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A TWO STAGE DYNAMIC TRILATERAL FILTER REMOVING IMPULSE PLUS GAUSSIAN NOISE

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Noise detection and Image restoration is a Universal research phenomena. There are number of existing techniques in terms of Noise Filters. Two of them are Trilateral filter proposed by Garnett, Huegerich and Chui [13] , and Dong, Raymond H. Chan, and Shufang Xu [17] are based on two types of Noise Model additive Gaussian noise and impulse noise, and there combination called mixed noise. Garnett, Huegerich and Chui introduce the ROAD ("Rank-ordered Absolute Differences") statistic into many existing filtering techniques, allowing them to detect and properly handle impulse-like pixels in a noisy image.

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 shows significant improvement over the number of existing techniques. Some examples illustrate the performance of our method.

Index Terms: Image Denoising, Gaussian Noise, Impulse Noise, Image Restoration, Bilateral Filter, random-valued impulse noise.

1. Introduction

Filtering is perhaps the most fundamental operation of image processing and computer vision. In image processing, images are often corrupted by additive Gaussian noise and impulse noise. In most applications, goal of noise removal is to suppress the noise while preserving image details. To this end, a variety of techniques have been proposed. One of the most popular methods is the median filter [9], which can suppress noise with high computational efficiency. Previously not much work has been carried out on building filters that can effectively remove both Gaussian and impulse noise, or any mixture thereof. Such "mixed noise" could occur, for instance, when sending an already noisy image over faulty communication lines. Some of them to mention are, Abreu, et al., proposed the median based SD-ROM filter [3], Peng and Lucke suggested a fuzzy filter designed specifically for mixed noise [14], many methods based on neuro-fuzzy system are proposed [5]–[10].

In order to process impulse pixels and edge pixels differently, Garnett, Huegerich and Chui [13] proposed simple statistic to detect impulse noise pixels in an image. Instead of applying the "detect and replace" methodology of most impulse noise removal techniques, they show how to integrate such a statistic into a filter designed to remove Gaussian noise. The behavior of the filter can be adaptively changed to remove impulses while retaining the ability to smooth Gaussian noise. They called it ROAD i.e. "Rank-ordered Absolute Differences".

Though ROAD is already a good statistic. However, for random-valued impulse noise, some noise values may be close to their neighbor's values, in which case, the ROAD value of the pixel may not be large enough for it to be distinguished from the noise-free pixels. Thus one way to improve the ROAD statistic is to find a way to increase these ROAD values, and yet keep the small ROAD values from increasing much. Dong, Raymond H. Chan, and Shufang Xu[2] use a logarithmic function to realize this goal as "Rank-Ordered Logarithmic Difference", and ROLD for short.

We proposed a new, dynamic two-stage trilateral filter which has an efficiency of universal noise removal filter proposed by Garnett *et al.* [17] 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 next section we explain bilateral filter. In section 3 and 4 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 5 we present our denoising scheme in section 6 provide visual examples and numerical results that demonstrate our method's soundness.

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2. 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 problem of deciding which pixels in an image is impulse is clearly not well-defined. Impulse noise removal methods use different techniques to determine whether a given pixel is an impulse in this sense. These approaches vary in complexity from being relatively simple to highly complex. One of the simplest and most intuitive methods is to compare 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 CSAM filter of Pok, *et al.* [6], use more complex criteria to judge whether a pixel is an impulse.

2.1 The Bilateral Filter

The bilateral filter, as described in [1], applies a nonlinear filter to image to remove Gaussian noise while retaining the sharpness of edges. Each pixel is replaced by a weighted average of the intensities in a $(2N + 1) \times (2N + 1)$ neighborhood. The weighting function is designed to smooth in regions of similar intensity while keeping edges intact, by heavily weighting those pixels that are both near the central pixel spatially and similar to the central pixel radiometrically. More precisely, let x be the location of the pixel under consideration, and let

$$\Omega = \Omega_x (N) \tag{1}$$

Be the set of pixels in a $(2N + 1) \times (2N + 1)$ neighborhood of x. The weight of each $y \in \Omega$ with respect to x is the product of two components, one spatial and one radiometric:

$$w(x, y) = w_s (x, y) \times w_r (x, y) \tag{2}$$

where

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

$$w_R\left(x,y\right) = e^{-\frac{\left|u_x - u_y\right|^2}{2\sigma_R^2}} \tag{4}$$

The weights must be normalized, so the restored pixel u'_x is given by

$$u'_x = \frac{\sum_{y\in\Omega} w(x,y)u_y}{\sum_{y\in\Omega} w(x,y)} \tag{5}$$

The $\boldsymbol{w_S}$ weighting function decreases as the spatial distance between x and y increases, and the $\boldsymbol{w_R}$ weighting function decreases as the radiometric "distance" between the intensities $\boldsymbol{u_x}$ and $\boldsymbol{u_y}$ increases.

3. RANK-ORDERED ABSOLUTE DIFFERENCE (ROAD)

Definition of the ROAD statistic- Let $x = (x_1, x_2)$ be the location of the pixel under consideration, and let-

$$\Omega_x (N): = \{x + (i, j): -N \le i, j \le N\}$$

Be the set of points in a $(2N + 1) \times (2N + 1)$ neighborhood centered at x for some positive integer N. In the following discussion, let us consider $N = 1$, though the same procedure can be extended to $N > 1$. Hence,

$$\Omega^0_x = \Omega_x (1) \setminus \{x\}$$

represents the set of points in a 3×3 neighborhood of $\boldsymbol{x}$. For each point $y \in \Omega^0_x$, define $\boldsymbol{d_{x,y}}$ as the absolute difference in intensity of the pixels between $\boldsymbol{x}$ and $\boldsymbol{y}$, i.e.

$$d_{x,\, y} = |u_x - u_y| \tag{6}$$

Finally, sort the $d_{x,y}$ values in increasing order and define -

$$\text{ROAD}_m (x) = \sum_{i=1}^{m} r_i (x) \tag{7}$$

where $2 \le m \le 7$ And $r_i(x)$ is the i^{th} smallest $\boldsymbol{d_{x,y}}$ for any $y \in \Omega^0_x$. Garnett *et al*. call the statistic defined as *ROAD* ("Rank-ordered Absolute Difference"). In this paper, we will consider $m = 4$ only, and set $\text{ROAD}(x) = \text{ROAD}_4(x)$.

The ROAD statistic provides that how much similar a pixel is from its most neighboring pixels. The logic behind this is impulse pixel have higher intensity values from most or all of their neighboring pixels. Fig. 1 shows examples from the Lena image showing comparison between an

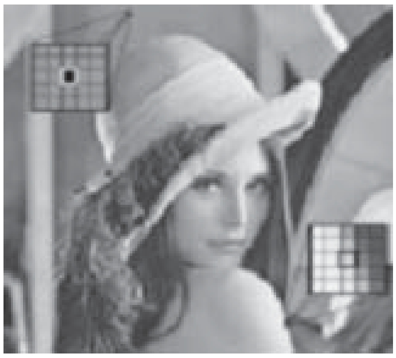


Figure 1: Close-ups of an Artificially Added Impulse (Upper Left), and a Typical Edge Pixel (Lower Right)

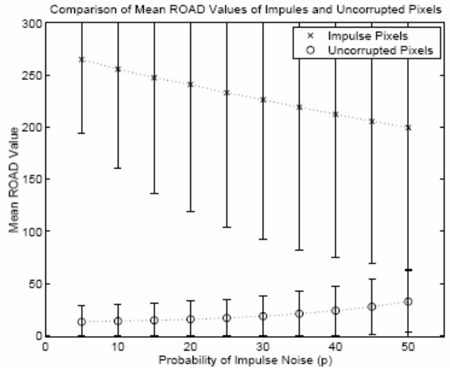


Figure 2: The Mean ROAD Values of Noise Pixels and Uncorrupted Pixels in the Lena Image

impulse noise pixel and edge pixel. Notice that the edge pixel has neighbors of similar intensity despite forming part of an edge, and thus has a significantly lower ROAD value.

3.1 Introducing the ROAD and Trilateral Filter

Garnett *et al.* incorporate the ROAD statistic into the bilateral filtering framework by introducing a third weight called as "Impulsive" weight $\boldsymbol{w}_I$. The $\boldsymbol{w}_I$ weight, at a point $\boldsymbol{x}$ is given by:

$$W_I(x) = e^{-\frac{ROAD(X)^2}{2\sigma_I^2}} \tag{8}$$

The σ_I parameter determines the approximate threshold above which to penalize high ROAD values. Garnett *et. al*. integrated this impulsive component into a nonlinear filter designed to weight pixels based on their spatial, radiometric, and impulsive properties. To add the impulsive weight with radiometric and spatial component of the bilateral filter, a switch were introduced. This switch determines how much to use radiometric and impulsive weight in pretense of impulse noise. If $\boldsymbol{x}$ is the central pixel under consideration, and $y \in \Omega_x(N)$ is a pixel in the neighborhood of $\boldsymbol{x}$, the "joint impulsivity" $\boldsymbol{J}$ of $\boldsymbol{y}$ with respect to $\boldsymbol{x}$ can be defined as

$$J(x,y) = 1 - e^{-\left(\frac{ROAD(X)+ROAD(Y)}{2}\right)} / 2\sigma^2 J \tag{9}$$

The $\boldsymbol{J(x, y)}$ function takes values in [0, 1]. If any one of $\boldsymbol{x}$ or $\boldsymbol{y}$ is impulse-like pixel and has a high ROAD value with respect to $\boldsymbol{\sigma_J}$, then $\boldsymbol{J(x, y) \approx 1}$. If neither pixel is impulse-like, then $\boldsymbol{J(x, y) \approx 0}$. When $J(x, y) \approx 0$ this switch uses the radiometric weight heavily to smooth regions without large impulses and less heavily when $J(x,y) \approx 1$. The final "Trilateral" weight of $\boldsymbol{y}$ with respect to the central point $\boldsymbol{x}$ is given as:

$$w(x, y) = w_S(x, y) \times w_R^{1-J(x,y)}(x,y) \times w_I^{J(x,y)}(x,y) \tag{10}$$

When $\boldsymbol{J(x, y) \approx 1}$ so that $\boldsymbol{1 - J(x, y) \approx 0}$, the radiometric threshold becomes very large so that radiometric differences become irrelevant, while the impulsive weight is unaffected. When $\boldsymbol{J(x, y) \approx 0}$, the opposite happens and only the radiometric weight is used to distinguish pixels because the effective impulsive threshold is so high. In this way, the appropriate weighting function is applied on a pixel-by-pixel basis. This nonlinear filter is of form with the weighting function $\boldsymbol{w(x, y)}$ given in the "trilateral filter," since it combines three different measures to determine its weight. This trilateral weighting function effectively removes impulse noise without compromising the bilateral filter's ability to remove Gaussian noise.

4. RANK-ORDERED LOGARITHMIC DIFFERENCE (ROLD)

Definition of the ROLD statistic as proposed by Dong *et. al* - To improve the 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 $\boldsymbol{d_{x,y}}$ defined below, we get

$$d'_{x,y} = \log_a |u_x - u_y| \text{ where } y \in \Omega_x^0,$$

In order to keep it in the dynamic range [0, 1], a truncation and a linear transformation were used –

$$d_{x,y} = 1 + \max\{\log_a |u_x - u_y|, -b\}/b \tag{11}$$

Where $y \in \Omega_x^0$ and a, b are positive numbers to be chosen. The value of $\boldsymbol{a}$ controls the shape of the curve of the logarithmic function and the value of $\boldsymbol{b}$ decides the truncation position. Dong *et al.* [2] name this statistic as "Rank-Ordered Logarithmic Difference", and ROLD for short.Like ROAD this local image statistic based on logarithmic function defined as

$$\text{ROLD}_m(x) = \sum_{i=1}^{m} r_i(x) \tag{12}$$

With ROLD, we can define 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. Where T_e is thresholds of the form $T_e = \mu + e.\sigma$, where μ and σ are the mean and the standard deviation of statistic values for all noisy pixels, and e [–0.5, 0.5].

5. OUR PROPOSED METHOD (TWO STAGE TRILATERAL FILTER)

The ROAD is already a good statistic, as proven by Garnett *et al.*, by incorporating ROAD into bilateral filters. However, for random-valued impulse noise, some noise values may be close to their neighbors' values, in which case, the ROAD value of the pixel may not be large enough for it to be distinguished from the noise-free pixels. To over come this Dong *et al*. suggested ROLD in stead of ROAD maps of noised Images. But still we have to kwon beforehand the noise level to choose which statistic to use.

Ours, proposed is a two-stage iterative method for removing random-valued impulse noise. By incorporating both ROAD and ROLD in single filter we can have advantages of trilateral filter. 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

Two Stage Trilateral Filter is a very effective noise 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.

$$\mathrm{ROAD}(u) = \mathrm{ROAD}_4(u) \tag{1}$$

$$\mathrm{ROLD}(u) = \mathrm{ROLD}_4(u) \tag{2}$$

Then find a threshold T_e such that,

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

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

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

and if false then calculate

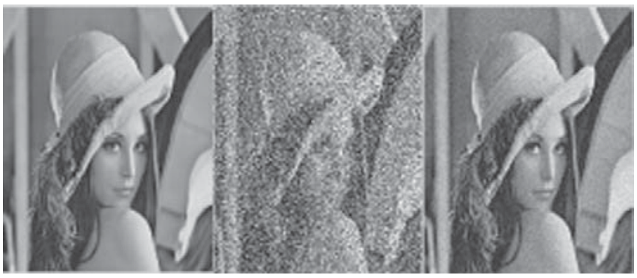
$$J(x,y) = 1 - e^{-\left(\frac{ROAD(x)+ROAD(y)}{2}\right)^2 \Big/ 2\sigma^2_J}$$

put this value in trilateral filter

$$w(x, y) = w_s(x, y) \times w_R(x, y) \times W_I(x, y)$$

6. EXPERIMENTAL RESULTS

We have extensively tested the noise removal capabilities of our proposed method. We find that our method produced results superior to the other methods. We have tried many commonly used images, for illustrations, the result for 512×512 RGB "Lena" image, and the 512×512 gray scale "Barbara" image are presented here.



(a) (b) (c)

Figure 3: (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

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 gray images our filters capability is shown through, applying it on gray Barbara image as below Fig. 5.

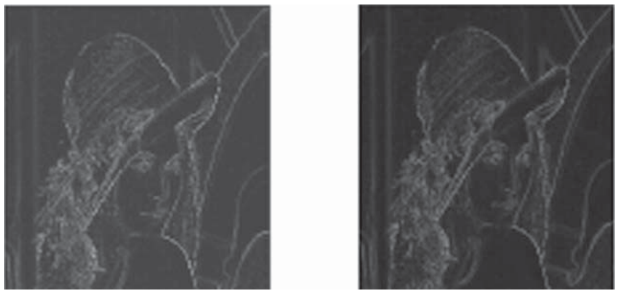
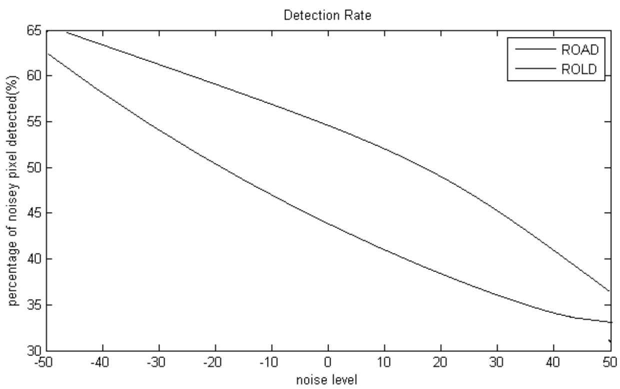


Figure 4: (a) ROAD Map, (b) ROLD Map of Lena Color Image

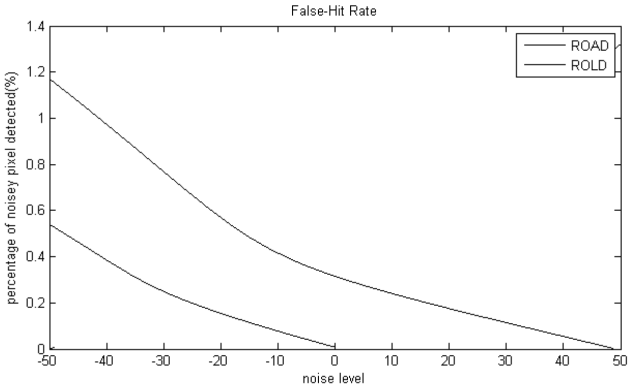
Figure 5: The Barbara Gray Image Corrupted with a High Level of Nixed Noise (p = 60%) and the Results of Applying Two Stage Trilateral Filter

Figure 6: (a) ROAD Map, (b) ROLD Map of Barbara Gray Image

In all the cases, a 3×3 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.



(a)



(b)

Figure 7: The Detection Rate (a) and False Hit Rate (b) for Two Statistic ROAD and ROLD

7. 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

[1] C. Tomasi and R. Manduchi, "Bilateral Filtering for Gray and Color Images," *Proc. 1998 IEEE Int. Conf. Computer Vision*, 839–846.

[2] D. Van De Ville, M. Nachtegael, D. Van der Weken, E. E. Kerre, W. Philips and I. Lemahieu, "Noise Reduction by Fuzzy Image Filtering," *IEEE Transactions on Fuzzy Systems*, **11**, (2003), 429–436.

[3] E. Abreu, M. Lightstone, S. Mitra, and K. Arakawa, "A New Efficient Approach for the Removal of Impulse Noise from Highly Corrupted Images," *IEEE Trans. Image Processing*, **5**, (June 1996), 1012–1025.

[4] E. Abreu, M. Lightstone, S. Mitra, and K. Arakawa, "A New Efficient Approach for the Removal of Impulse Noise from Highly Corrupted Images," *IEEE Trans. Image Processing*, **5**, (June 1996), 1012–1025.

[5] F. Russo, "Hybrid Neuro-fuzzy Filter for Impulse Noise Removal," *Pattern Recognition*, **32**, (1999), 1843–1855.

[6] G. Pok, J. Liu, and A. S. Nair, "Selective Removal of Impulse Noise based on Homogeneity Level Information," *IEEE Trans. Image Processing*, **12**, (Jan. 2003), 85–92.

[7] H. Xu, G. Zhu, H. Peng and D. Wang, "Adaptive Fuzzy Switching Filter for Images Corrupted by Impulse Noise," *Pattern Recognition Letters*, **25**, (2004), 1657–1663.

[8] K. J. Overton and T. E. Weymouth, "A Noise Reducing Preprocessing Algorithm," *Proceedings of the IEEE Computer Science Conference on Pattern Recognition and Image Processing*, Chicago, IL, (1979), 498–507.

[9] M. Hanmandlu, Anuj K. Tiwari, Vamsi K. Madasu, Shantaram Vasikarla,"Mixed Noise Correction In Gray Images Using Fuzzy Filters", *IEEE Proceedings of the 3rd International Conference on Information Technology: New Generations* (ITNG'06), (2006).

[10] M. E. Yüksel, "A Hybrid Neuro-fuzzy Filter for Edge Preserving Restoration of Images Corrupted by Impulse Noise," *IEEE Transactions on Image Processing*, **15**, (2006), 928–936.

[11] Michael Elad "On the Origin of the Bilateral Filter and Ways to Improve It" , *IEEE Transactions On Image Processing*, **11**, (10), (October 2002).

[12] P. Perona and J. Malik, "Scale-space and Edge Detection Using Anisotropic Diffusion," *IEEE Trans. Pattern Anal. Machine Intell.*, **12**, (1990), 629–639.

[13] R. Garnett, T. Huegerich, C. Chui and W. J. He, "A Universal Noise Removal Algorithm With An Impulse Detector", *IEEE Transactions on Image Processing*, **14**, (2005), 1747–1754.

[14] S. Peng and L. Lucke, "Multi-level Adaptive Fuzzy Filter for Mixed Noise Removal," *Proc. IEEE Int. Symp. Circuits Syst.*, Seattle, WA, **2**, (Apr. 1995), 1524–1527.

[15] S. Zhang, M. A. Karim, "A New Impulse Detector for Switching Median Filters," *IEEE Signal Processing Letters*, **9** (2002), 360–363.

[16] T. Sun and Y. Neuvo, "Detail-Preserving Median based Filters in Image Processing," *Patt. Recogn. Lett.*, **15** (Apr. 1994), 341–347.

[17] Yiqiu Dong, Raymond H. Chan, and Shufang Xu, "A Detection Statistic for Random-valued Impulse Noise" *IEEE Transactions on Image Processing*, (2007), 1057–7149.