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An Improved Trilateral filter for Gaussian and Impulse Noise Removal

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***Abstract*—In this paper, we improve the trilateral filter for removing the mix of Gaussian and impulse noise. The new algorithm incorporates Rank-Ordered Absolute Differences (ROAD) Statistic for detecting outliers in gradient domain and intensity domain of image with impulse noise. A switching mechanism is adopted in gradient bilateral filter and intensity bilateral filter for smoothing the gradients and intensities of impulse noise samples and impulse noise-free samples with different parameters. By introduce the impulse detector in both gradient domain and intensity domain, the proposed algorithm has demonstrated superior performance in suppressing noise, which include Gaussian, impulse, and mixed noise. Compared to most other nonlinear filters, the proposed algorithm consistently yields good results in a sharply-bounded, gradient piecewise-linear approximation which provides stronger noise reduction and better edge-limited smoothing behavior.**

Keywords-Trilateral filter, Rank-ordered Absolute Differences (ROAD) Statistic, Gaussian noise, Impulse noise, mixed noise, noise removal, Nonlinear filter

I. INTRODUCTION

Additive white Gaussian noise is a kind of statistical noise that has a probability density function of a zero-mean Gaussian distribution. It is usually introduced during image acquisition which mainly caused by electronic instability of the image signal and electromagnetic interferences. Many classical linear filters, such as Gaussian filter and Median filter, are developed to remove Gaussian noise by averaging local pixels efficiently. Unfortunately, edges and details of image are blurred significantly. Impulse noise is mainly the result of transmission errors, which is mostly introduced during image transmission. Impulse noise always has short duration and high energy, and it changes the values of a portion of pixels with random values, leaving the remaining pixels unchanged. Because of the high energy of impulsive noise, the intensities of the corrupted pixels are much different from their neighbors. Many kinds of nonlinear filters, such as extensions of the median filter, or otherwise use rank statistics [1], have been developed for the removal of impulse noise. In these filters, the pixels corrupted with impulse noise are replaced with estimated values, and leave the impulse noise-free pixels unchanged.

Removing the mix of Gaussian and impulse noise is difficult and there has not been much work carried out on building these filters. Peng and Lucke proposed Multi-level adaptive fuzzy filter for mixed noise removal [2]. Abreu and Lightstone et al. presented the median-based SD-ROM filter for the removal of impulse noise from highly corrupted images [3]. In 2005, R. Garnett, T. Huegerich and C. Chui [4] described a universal noise removal algorithm with impulse detector. This news algorithm combined bilateral filter, which is effective to remove Gaussian noise, with an impulse weight based on ROAD statistics, which is successful on filtering impulse noise. Although the result is visually impressive, the details on ridge-like and valley-like edges and high gradient regions, as shown in Figure 1(b), are smoothed significantly.

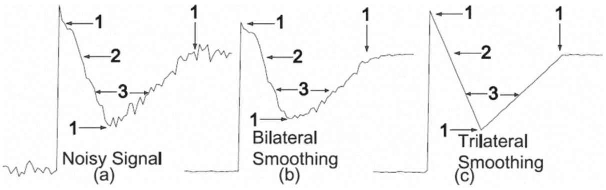

Figure 1. Difficult feature in 1-D signal[5]: (1) Ridge-like and valley-like edges, (2) High gradient regions, (3) Similar intensities in disjoint regions.

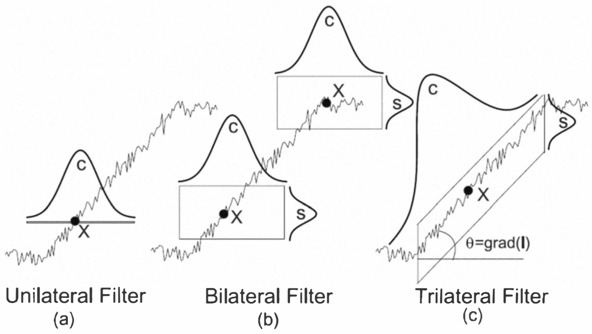

Figure 2. Unilateral, Bilateral and Trilateral filter windows for 1-D signal[5].

In this paper, an improved trilateral filter for removal the mix of Gaussian and impulse noise is presented. Our work is motivated by the idea of adding impulse detector to the gradient bilateral filter, and preprocessing the input image before intensity bilateral filter of trilateral filter. The behavior of the filter can remove the mix of Gaussian and impulse noise efficiently in either high gradient regions or low gradient regions without smooth the ridge-like and valley-like edges. The paper is organized as follows. In Section II, we briefly explain bilateral filter, Rank-ordered Absolute Differences (ROAD) Statistics, the switching mechanism and trilateral filter. In Section III, we describe how the improved trilateral filter works. In Section IV, experimental examples and numerical results are given to demonstrate our method's effectiveness. Finally, conclusions are drawn in Section V.

II. RELATED WORK

A. Bilateral Filter

The bilateral filter is a nonlinear filter proposed by Aurich and Weule [6], Smith and Brady [7], and Tomasi and Manduchi [8] to smooth images. It has been adopted for filtering additive white Gaussian noise (Tomasi and Manduchi [8]). The rationale of bilateral filter is that two pixels are close to each other not only if they occupy nearby spatial locations but also if they have some similarity in the photometric range [9]. The weight $w(x,y)$ of each neighbor combines a spatial weight component $w_R(x,y)$ that penalizes distant pixels, with a range weight component $w_R(x,y)$ that penalizes pixels with different between the intensities of central pixel $I(x)$ and its neighboring pixel $I(y)$.

$$I_{out}(x) = \frac{1}{k(x)} \sum\nolimits_{y\in\Omega} w_S(x,y) w_R(x,y) I(y) \quad (1)$$

$$k(x) = \sum\nolimits_{y\in\Omega} w_S(x,y) w_R(x,y) \quad (2)$$

$$w_S(x,y) = e^{-\frac{|x-y|^2}{2\sigma_S^2}} \quad (3)$$

$$w_R(x,y) = e^{-\frac{|I(x)-I(y)|^2}{2\sigma_R^2}} \quad (4)$$

Only the input pixels within the rectangular filter window Ω shown in Figure 2(b) can strongly affect the output value $I_{out}(x)$. In some practical situation, the bilateral filter can be used to smooth an input image corrupted by Gaussian noise while preserving its edges.

B. Rank-ordered Absolute Differences (ROAD) Statistics

Rank-ordered Absolute Differences Statistics [4] is a local image statistics proposed to detect outliers in image in 2005. It provides a measure of how close a pixel value is to its m most similar neighbors in intensity. Let x be the central pixel of its $(2N+1)\times(2N+1)$ neighborhood in the input image. For each pixel $y\in\Omega$, we define $d_{x,y}$ as the absolute difference in intensity between x and y:

$$d_{x,y} = |I(x) - I(y)| \quad (5)$$

Then we sort the eight $d_{x,y}$ values, and add the smallest m values together to form the Rank-ordered Absolute Differences (ROAD) Statistics:

$$ROAD_m(x) = \sum_{i=1}^{m} r_i(x) \quad (6)$$

where $2 \le m \le 7$, and $r_i(x) = i$ th smallest $d_{x,y}$ for $y \in \Omega$.

C. Switching Mechanism

By incorporating the ROAD statistics into the bilateral filter, a switching mechanism [4] is proposed. To add the impulsive weight while still retaining the intensity component of the bilateral filter, a "joint impulsivity" J is defined as:

$$J(x,y) = 1 - e^{-\left(\frac{ROAD(x)+ROAD(y)}{2}\right)^2 / 2\sigma_J^2} \quad (7)$$

which determines how much to use the intensity component in the present of impulse noise. After the introduction of "joint impulsivity" J, the weight function is modified as:

$$w(x,y) = w_S(x,y) w_R(x,y)^{1-J(x,y)} w_I^{\,J(x,y)} \quad (8)$$

$$w_I(x) = e^{-\frac{(ROAD(x))^2}{2\sigma_I^2}} \quad (9)$$

In the region affected by impulse noise, $J(x,y) \approx 1$, the intensity component is less heavily and the impulse component is more heavily. Conversely, in the region without large impulse noise, $J(x,y) \approx 0$, the intensity component is more heavily and the impulse component is less heavily.

D. Trilateral Filter

The trilateral filter is a nonlinear filter proposed by Choudhury and Tumblin [5] addressing HDR Tone Mapping, Contrast Reduction and Mesh Smoothing, by combining a gradient bilateral filter and an intensity bilateral filter with a pyramid-based method to limit filter window. They adopt a gradient bilateral filter to the image gradients to estimate the high gradient regions and separate image areas. Using the smoothed gradient, they "tilt" the filter window of intensity bilateral filter. As shown in Figure 2(c), the extension of intensity bilateral filter window restores the effectiveness of the spatial filter term. A connected set of pixel that share similar filtered-gradient values will be in one window of this tilted bilateral filter for each output pixel. To find the connected region with similar filtered-gradient value, a pyramid-like structure is proposed, which reduces the computing time significantly. All the internal parameters used in trilateral filter can be derived from a single user-supplied value. Avoiding hand-tuned parameters improves the usefulness and generality of the trilateral filter.

III. FILTER PRELIMINARIES

The trilateral filter, as described in [5], applies a nonlinear filter to remove Gaussian noise while retaining the sharp, ridge-like and valley-like edges. Because of the short duration and high energy, the intensities of the pixels corrupted by impulse noise are much different from their neighbors. The significant differences bring gradient and intensity outliers. By introducing the impulse detector to the gradient bilateral filters, and preprocessing the input image before intensity bilateral filter of trilateral filter, the trilateral filter can be easily improved to remove the mix of Gaussian and impulse noise.

We combine impulse detector with gradient bilateral filter to smooth the original row gradient image G_R and column gradient image G_C which can remove gradient outliers efficiently. The row bilaterally-smoothed gradient $G_{Rsmoothed}$ is calculated by:

$$G_{Rsmoothed}(x) = \frac{1}{k_G(x)} \sum_{y\in\Omega_G} G(y) w_S(x,y) w_G(x,y)^{1-J_{GI}(x,y)} {w_{GI}}^{J_{GI}(x,y)} \tag{10}$$

$$k_G(x) = \sum_{y\in\Omega_G} w_S(x,y) w_G(x,y)^{1-J_{GI}(x,y)} {w_{GI}}^{J_{GI}(x,y)} \tag{11}$$

$$w_{GI}(x,y) = e^{-\frac{ROAD_R(\nabla I(x))^2}{2\sigma_{GI}^2}} \tag{12}$$

$$J_{GI}(x,y) = 1 - e^{-\frac{(ROAD_R(\nabla I(x)) + ROAD_R(\nabla I(y)))^2}{2\sigma_{GJ}^2}} \tag{13}$$

By adding impulse detector to bilateral filter, a universal noise removal algorithm is proposed in [4]. Before intensity bilateral filter, we use the universal noise removal algorithm to preprocess input image. A threshold $ROAD_{th}$ is proposed to get better edge-limited smoothing behavior. All the pixels whose ROAD is bigger than $ROAD_{th}$ are smoothed by the universal noise removal algorithm. We consider $ROAD_{th} = 256$ in the following discussion.

The improved trilateral filter consists of six steps, which are outlined as follows:

- Calculate the row gradient image G_R and column gradient image G_C using forward differences.
- Compute the row ROAD statistics $ROAD_R$ from G_R, and the column ROAD statistics $ROAD_C$ from G_C.
- Calculate the row gradient $G_{Rsmoothed}$ and column gradient $G_{Csmoothed}$ using the universal noise removal algorithm.
- Use the pyramid-like structure to find the largest inscribed square neighborhood for each pixel of input image.
- Compute the $ROAD$ statistics from I_{in}. Smooth the pixels whose $ROAD$ is bigger than $ROAD_{th}$ using the universal noise removal algorithm.
- Reconstructing the final image I_{out} from the intensity bilateral filter.

IV. EXPERIMENT AND RESULTS

We have extensively tested the validity of our algorithm and compared the results with some existing methods. In the experiments, we used a 5×5 window for gradient bilateral filter, a 3×3 window for preprocessing the input image and intensity bilateral filter, and image boundaries were handled by symmetric boundary conditions. Some of the experimental images are demonstrated in Figure 3. As shown in the figures, the results of our method are superior to the other methods in both visual image quality and quantitative measure.

In this paper, we use the signal-to-noise ratio (SNR) to give quantitative measures of images de-noised by different filters. In [10], if $\widetilde{I}$ is a de-noised image, the SNR of $\widetilde{I}$ is estimated by the ratio of the maximum and minimum of local variance. Experience has shown that appropriate correction will make the result more accurately.

The local variance of image $\widetilde{I}$ is defined as:

$$\sigma_I(i,j) = \frac{1}{(2P+1)(2Q+1)} \sum_{k=-P}^{P} \sum_{l=-Q}^{Q} [I(i+k, j+l) - \mu_I(i,j)]^2 \tag{14}$$

$$\mu_I = \frac{1}{(2P+1)(2Q+1)} \sum_{k=-P}^{P} \sum_{l=-Q}^{Q} I(i+k, j+l) \tag{15}$$

The SNR of the image is calculated by:

$$SNR = 10.4 * \log 10(\max(\sigma(I)) / \min(\sigma(I))) - 7 \tag{16}$$

The $(2P+1)\times(2Q+1)$ is the neighborhood of the central pixel. We consider $P = Q = 2$ in the following discussion.

TABLE I. SNR COMPARISION TABLE

Method	Signal-to-noise Ratio (dB)			
	Parrots	***Church***	***Road***	***Chairs***
Median filter	29.11	29.52	28.55	27.73
MBF	35.20	31.51	33.92	34.15
Our method	45.90	38.64	36.14	37.91

V. CONCLUSION

In this paper, we introduce a new improved trilateral filter for removing the mix of Gaussian and impulse noise. Built from Prasun Choudhury and Jack Tumblin's trilateral filter, the new algorithm incorporates Rank-Ordered Absolute Differences (ROAD) Statistic for detecting outliers in gradient domain and intensity domain of image with impulse noise. By introduce the impulse detector in both gradient domain and intensity domain, the proposed algorithm has demonstrated superior performance in suppressing noise, which include Gaussian, impulse, and mixed noise. Compared to most other nonlinear filters, the proposed algorithm consistently yields good results in a sharply-bounded, gradient piecewise-linear approximation which provides stronger noise reduction and better edge-limited smoothing behavior.

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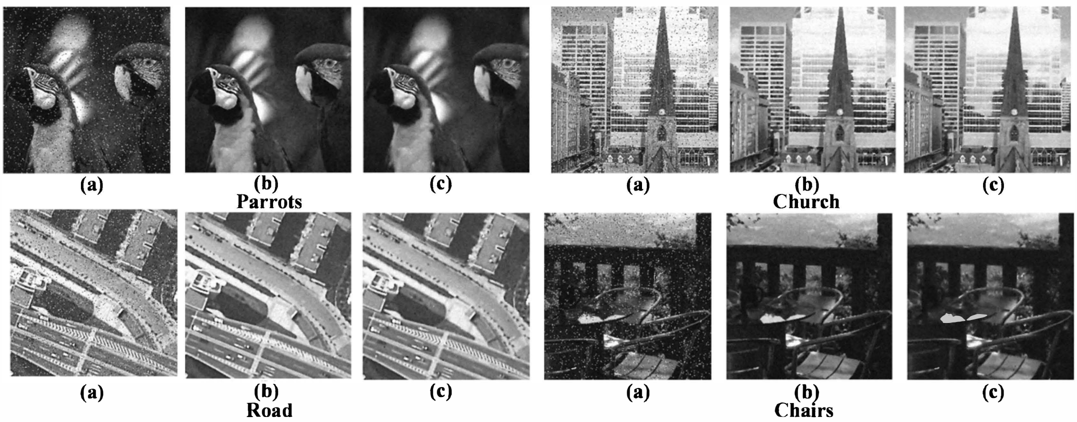

Figure 3. (a) Image corrupted by mixed noise ($\sigma = 10$, $p = 5\%$), (b) De-noised with MBF [4] (c) De-noised with our method.