}, B_{i,j-1}, B_{i,j+1}, B_{i,j+2}\} \\
d_3 = \{B_{i-2,j+2}, B_{i-1,j+1}, B_{i+1,j+1}, B_{i+2,j+2}\} \\
d_4 = \{B_{i-2,j-2}, B_{i-1,j-1}, B_{i+1,j-1}, B_{i+2,j-2}\} \quad (2)
\]

Detecting pixels representative of random noise involves splitting the image into red, green, and blue channels. The proposed detector proceeds through the following steps:

**Step 1)** For each channel in a \((2W + 1)\times(2W + 1)\) detection window, \(C_{i,j}\) represents the set of peer-group members defined using (3). The suggested range for \(T_d\) is between 8 and 20. \(SC_{i,j}\) is the size of peer-group set. In Eq. (5), \(B_{i,j}\) registers the results of the pixel with the following

\[
C_{i,j} = \{X_{i,u,v} - X_{i,j} \leq T_d, \quad -W \leq u,v \leq W\} \quad (3)
\]

\[
SC_{i,j} = \text{size\_number of } C_{i,j} \quad (4)
\]

\[
B_{i,j} = \begin{cases} 1, & \text{if } SC_{i,j} \geq T_i \\ 0, & \text{otherwise} \end{cases} \quad (5)
\]

where \(T_i\) represents the threshold value of the peer-group.

**Step 2)** Based on the results obtained in Step 1), for each channel in a detection window, we obtain the set of strong peer-group \(P_{i,j}\) using Eq. (7). \(SP_{i,j}\) denotes the size of strong peer-group set. In cases where a pixel is random impulse noise, its peer-group size should be very small. To avoid interference, we set \(G_{i,j}\) at 0.

\[
P_{i,j} = \{X_{i,u,v} - X_{i,j} \leq T_d \quad \& \quad B_{i,u,v} = 1, \quad -W \leq u,v \leq W\} \quad (6)
\]

\[
SP_{i,j} = \text{size\_number of } P_{i,j} \quad (7)
\]

\[
G_{i,j} = \begin{cases} 0, & \text{if } X_{i,j} = S_{\text{min}} \text{ or } S_{\text{max}} \\ SP_{i,j}, & \text{otherwise} \end{cases} \quad (8)
\]
Step 3) Calculate the weighted number \( N_{i,j} \) of the peer group. In Eq. (8), \( \delta_{i,j} \) is a switch for directional weighting. If the member of peer-group aligns with one of the main direction is more than two, the value \( \delta_{i,j} \) will be set to 1. Thus, the peer-group size of the central pixel is given additional weighting. Again, \( \beta_{i,j} \) is the gatekeeper preventing interference from S&P noise during image processing. \( \beta_{i,j} \) is set to 0 if the pixel value is either the maximum or minimum.

\[
N_{i,j} = \beta_{i,j} \left( G_{i,j} + \delta_{i,j} \times (2W + 1) \right) \tag{9}
\]

\[
\beta_{i,j} = \begin{cases} 
0, & \text{if } X_{i,j} = S_{\text{min}} \text{ or } S_{\text{max}} \\
1, & \text{otherwise}
\end{cases} \tag{10}
\]

\[
\delta_{i,j} = \begin{cases} 
1, & \text{if } \text{sum}(d_i) \geq 2, \quad 1 \leq i \leq 4 \\
0, & \text{otherwise}
\end{cases} \tag{11}
\]

Step 4) To decide the pixel is corrupted or not, the simple judgment is according to \( N_{i,j} \) produce in step 3. Threshold \( T \) is used to determine whether a pixel represents noise; i.e., \( T \) denotes the noise-free threshold. If \( N_{i,j} \) in a 3×3 window is less than three, then the testing pixel is non-directional and deemed to be affected by noise. \( T \) in a 5×5 window is 7, which indicates that the center pixel does not represent noise (with 70% reliability). Finally, a noise map is built as follows:

\[
F_{i,j} = \begin{cases} 
\text{noise pixel,} & \text{if } N_{i,j} \leq T \\
\text{noise-free pixel,} & \text{otherwise}
\end{cases} \tag{12}
\]

**C. 3D Switching Mean Filter**

A switching mean filter is applied only to noise pixels, which means that it does not affect data related to noise-free pixels, thereby helping to preserve precious detail. Furthermore, only noise-free pixels are used as reference pixels. When denoise a channel, the same window in the other two channels will also be used.

The steps of filter are as follow:

Step 1) Record the result of map \( F \) dot noise image \( X \) in map \( M \). In map \( M \), all noise is recorded as zeros in order to retain the noise-free values. This makes it easy to identify the location of noisy and noise-free pixels.

\[
M_{i,j} = F_{i,j} \cdot X_{i,j} \tag{13}
\]

Step 2) The 3D filter is employed to find the two pixels with the minimum distance along these four directions. Here, we use Eq. (15) to ensure that the three channels of the two pixels are the same.

\[
T_{i,j,k} = \begin{cases} 
\sum_{\tau=1}^{3} [M_{i+\tau,j+k} - M_{i,j,k}] & \text{if } Q_{i,j,k} = 1 \\
\sum_{\tau=1}^{3} [M_{i+\tau,j+k} + M_{i,j+k} - X_{i,j}] & \text{otherwise}
\end{cases} \tag{14}
\]
where \( I \) denotes one of the three channels (i.e., red, green, or blue). Symbol \( k \) represents the pixels in one of these four directions, and two pixels of these four directions are located in \((i+s, j+t)\) and \((i+\bar{s}, j+\bar{t})\), and \((s, t, \bar{s}, \bar{t}) \in \{(-1,0,1,0),(0,-1,0,1),(-1,1,1,1),(-1,1,1,-1)\}\). The minimum distance along these four directions is calculated as follows:

\[
[V, \bar{V}] = \min_{k=1}^{4}(T_{i,j,k})
\]  

where symbols \( V \) and \( \bar{V} \) respectively denote the minimum distance value and the direction of minimum distance.

Step 3) Noisy pixels are filtered out using these two pixels along the minimal distance direction.

\[
y_{i,j} = \frac{M_{i+s,i+t} + M_{i+\bar{s},i+\bar{t}}}{2}
\]

The proposed algorithm proceeds through two iterations involving the processing of the red, green, and blue channels.

**Experimental Results**

In this section, we examine the degree to which image quality can be enhanced through restoration using the proposed algorithm. We tested the 24-bit image Lena at a resolution of 512\( \times \)512. The quality of reconstruction was measured using peak-to-signal ratio (PSNR), mean absolute error (MAE) and the normalized color difference (NCD) [11]. Figure 1 illustrates the visual quality of filtered images and noisy images with noise ratios from 5% to 25%. Clearly, the proposed 3DPGF achieves superior image quality by providing the best noise suppression effects while preserving more of the image detail.

The performance of the proposed algorithm was also compared with other impulse noise filters: classical vector filters such as vector median filter (VMF) [1], basic vector directional filter (BVDF) [2], and directional-distance filter (DDF) [3], and other well-known vector filters such as adaptive vector median filter (AVMF)[4], robust switching VMF (RSVMF)[5], edge detection based switching VMF (EDSVMF)[6], fast peer group filter for VMF (FPGFvmf) [7], fast averaging peer group filter (FAPGF) [8], quaternion switching VMF(QSVMF) [9], quaternion directional switching VMF (QDSVMF) [10], and two-stage quaternion switching vector filter (TQSVF) [11].
Figure 1. Results of proposed 3DPGF filter in restoring Lena image distorted by (from left to right) 5%, 10%, 15%, 20%, and 25% of random impulse noise.

Table I. Comparison of various filters in restoring Lena image corrupted by impulse noise.

<table>
<thead>
<tr>
<th>Methods</th>
<th>p</th>
<th>0.05</th>
<th>0.1</th>
<th>0.15</th>
<th>0.2</th>
<th>0.25</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>PSNR</td>
<td>MAE</td>
<td>NCD</td>
<td>PSNR</td>
<td>MAE</td>
<td>NCD</td>
</tr>
<tr>
<td>VMF</td>
<td>32.37</td>
<td>3.60</td>
<td>0.0311</td>
<td>30.80</td>
<td>4.16</td>
<td>0.0378</td>
</tr>
<tr>
<td>BVDF</td>
<td>31.13</td>
<td>4.14</td>
<td>0.0344</td>
<td>29.10</td>
<td>4.79</td>
<td>0.0396</td>
</tr>
<tr>
<td>DDF</td>
<td>32.32</td>
<td>3.63</td>
<td>0.0330</td>
<td>30.84</td>
<td>4.16</td>
<td>0.0375</td>
</tr>
<tr>
<td>AVMF</td>
<td>34.33</td>
<td>1.01</td>
<td>0.0198</td>
<td>31.60</td>
<td>2.03</td>
<td>0.0318</td>
</tr>
<tr>
<td>RSVMF</td>
<td>33.03</td>
<td>1.03</td>
<td>0.0107</td>
<td>25.57</td>
<td>2.99</td>
<td>0.0332</td>
</tr>
<tr>
<td>EDSVMF</td>
<td>33.72</td>
<td>1.30</td>
<td>0.0106</td>
<td>32.10</td>
<td>2.09</td>
<td>0.0181</td>
</tr>
<tr>
<td>FPGPvMf</td>
<td>35.64</td>
<td>0.95</td>
<td>0.0091</td>
<td>32.18</td>
<td>1.98</td>
<td>0.0183</td>
</tr>
<tr>
<td>FAPGF</td>
<td>34.38</td>
<td>1.02</td>
<td>0.0096</td>
<td>32.04</td>
<td>1.83</td>
<td>0.0199</td>
</tr>
<tr>
<td>QSVMF</td>
<td>35.84</td>
<td>0.86</td>
<td>0.0076</td>
<td>32.33</td>
<td>1.78</td>
<td>0.0158</td>
</tr>
<tr>
<td>QDSVMF</td>
<td>35.64</td>
<td>0.87</td>
<td>0.0077</td>
<td>32.79</td>
<td>1.67</td>
<td>0.0148</td>
</tr>
<tr>
<td>TQSVF</td>
<td>37.04</td>
<td>0.83</td>
<td>0.0075</td>
<td>34.16</td>
<td>1.61</td>
<td>0.0143</td>
</tr>
<tr>
<td>3DPGF</td>
<td>37.95</td>
<td>0.45</td>
<td>0.0060</td>
<td>36.19</td>
<td>0.73</td>
<td>0.0106</td>
</tr>
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</table>

Table I lists result of the performance comparison in terms of PSNR, MAE, and NCD. Images used in the comparisons were distorted by applying random impulse noise at ratios of between 5% and 25%. A higher PSNR value and lower MAE and NCD are indicative of high-quality reconstruction. Table I presents a comparison of restoration results on the Lena image corrupted by impulse noise. Clearly, VMF, BVDF, DDF, and RSVMF are poorly suited to the task of removing impulse noise. FAPGF, QDSVMF, EDSVMF and TQSVF achieved excellent noise suppression performance. The proposed 3DPGF achieved excellent performance in terms of PSNR, MAE, and NCD. Furthermore, at higher noise ratios, the proposed 3DPGF achieved a PSNR approximately 3 dB higher than that of the other methods.

Conclusion

This paper presents a simple, high-performance impulse filter based on the directional weighted peer-group and 3D switching mean methodology. The novel algorithm outperforms other state-of-the-art filters, particularly in dealing with images with high noise levels of unknown origin.

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References


