SWITCHING BILATERAL FILTER WITH A TEXTURE/NOISE DETECTOR FOR UNIVERSAL NOISE REMOVAL

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ABSTRACT

In this paper, we propose a switching bilateral filter (SBF) with a texture and noise detector for universal noise removal. Operation was carried out in two stages: detection followed by filtering. For detection, we propose the sorted quadrant median vector (SQMV) scheme, which includes important features such as edge or texture information. This information is utilized to allocate a reference median from SQMV, which is in turn compared with a current pixel to classify it as impulse noise, Gaussian noise, or noise-free. The SBF removes both Gaussian and impulse noise without adding another weighting function. The range filter inside the bilateral filter switches between the Gaussian and impulse modes depending on the noise classification result. Simulation results show that our noise detector has a high noise detection rate as well as a high classification rate for salt-and-pepper, uniform impulse noise and mixed impulse noise. Unlike most other impulse noise filters, the proposed SBF achieves high peak signal-to-noise ratio and great image quality by efficiently removing both types of mixed noise, salt-and-pepper with uniform impulse noise and mixed impulse noise. Unlike most other impulse noise filters, the proposed SBF achieves high peak signal-to-noise ratio and great image quality by efficiently removing both types of mixed noise, salt-and-pepper with uniform impulse noise and mixed impulse noise

Index Terms— switch bilateral filter, image restoration, Gaussian noise, impulse noise, mixed noise

1. INTRODUCTION

An important problem of image processing is to effectively remove noise from an image while keeping its features. There are two noise models can be used to represent most noise in images: additive Gaussian noise and impulse noise. Additive Gaussian noise is characterized by adding to each image pixel a value with a zero-mean Gaussian distribution. Such noise is usually introduced during image acquisition. Bilateral filter [1] utilize local measures such as weighting to smooth the noise in the image. Impulse noise is characterized by replacing a portion of an image’s pixel with noise values, leaving the remainder unchanged. Such noise can be introduced due to transmission errors. Separate classes of non-linear filters have been developed specifically for the removal of impulse noise; including extensions of the median filter [2], [3], rank statistics [4], and learning algorithm [5]. The common idea among these filters is to detect the impulse pixels and replace them with estimated values, while leaving the remaining pixels unchanged.

In this paper, we create a universal noise removal filter based on the detect and replace methodology. To detect noise, the absolute difference between a current pixel value and the reference median is computed. In order to find the proper reference median, we have to understand the properties such as edge or texture in the current window. We define a sorted quadrant median vector (SQMV) and present an approach to recognize edge and texture. To achieve good visual image quality, it is important that the estimator not only replaces noisy pixel but also preserves edge. We propose a switching bilateral filter (SBF) for removing both Gaussian and impulse noise. The SBF shows very good results in removing mixed noise.

This paper is arranged as follows. In Section II, we propose the SQMV scheme, and its utilization for detecting noise are discussed. Section III presents, the two-stage detection method and the switching bilateral filter for universal noise removal. In Section IV, experimental results are presented with visual examples and numerical results. Finally, a brief conclusion is given in Section V.

2. SQMV FOR NOISE DETECTION

For a larger window with size \((2N + 1) \times (2N + 1)\), we divide it into four sub-windows of size \((N + 1) \times (N + 1)\), with the central pixel as the corner pixel in the four sub-windows as shown in Fig. 1, where \(N = 2\) in the following discussion. Let \(x_{i,j}\) be the luminance of the central pixel located at the position \((i, j)\) in a window. Then, the set of points in a window can be expressed as

\[
\Omega Q_0 = \{x_{i+s,j+t}: -N \leq s \leq N, -N \leq t \leq N\} \quad (1)
\]

The set of pixels in the four sub-window blocks of size \((N + 1) \times (N + 1)\) are defined as

\[
\Omega Q_1 = \{x_{i+s,j+t}: 0 \leq s \leq N, 0 \leq t \leq N\} \quad (2)
\]
Fig. 1. Four quadrant blocks in a single 5×5 window.

$$\Omega_Q2 = \{x_{i+s,j+t} : -N \leq s \leq 0, 0 \leq t \leq N\}$$ (3)

$$\Omega_Q3 = \{x_{i+s,j+t} : -N \leq s \leq 0, -N \leq t \leq 0\}$$ (4)

$$\Omega_Q4 = \{x_{i+s,j+t} : 0 \leq s \leq N, -N \leq t \leq 0\}$$ (5)

With the medians values in the sub-window and edge/texture information in the larger window, the median drifting problem in a larger window or lack of texture information problems can be avoided. Each quadrant block has a median value which can be expressed as

$$m_k = \text{median} \{\Omega_{Q_k}\}, \text{k = 1 to 4}$$ (6)

where $$m_1, m_2, m_3,$$ and $$m_4$$ are sorted in an increasing order and SQMV is defined as

$$SQMV = [SQM1, SQM2, SQM3, SQM4]$$ (7)

The clusters of SQMV provide edge and texture information within a window for an image. Although there are several patterns for classifying the geometric shape and clusters from SQMV, we can condense these patterns into three edge/texture cases based on the cluster distribution. To determine the cluster distribution, we define $$SQMdB$$ as the difference between the two boundary values of the sorted quadrant medians and $$SQMdc$$ as the difference between the two center values of the sorted quadrant medians.

$$SQMdB = SQM4 - SQM1$$ (8)

$$SQMdc = SQM3 - SQM2$$ (9)

Based on the information of $$SQMdB$$ and $$SQMdc$$, we propose the edge/texture detector that is summarized below.

\[
\begin{align*}
\text{Without edge,} & \quad SQMdB \leq \rho \\
\text{weak edge,} & \quad SQMdB \geq \rho \wedge SQMdc \leq \rho \\
\text{strong edge or texture,} & \quad SQMdc \geq \rho
\end{align*}
\] (10)

Using the edge/texture detector to classify SQMV into three simple cases, we can analyze the texture information in the window. SQMV is an efficient and robust edge detection scheme for a noisy image. We found through experimentation that a good value of $$\rho$$ lies in the interval [25, 40].

Fig. 2. Direction average: the pixels in black box that are needed in each case. (a) vertical (b) horizontal (c) diagonal directions

2.1. Reference Median

When the difference between the current pixel value and the reference median is large, then the current pixel is very likely to be a noise pixel. In the without edge or weak edge cases, the cluster contain $$SQM2$$ and $$SQM3$$ represents the majority cluster. The average of $$SQM2$$ and $$SQM3$$ is used as the reference median value for comparison.

For the cases strong edge or texture, there is no major cluster in the SQMV. It is necessary to decide which cluster the current pixel falls into. From the order of four $$m_k$$ values, the pattern in this window can be classified into the three cases: vertical edge, horizontal edge, diagonal line or texture. A direction average approach is adopted to determine which cluster is more similar to the current pixel. Depending on the case, the four pixels in the major pattern are averaged, represented by $$dav$$:

$$dav = (x_1 + x_2 + x_3 + x_4)/4$$ (11)

As shown in Fig. 2, the four pixel values of the major pattern within the block are averaged. For example, if $$dav$$ is close to $$(SQM1, SQM2)$$, then $$SQM2$$ is chosen as the reference median value in the window. On the other hand, if it is close to $$(SQM3, SQM4)$$, then $$SQM3$$ is the reference median value. Finally, we define $$SQMR$$ as the reference median.

$$SQMR$$

\[
\begin{align*}
(SQM3 + SQM2)/2, & \quad SQMdc \leq \rho \\
SQM3, & \quad SQMdc \geq \rho \wedge \\
SQM2, & \quad dav \in (SQM3, SQM34) \\
\end{align*}
\] (12)

3. SWITCHING BILATERAL FILTER

In the switching scheme, the noise detector searches for noisy pixels and tries to distinguish them from uncorrupted ones. We propose an extension to the standard switching-scheme, which uses an additional detector to identify edge or detail in a current window. This information is used in the noise detector to decide the reference median for noise identification. The noise detector also decides whether a current pixel
should be filtered by using an SBF or whether it should bypass the SBF. There are two kinds of SBF, SBF_{im} and SBF_{ga}. The former is a bilateral filter for impulse noise and the latter is for Gaussian noise. Let \( u_{i,j} \) and \( \tilde{u}_{i,j} \) denote the noisy pixel and the filtered pixel, respectively. Also, let \( S_1 \) and \( S_2 \) denote binary control signal generated by the noise detector. The proposed two-stage filter is shown in Fig. 3, and the filtered image is defined as follow:

\[
\tilde{u}_{i,j} = \begin{cases} 
SBF_{im}, & S_1 = 1 \land S_2 = 1 \\
SBF_{ga}, & S_1 = 1 \land S_2 = 0 \\
u_{i,j}, & S_1 = 0 \land S_2 = 0 
\end{cases}
\] (13)

The switching scheme is implemented in a recursive manner, similar as in [3]. Noise in the pixels processed in the previous step are likely to be moved so recursive implementation produces better result than non-recursive one.

### 3.1. Noise Detector Design

This decision is made using the features of SQMV which can show the property of the background and is more reliable than only one median value. We obtain the reference median for noise identification from SQMV. When a current pixel is very different from the reference median, it is identified as an impulse noise. When the difference between the current pixel and reference median is not too much, it may be a Gaussian noise or a noise-free pixel. The decision making mechanism is realized by employing a reference median and two thresholds \((Tk_1 \text{ and } Tk_2)\) and the noise detection algorithm is shown in Fig. 4.

\[
(1) \quad \text{If } |x_{i,j} - SQMR| \geq Tk_1  \\
(2) \quad S_1=1, S_2=1 \quad \text{(} x_{i,j} \text{ is impulse noise)}  \\
(3) \quad \text{Else if } |x_{i,j} - SQMR| \leq Tk_2  \\
(4) \quad S_1=1, S_2=0 \quad \text{(} x_{i,j} \text{ is Gaussian noise)}  \\
(5) \quad \text{Else}  \\
(6) \quad S_1=0, S_2=0 \quad \text{(} x_{i,j} \text{ is noise-free)}  \\
(7) \quad \text{End}
\]

Fig. 4. Pseudo-code of noise detector.

\( Tk_1 \text{ and } Tk_2 \) are thresholds for identifying impulse noise or Gaussian noise. The salt-and-pepper impulse noise contains either the maximum or minimum value so it is easy to detect. The selection of \([Tk_1, Tk_2] = [30, 15] \) yields satisfactory results in filtering salt-and-pepper impulse noise, while the setting of \([Tk_1, Tk_2] = [25, 5] \) consistently performs well in removing uniform impulse and Gaussian noise.

### 3.2. Switching Bilateral filter

In this section, we propose a new universal noise removal algorithm: the switching bilateral filter (SBF). Let \( x_{i,j} \) be the current pixel, and let \( x_{i+s,j+t} \) be the pixels in a \((2N + 1) \times (2N + 1)\) window surrounding \( x_{i,j} \). Finally, the SBF is defined as follows:

\[
u_{i,j} = \frac{\sum_{s=-N}^{N} \sum_{t=-N}^{N} W_G(s,t)W_R(s,t)x_{i+s,j+t}}{\sum_{s=-N}^{N} \sum_{t=-N}^{N} W_G(s,t)W_R(s,t)}
\] (14)

where

\[
W_G(s,t) = \exp \left( \frac{(i-s)^2 + (j-t)^2}{2\sigma^2} \right)
\] (15)

\[
W_R(s,t) = \exp \left( \frac{(I-x_{i+s,j+t})^2}{2\sigma^R} \right)
\] (16)

and

\[
I = \begin{cases} 
SQMR, & s_2 = 1 \text{ for } SBF_{im} \\
x_{i,j}, & s_2 = 0 \text{ for } SBF_{ga}
\end{cases}
\] (17)

By replacing \( x_{i,j} \) with \( SQMR \) of the window, we can remove impulse noise without adding another weighting function. The difference between neighbors and median would not be too large, and thus, the edges and details can be preserved while removing the noise. The experiments showed that the SBF_{im} function gives better noise removal results than the median function alone. There are two parameters \( \sigma_S \text{ and } \sigma_R \) that control the SBF. We take different values for the two parameters in the different noise models. Through our experiment, when an edge is detected by the edge detector, we take \( \sigma_S = 3 \), and \( \sigma_S = 1 \) otherwise. A good initial value of \( \sigma_R \) is 40 and any value in the interval \([30, 50]\) should work well to remove both impulse noise and mixed impulse noise.

### 4. EXPERIMENTAL RESULT

Our method produced results superior to other methods in both visual image quality and quantitative measures. Simulation were made on 512 \times 512 8-bit grayscale test images corrupted with mixed impulse, and Gaussian noise. The SBF can restore an image corrupted with mixed noise, as demonstrated by the Lena image corrupted by mixed salt-and-pepper and uniform impulse noise with \( p = 30\% \). The original, noisy image and the one filtered by our proposed SBF are compared with median filter, SDROM [3], trilateral [4], GP [5] as shown in Fig. 5. It is clear that the SBF filter can eliminate noise...
while preserving the edge and fine details. The PSNR is used as a quantitative measure for comparison. Table I shows the PSNR values on three cases of mixed noise. In TABLE I(a), the SBF shows the best values followed by the trilateral filter. In TABLE I(b), the trilateral filter shows better results in most of the images and the SBF is very close to it. In TABLE I(c), the SBF filter consistently yields the highest PSNR for each image.

5. CONCLUSION

The major contribution of this paper is to propose SQMV for edge/texture detection, noise detection, and the switching bilateral filter. The edge detector, with a simple structure, obtains a reference median value for noise detection, which detects impulse and Gaussian noise. Both detectors are based on robust estimators of SQMV. We incorporate SQMV into switching bilateral filtering by replacing the current pixel with a proper median value. The proposed filter outperforms other filters, both in PSNR and visually. Moreover, it shows excellent performance in the simultaneous removal of both impulse and Gaussian noise and without adding another weight-

| Table 1. Comparative Restoration Results in PSNR (dB) for Mixed-Noise |
|---------------------------|--------------|--------------|--------------|------------|
| (a) Salt-and-Pepper and Gaussian $p = 20\%$, $\sigma = 10$ | Filters     | Lena          | Boats        | Bridge      | Airplane   |
| MED3x3                      | 29.52        | 27.61         | 24.02        | 26.91       |
| SDROM                       | 28.38        | 27.07         | 24.99        | 26.11       |
| Trilateral                  | 29.78        | 28.59         | 24.23        | 27.35       |
| GP                          | 30.07        | 28.16         | 24.54        | 27.50       |
| Proposed                    | 30.84        | 28.58         | 25.33        | 27.88       |
| (b) Uniform Impulse and Gaussian $p = 20\%$, $\sigma = 10$ | Filters     | Lena          | Boats        | Bridge      | Airplane   |
| MED3x3                      | 29.41        | 27.44         | 23.86        | 26.81       |
| SDROM                       | 28.24        | 26.95         | 24.71        | 26.36       |
| Trilateral                  | 30.13        | 28.72         | 24.19        | 28.33       |
| GP                          | 28.92        | 27.46         | 25.23        | 26.93       |
| Proposed                    | 29.68        | 27.78         | 24.41        | 26.48       |
| (c) Salt-and-Pepper and Uniform Impulse $p = 30\%$ | Filters     | Lena          | Boats        | Bridge      | Airplane   |
| MED3x3                      | 29.21        | 27.22         | 23.38        | 26.36       |
| SDROM                       | 31.23        | 28.89         | 25.23        | 27.58       |
| Trilateral                  | 29.45        | 27.90         | 23.43        | 27.05       |
| GP                          | 29.85        | 27.74         | 23.89        | 27.03       |
| Proposed                    | 31.57        | 29.11         | 25.46        | 28.24       |

6. REFERENCES


