A Universal Noise Removal Algorithm With an Impulse Detector

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***Abstract*— A local image statistic is incorporated in the bilateral filter for identifying pixels corrupted with impulse noise. The resulting trilateral filter is shown to be capable of removing both additive Gaussian noise and impulse noise effectively.**

***Index Terms*— Mixed noise, Trilateral filter, image processing.**

I. Introduction

The bilateral filter in [1] is designed for edge preserving removal of additive Gaussian noise. It is unable to remove impulse noise since the impulses are considered as edges to be preserved. Most noise can be modelled as a mixture of Gaussian and Impulse noise and a MATLAB implementation of the trilateral filter proposed in [2] has been shown to be effective at removing such mixed noise. Evaluation is based on perceived improvement as well as quantitative measures, i.e the Peak Signal to Noise ratio (PSNR). This report is arranged as follows. In Section II, we will explain the local image statistic to detect impulses. In Section III, we explain how to include this statistic in the bilateral filter to create the universal noise removing trilateral filter (UNF). In section IV we show the results of the MATLAB implementation and compare the UNF with the median filter. Section V explains how to run the code files in the GitHub repository.

II. Rank Ordered Absolute Differences (ROAD)

We are considering an MXN grayscale image. Let x = (m,n) be the location of the pixel in the m'th row and n'th column. We define

$$\Omega_x(N) = \{x + (i,j) : -N \leq (i,j) \leq N\} \tag{1}$$

as the N-neighbourhood of the pixel at x.

$$\Omega_x^0(N) = \Omega_x(N) \backslash \{x\} \tag{2}$$

is the deleted N-neighbourhood of x. Radiometric distance is defined as

$$d(x,y) = |i(x) - i(y)| \; \forall \; y \in \Omega_x^0(N) \tag{3}$$

where i(x) is the intensity of the image at pixel location x.

$$ROAD_m(x) = \sum_{i=1}^{m} r(i) \tag{4}$$

The vector r is defined as the vector d sorted in ascending order. Here the value of m is fixed at 4. The ROAD statistic is highly correlated with impulse noise error probability as shown in Fig.1 and clearly separates most of the impulse noise pixels Fig.2 . The noise pixels consistently have much higher mean ROAD values than the uncorrupted pixels, whose mean ROAD values remain nearly constant even with very large amounts of noise.

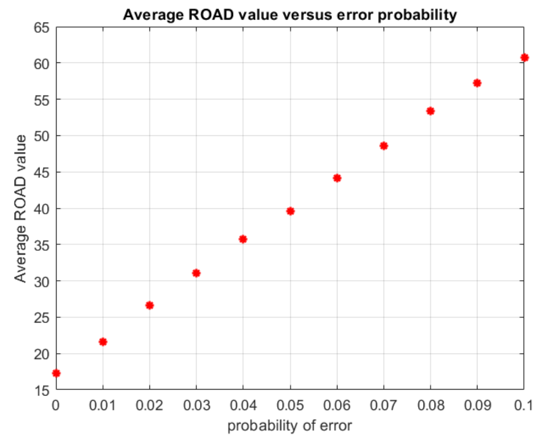

Fig. 1. ROAD versus error probability

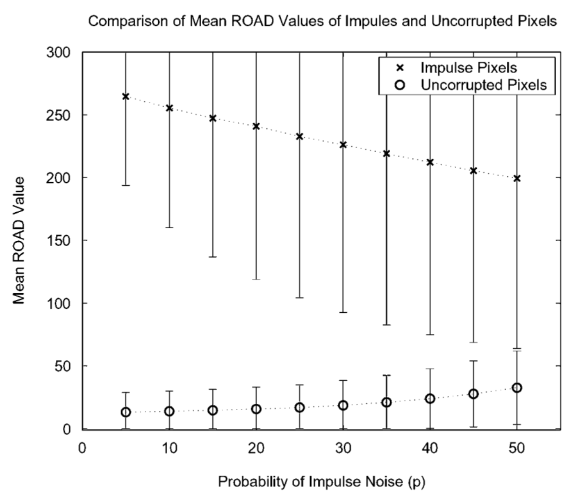

Fig. 2. ROAD as an impulse detector

III. Including ROAD in the bilateral filter

Gaussian blurring removes additive white gaussian noise but blurs the edges. The simple bilateral filter is designed to average over pixels of similar intensity in an attempt to preserve edges and results in higher PSNR. It has an additional radiometric term $w_i(x,y)$ along with the standard spatiometric term $w_s(x,y)$.

$$w_s(x,y) = e^{-\frac{|x-y|^2}{2\sigma_s^2}} \tag{5}$$

$$w_r(x,y) = e^{-\frac{|i(x)-i(y)|^2}{2\sigma_r^2}} \tag{6}$$

Fig. 3. Image corrupted with Mixed Noise, Median Filtered Image, and the Trilateral Filtered Image

If the point under consideration were an impulse, the radiometric component would weight any other impulses of similar intensity in the neighborhood much more than the uncorrupted pixels. The radiometric term was not designed to remove such impulse noise. The new "impulsive" weight $w_i(x)$ using (4) can detect such impulses.

$$w_i(x) = e^{-\frac{ROAD(x)^2}{2\sigma_i^2}} \tag{7}$$

However it cannot be directly multiplied with the bilateral filter since the radiometric term would continue to suppress uncorrupted pixels. So we switch between the impulsive and radiometric weights depending on the presence of large impulses. This is done using the Joint Impulsivity J(x,y) between the centre pixel x and a pixel y $\in \Omega_x(N)$, given by

$$J(x,y) = 1 - e^{-\frac{ROAD(x)+ROAD(y)}{2}^2 / 2\sigma_j^2} \tag{8}$$

The joint impulsivity will be ~ 1 when there is a large impulse in the neighbourhood. So the impulsive weight is raised to J while the radiometric weight is raised to 1-J. The final trilateral weight is given by

$$w(x,y) = w_s(x,y) * w_r(x,y)^{1-J(x,y)} * w_i(y)^{J(x,y)} \tag{9}$$

The noise is a mix of impulse and additive white gaussian noise, and the optimum value of the standard deviation of the radiometric term σ_r (peak of each curve) is shown in Fig.4 to be $\sim$ 2 times the standard deviation of quasi-Gaussian noise.This is estimated using a slight modification of the method proposed in [3]. Noise standard deviation is estimated as

$$\sigma_{\hat{QGN}} = \sqrt{(\frac{\pi}{2})}\frac{1}{6\sum_{i,j=1}^{m,n} w_i(i,j)} \sum_{i,j=1}^{m,n} |I * L|_{i,j} w_i(i,j) \tag{10}$$

where L = $\begin{pmatrix} 1 & -2 & 1 \\ -2 & 4 & -2 \\ 1 & -2 & -1 \end{pmatrix}$

is the 3X3 Laplacian filter.

IV. Results and Conclusion

Parameters used were as follows :

$$\sigma_s = 0.7 \text{ ; } \sigma_r = 2\sigma_{\hat{QGN}} \text{ ; } \sigma_j = 50 \tag{11}$$

σ_i is dynamically set for each neighbourhood by using the $ROAD$ value at the pixel and using 60 as the threshold for impulse noise. The σ_i value is then clamped between $[25, 55]$ [2] using a sigmoid function.

$$\sigma_i = 25 + \frac{30}{1 + e^{ROAD(y)-60}} \tag{12}$$

The filtered images were evaluated qualitatively based on visible improvements as well as quantitative measures with the PSNR, computed as

$$PSNR = 10\log_{10}\frac{\sum_{i,j=1}^{m,n} 255^2}{\sum_{i,j=1}^{m,n}(\tilde{u_{i,j}} - u_{i,j}^0)^2} \tag{13}$$

where $\tilde{u}$ is the filtered image and u^0 is the original image.

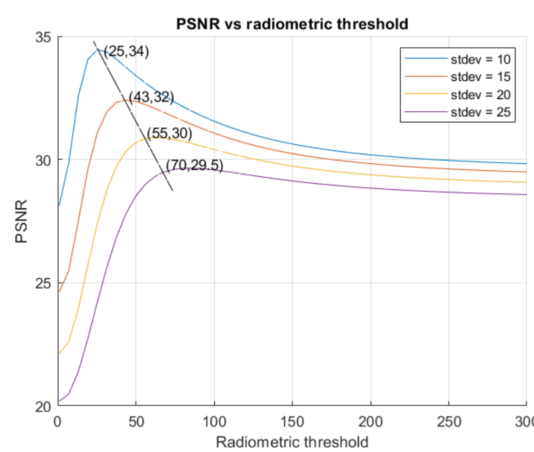

Fig. 4. Variation of optimum threshold with noise variance

V. Accessing the Code

The code can be found at `https://github.com/AryamanIIT20/Universal_Noise_Filter`. The entire repository can be loaded as a zip file by clicking the drop down menu from "<> Code". Navigate to the 20EE38033 20EE38031 DIP Project folder and extract all to a local folder. The main.m file has options to vary the noise and filter characteristics and can be run directly without any manipulation to the other scripts.

REFERENCES

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