Noise Cancellation Using Adaptive Trilateral Filter

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In this work we propose and justify here an algorithm employing two stage trilateral filter, a combination of above mentioned filters, which has an ability to detect impulse noise ratio in mixed noise and restore the corrupted pixel. Following theoretical derivation based on both authors model (Garnett et al. and Dong et al.), we decouple the problem into two phases. First, we identify the candidates, the pixels that are likely to be corrupted by the impulse noise, and the noise ratio. In second phase, the image is deblurred and denoised simultaneously using the trilateral filter [13].

Our approach is to dynamically implement ROAD as well as ROLD. In terms of noise suppression and edge preservation, our restored images show significant improvement over the number of existing techniques. Some examples illustrate the performance of our method.

Index Terms— Gaussian Noise, Impulse Noise, image restoration, bilateral filter, random-valued impulse noise, edge-preserving regularization.

I. INTRODUCTION

There are number of existing techniques in terms of image restoration and noise detection. In image processing, images are often corrupted by two types of Noise Model, additive Gaussian noise and Impulse noise, and there combination called mixed noise. To this end, a variety of techniques have been proposed to remove noise. As one of the most popular methods is the median filter [9], which due to its high computational efficiency can suppress noise effectively.

Previously less amount of work has been carried out on building filters that can effectively remove both Gaussian and impulse noise, or any mixture of them. This “mixed noise” may occur while sending an already corrupted image over faulty channels. In context of the same, some work has been proposed by Abreu et al. [6] in 1996, they have proposed median based SD-ROM filter to remove impulse noise and this method actually proved to be very effective. They proved theoretically that their method also has the ability to remove Gaussian noise as well as mixed Gaussian and impulse noise. Many methods based on fuzzy techniques have been developed in last few years for noise removal [2], [7]. Fuzzy system is well-suited to model the uncertainty that occurs when both noise removal and detail preservation are required. But when the images are highly corrupted, discovering the rule base structure becomes quite difficult. In order to overcome this difficulty, many methods based on neuro-fuzzy system are proposed [5], [10], which make full use of the ability of neural networks to learn from examples. With suitable and sufficient training, they can preserve the image details during noise removal.

After exhaustive study of most of the filters, we come across a universal noise removal filter proposed by Garnett, Huegerich and Chui [13]. They called their simple statistic to detect impulse noise pixels in an image, ROAD (“Rank-Ordered Absolute Differences”). Another work carried out by Dong, Raymond H. Chan, and Shufang Xu [17] gives an extension to Garnett et al. work by implementing logarithmic function, to identify noise pixels with high impulse noise of random values, introduced as “Rank-Ordered Logarithmic Difference”, and ROLD for short [17].

We proposed a new, dynamic two-stage trilateral filter which has an efficiency of universal noise removal filter proposed by Garnett et al. [13] for denoising images corrupted with mixed noise, and where ROAD statistics fails, it takes an advantage of ROLD, as described.

The outline of the paper is as follows - in the next section we introduce a Noise models. In section III we explain bilateral filter. In section IV and V we briefly describe Local image statistic for detecting impulse and describe how to incorporate the statistic into the filter to create a Trilateral filter. In section VI we present our denoising scheme and finally in section VII provide visual examples and numerical results that demonstrate our method’s soundness.

II. NOISE MODEL

Fortunately, two noise models can adequately represent most noise added to images, Gaussian noise (additive) and impulse noise (multiplicative) [13].

A. Additive Gaussian Noise

Gaussian noise is characterized by adding to each image pixel a value from a zero-mean Gaussian distribution. For the case of additive Gaussian noise, the noisy image \( u \) is related to the original image \( u_0 \), by

\[
\hat{u}_{ij} = u_{0ij} + n_{ij}
\]

where each noise value \( n \) is drawn from a zero-mean Gaussian distribution.

B. Impulse Noise

In this type of noise, pixels in the image are very different in color and intensity from their surrounding pixels, the
defining characteristic is that the value of noisy pixel bears no relation to the color of surrounding pixel. This is to notice that only a part of pixels is actually corrupted while others are kept noise free. To be precise, let \( u_{ij} \) and \( u_{ij}^{'} \) be the pixel values at location \((i, j)\) in the original image and the noisy image, respectively. If the noise ratio is \( p \), then -

\[
\begin{align*}
    u_{ij} &= n_{ij}^{'} \text{ with probability } p \\
    u_{ij} &= u_{ij}^{'} \text{ with probability } (1-p)
\end{align*}
\]

Where \( n_{ij} \) is the gray-level value of the noisy pixel.

III. EXISTING FILTERS

The existing Gaussian and impulse noise filters are good enough only if the respective noise is present, and if the type of noise is determined beforehand. The effect of using a mismatched filter can result in further degradation of the image rather than improvement. In applications where we are never sure of the kind of filter to be used, the two filters must be combined into a single filter for determination and correction of either kind of noise and for providing better results than with a single filter, which is only meant to do filtering for a particular kind of noise [9].

It is very difficult to determine whether a given pixel is impulse noise pixel or not. Impulse noise removal methods use many different techniques to identify that whether a pixel under consideration is like an impulse. These approaches vary in complexity relatively from being simple to highly complex. The simplest and most intuitive method is comparing a pixel’s intensity with the median intensity in its neighborhood, as in [16]. Other methods, such as the two-state SD-ROM filter of Abreu, et al. [3] and the recent CSAM filter of Pok, et al. [6], use more complex criteria to judge whether a pixel is an impulse. The advantage of these two-state methods is their simplicity, which makes them easily customizable.

A. The Bilateral filter

The bilateral filter, as described in [1], applies a nonlinear filter to a noisy image \( u \) to remove Gaussian noise while retaining the sharpness of edges. In this filter each pixel is restored by a weighted average of the intensities in a \((2N+1)X(2N+1)\) neighborhood of that pixel. This weighting function smoothes region of similar intensity while keeping edges sharp, by weighting those pixels heavily which are both near the central pixel spatially and are similar to the central pixel radiometrically. For More precision, let \( x \) be the location of the pixel under consideration, and let -

\[
\Omega = \Omega_x (N)
\]

Eq. (1) gives the set of pixels in \((2N + 1) \times (2N + 1)\) neighborhood of central pixel \( x \). The weight of each pixel \( y \in \Omega \) with respect to \( x \) is the multiplication of spatial and radiometric component and is given by -

\[
\begin{align*}
    w(x, y) &= w_s(x, y) \times w_r(x, y) \\
    w_s(x, y) &= e^{-\frac{(x - y)^2}{2\sigma_s^2}} \\
    w_r(x, y) &= e^{-\frac{|u_x - u_y|^2}{2\sigma_r^2}}
\end{align*}
\]

From Eq. (2) weight for restored pixel \( u_x^{'} \) is given by -

\[
u_x^{'} = \frac{\sum_{y \in \Omega} w(x, y) u_y}{\sum_{y \in \Omega} w(x, y)}
\]

Here \( w_s \) (spatial) and \( w_r \) (radiometric) weighting functions are any nonnegative functions that decrease to zero.

IV. GARNETT ET. AL UNIVERSAL NOISE REMOVAL FILTER

Definition of the ROAD statistic as proposed by Garnett et al.-

Let \( x = (x_1, x_2) \) be the location of the pixel under consideration, and let –

\[
\Omega_x (N) := \{ x + (i, j) : -N \leq i, j \leq N \}
\]

Represents set of all pixels in a \((2N+1)X(2N+1)\) neighborhood of central pixel \( x \) where \( N \) is a positive integer. Let us for now consider \( N = 1 \). Hence,

\[
\Omega_x^0 = \Omega_x (1) \setminus \{ x \}
\]

be the set of points in a \(3 \times 3\) neighborhood of central pixel \( x \). For each pixel \( y \in \Omega_x^0 \), define \( d_{x,y} \) as the absolute difference in intensity of the pixels \( x \) and \( y \), i.e.

\[
d_{x,y} = |u_x - u_y|
\]

The \( d_{x,y} \) values are then sorted in increasing order and define-

\[
\text{ROAD}_m(x) = \sum_{i=0}^{m} \tau_i(x)
\]

Where \( 2 \leq m \leq 7 \) And \( \tau_i(x) \) is the \( i \)th smallest \( d_{x,y} \) for any \( y \in \Omega_x^0 \). Garnett et al. called this statistic as ROAD (“Rank-ordered Absolute Difference”). In this discussion we will consider \( m = 4 \) only, and set \( \text{ROAD}(x) = \text{ROAD}_4(x) \).

The ROAD is a good statistic. It provides a measured method to identify how much close a pixel is from its neighboring pixels. Fig.1 shows example from the Lena image comparing an impulse noise pixel to an edge pixel. From the figure it can be seen that the edge pixel has at least
half of its neighbors of similar intensity, and thus has a significantly lower ROAD value. Fig. 2. shows the comparison between ROAD value of impulse pixel and uncorrupted pixel.

A. Introducing ROAD and Trilateral filter

Garnett et al. introduced the ROAD statistic into the bilateral filtering framework by mean of a third weighting function. The “impulsive” weight, \( w_I \), at a point \( x \) is given by:

\[
\frac{1}{\sigma_I^2} \exp\left( -\frac{\text{ROAD}(x)^2}{2\sigma_I^2} \right)
\]

The \( \sigma_I \) parameter determines the approximate threshold above which to penalize high ROAD values. Garnett et al. integrated this impulsive component into a nonlinear filter which is designed to assign weight to pixels based on their corresponding merit of spatial, radiometric, and impulsive properties. A switch was introduced to add impulsive weight while still retaining the radiometric component. This switch determines how much to use the radiometric weight in the presence of impulse noise. If \( x \) is the central pixel under consideration, and \( y \in \Omega \) is pixel in some neighborhood of \( x \), then the “joint impulsivity” \( J \) of \( y \) with respect to \( x \) can be defined as:

\[
J(x,y) = 1 - e^{-\left( \frac{\text{ROAD}(x) \cdot \text{ROAD}(y)}{2\sigma_I^2} \right)^2}
\]

Let the function \( J(x,y) \) takes values in \([0,1]\). If either \( x \) or \( y \) is impulse-like and has a high ROAD value with respect to \( \sigma_I \), then \( J(x,y) \approx 1 \). When \( J(x,y) \approx 0 \), we will use radiometric weight more heavily to smooth regions with less impulses and less heavily when \( J(x,y) \approx 1 \). With this consideration, we define the final, “trilateral” weight of \( y \) with respect to the central point \( x \) as:

\[
w(x,y) = w_s(x,y) \times w_R(x,y) \times w_I(x,y)
\]

When \( J(x,y) \approx 1 \) so that \( 1 - J(x,y) \approx 0 \), the radiometric component becomes irrelevant as the radiometric threshold becomes very large and the impulsive weight component remains unaffected. When \( J(x,y) \approx 0 \), in complete contrast only the radiometric weight is used. In this way, the appropriate weighting function is applied on a pixel-by-pixel basis. We will call filter of this nonlinear form with the weighting function \( w(x,y) \) as in Eq. (10), the “Dynamic trilateral filter,” since it is a combination of spatial, radiometric and impulsive weight components. The trilateral weighting function effectively removes impulse noise as well as Gaussian noise.

V. DONG ET AL. RANK-ORDERED LOGARITHMIC DIFFERENCE (ROLD)

Definition of the ROLD statistic as proposed by Dong et al. – The ROAD is already a good statistic to identify impulse noise pixels in an image, but for random-valued impulse noise, some noisy pixels may have intensity values close to their surrounding pixels, in such a case, the ROAD value of the pixel may not be large enough for distinguishing it from the noise-free pixels. To improve ROAD statistic i.e. to find a way to increase ROAD values and yet keep the small ROAD values from increasing much, Dong et al. use a logarithmic function. Using the logarithmic function on the absolute difference \( d_{xy} \) defined below, we get:

\[
d_{x,y}^d = \log_{a} \left| \frac{u_x - u_y}{b} \right|
\]

A truncation and a linear transformation were used to keep it in dynamic range \([0,1]\) –

\[
d_{x,y} = \max \left\{ \log_{a} \left| \frac{u_x - u_y}{b} \right| - b, 0 \right\}
\]

Where \( y \in \Omega \), and \( a, b \) are positive numbers. The value of \( a \) controls the shape of the curve of logarithmic function and the truncation position is decided by value of \( b \).

Accuracy of impulse detection is greatly affected by choosing the value for \( a \) and \( b \). Dong et al. [17] name this statistic as “Rank Ordered Logarithmic Difference” or we can also call it as ROLD. Like ROAD this local image statistic based on logarithmic function defined as:

\[
\text{ROLD}_m(x) = \sum_{i=1}^{m} r_i(x)
\]
We can define with ROLD, a noise detector by employing a threshold $T_e$, a pixel $x_{i,j}$ is detected as noisy if $\text{ROLD}_m(x_{i,j}) > T_e$, and noise-free if otherwise. Here $T_e$ is thresholds of the form $T_e = \mu + e \sigma$, where $\mu$ and $\sigma$ are the mean and the standard deviation of statistic values for all noisy pixels, and $e \in [-0.5,0.5]$.

VI. PROPOSED METHOD

Ours, proposed is a two-stage iterative method for removing random-valued impulse noise. In the first phase, we calculate the ROAD and ROLD maps of noised images, to identify pixels which are likely to be corrupted (noise candidates). In the second phase, these noise candidates are restored by using the trilateral filter proposed by Garnett et al. We proved experimentally, our method can restore noise how high it may be. When the random valued impulse noise ratio is as high as 60%, it still can remove most of the noise while preserving image details.

**Implementation**: Ours is a very effective trilateral filter, since ROAD and ROLD are excellent noise detectors, combined with bilateral filter, gives excellent result. It has the advantage of ROAD trilateral filters for removing low impulse noise as well as ROLD’s advantage to detect high impulse noise to get a powerful method for removing random-valued impulse noise. First we calculate ROAD and ROLD maps for a given image. Let $u$ be a given image.

1) $\text{ROAD}(u) = \text{ROAD}_4(u)$.
2) $\text{ROLD}(u) = \text{ROLD}_4(u)$.

Then find a threshold $T_e$ such that

$$T_e = \mu + e \sigma$$

Check for every pixel if its ROLD value is $\text{ROLD}(x_{i,j}) > T_e$, then calculate

$$J(x,y) = 1 - e \left( \frac{\text{ROLD}(x) - \text{ROLD}(y)}{2\sigma^2} \right)$$

And if false then we calculate

$$J(x,y) = 1 - e \left( \frac{\text{ROAD}(x) - \text{ROAD}(y)}{2\sigma^2} \right)$$

put this value in trilateral filter

$$w(x,y) = w_s(x,y) \times w_r(x,y) \times w_l(x,y)$$

VII. EXPERIMENTAL RESULTS

We have extensively tested the noise removal capabilities of our proposed method. We find that our method produces results superior to the other methods. We have tried many commonly used images, for illustrations, the result for 512 X 512 RGB “Lena” image, and the 512X512 grey scale “Barbara” image are presented here.

![Fig. 3](image1.png)

(a) The Lena color image (b) Image corrupted with a high level of mixed noise (p=60%) and (c) The results of applying Two Stage Trilateral Filter.

![Fig. 4](image2.png)

(a) ROAD map , b) ROLD map of Lena color image

For color images denoising effect is clearly visible in fig 3. and their respective ROAD and ROLD maps are shown in fig 4.a) and fig 4.b). Though the ROAD and ROLD values differ but there visual effect is same i.e. both statistics detect noise pixel accurately. For grey images our filters capability is shown through, applying it on grey Barbara image as below Fig.5.

![Fig. 5](image3.png)

(a) The Barbara grey image corrupted with a high level of mixed noise (p=60%) and the results of applying Two Stage Trilateral Filter.
In all the cases, a 3X3 window is applied, sliding from pixel to pixel in raster scanning fashion. An important observation is for all simulations the proposed method provides stable performance over a variety of test images. In Fig. 7, we plot a graph to show the detection efficiency and false hit rate of our method.

VIII. Conclusions

In this paper we proposed framework for two stage trilateral filter based on Rank Ordered Absolute Differences (ROAD) and Rank-Ordered Logarithmic Difference (ROLD) in some neighborhood of a pixel. These statistics identify impulse noise pixel in an image providing that greater values of impulse noise pixels have greater ROAD and ROLD value.

The ROAD, ROLD statistic are then clubbed with bilateral filter to get “Dynamic trilateral filter”. Weighting function of new trilateral filter combines three different measures of neighboring pixels. A switch is also adopted to adjust weight distribution between the radiometric and impulsive components. The resulting trilateral filter effectively removes Gaussian and Impulse noise and also any mixture of them. Simulation results have shown the soundness of our proposed method.

REFERENCES