



REVIEW OF NON-LINEAR FILTERS FOR NOISE REMOVAL IN DIGITAL IMAGES

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Abstract: Noise removal is one of the basic task to be executed in image processing. Noise removal is an important task in medical images, satellite and GIS application. Keeping intact the edges and texture is crucial and important task while removing the noise. The smoother region should remain smooth and the edges and texture information should be preserved. Also it should be noted that no artificially generated artifact should be added in noise removal process. Different types of noise should be treated differently, also depending on the noise level. Many techniques has been developed so far starting from simple mean and simple median filter to recent advance techniques combining spatial and frequency domain methods. This paper critically examines and reviews methods in spatial domain for nonlinear filter such as median filter, bilateral filter, trilateral filter and nonlocal mean filter.

Keywords: Non-linear filter, Impulse noise, Gaussian noise, Bilateral filter, Trilateral filter, Non local Mean filter.

I. INTRODUCTION

Image denoising is one of the predominant fields in image processing. In real world situation cleaning and denoising the image before its usage becomes a crucial factor. Image denoising is basically removing the noise from the original image while preserving the original features such as edges and texture information in the image. Image denoising is used as a preprocessing step in many real-life scenarios such as medical images, satellite images. In such domain it becomes very important to use denoised images to observe fine details. Images obtained from satellites has wide area of application such as tracking of earth resources, geographical mapping, prediction of agricultural crops, urban growth, weather, flood and fire control etc. Various image denoising techniques has been developed in spatial and frequency domain. Some of the reasons due to which noise is being added to images are during image acquisition, image transmission, atmospheric condition, faulty hardware sensors, Interference in the transmission channel. Some of the noise models studied here are impulse noise and Gaussian noise models.

I. Impulse noise is observed in an image may be due to bit error occurrence during transmission, hardware having a faulty memory location or fault in image sensors. Impulse noise is a substitutive noise, it will replace the pixels intensity. Based on the replacement value Impulse noise is further classified as (i) Salt and pepper impulse noise: It replaces the pixel intensity with either 0 or 255 if considering a 8-bit image (ii) Random valued impulse noise: It replaces the pixel intensity with a value uniformly distributed between 0 and 255. Removing salt and pepper impulse noise is easier as they take only the extreme value. Random valued impulse noise removal is relatively difficult as it looks similar to pixels intensity and thus making its identification difficult. Median filter is one of the basic filter used for impulse noise removal. Median filter removes impulse noise effectively but could not retain the edges and texture information. As in median filter all the pixels are replaced by the median in its window, therefore in process of removing a noisy pixel an uncorrupted pixel is also replaced by its median. II. Gaussian noise replaces each pixel by the sum of the original pixel intensity and the noise evenly distributed over signal. Gaussian is a kind of additive noise and is irrespective of the pixel intensity. Gaussian noise follows a normal distribution. Various types of techniques used for image denoising are broadly classified into spatial domain and frequency domain. Spatial domain filters are further classified as linear and nonlinear filters. Linear filters like mean filter are easier to implement and fast but they fail to preserve the edges and texture in the image. Nonlinear filters such as median filter, weiner filter, max filter, min filter, bilateral and trilateral filter are relatively harder to implement but they provide better result at preserving edges and texture in the image.

II. RELATED WORK

In Image denoising various algorithm has been studied based on spatial or transform domain filtering for removal of different types of noise. In Bilateral filter [1], the weights are assigned based on spatial proximity of pixels in the window and based on how close are the pixels intensities. As the distance of the pixel increases with the centre pixel the spatial weight tends to decrease and radiometric weight decrease as the similarity between pixels increases. Thus, it helps to maintain a balance between weighting pixels based on how close they are and how similar values they have. Bilateral filter effectively removes Gaussian noise. Trilateral filter [2] was designed as an extension of bilateral filter to effectively remove impulse noise, Gaussian noise or a mixture of impulse and Gaussian noise. In this method a ROAD statistic (Rank Order Absolute Difference) was developed which was proved to be a good statistic for impulse pixel identification. Taking

the absolute difference of the pixel with the centre pixel and then taking sum of the first four pixel ranked in increasing order. It stated that a pixel corrupted by impulse noise will significantly have higher mean ROAD value than the mean ROAD value of an uncorrupted pixel. Only the pixel identified to be impulsive need to apply the impulsive weight. A joint impulsivity was derived

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

This joint impulsivity act as a switch between radiometric and impulse weight. The total weight assigned is given by

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

where w_S, w_R, w_I denotes spatial, radiometric and impulsive weights respectively. Techniques used for image denoising are mostly two step processes namely noise pixel identification and noisy pixel correction. Noise pixel identification as the pre-processing step helps to get better result as only the pixel assumed to be noise pixel are only used in the next step for correction and other pixels remains intact.

III. ANALYSIS OF VARIOUS NONLINEAR FILTER FOR IMPULSE, GAUSSIAN AND MIXTURE OF IMPULSE AND GAUSSIAN NOISE REMOVAL

3.1 Dissimilar pixel counting based impulse detector for two-phase mixed noise removal [3]

A method for impulse pixel detection is established using dissimilar pixel counting. It is an iterative process in which least number of iterations are used for accuracy detection. This paper is divided in two stages first stage consists of noise pixel detection where an average difference scheme with threshold is used and the second stage comprises of an extended version of trilateral filter. Dissimilar Pixel Counting-Impulse Noise Removal (DPC-INR) algorithm, uses Average Difference (AD) statistic to identify similar pixels in its neighbourhood. The author prevents the use of Mean Absolute Deviation (MAD) as it measures the central tendency and an impulse noise pixel may be present in the window. A pixel is believed to be dissimilar pixel if it acts as an outlier upon calculating AD. A larger window $(2N+1) \times (2N+1)$ is used consisting of smaller sub window with size $(N+1) \times (N+1)$, the centre of each smaller sub window is the immediate neighbour of the centre pixel of larger window in all the direction. The central pixel's (i, j) window is obtained by

$$\Omega_0 = \{x_{i+s, j+t} : -N \leq s \leq N, -N \leq t \leq N\}$$

Similarly, other eight smaller windows will be obtained surrounding this centre pixel. AD is applied on all the sub window and the DP count is incremented if absolute difference of centre pixel in larger window and the centre pixel in sub window is greater than AD of that particular sub window.

A threshold NDPCT (NDP comparison threshold) is used with respect to DP count to check the noisy pixel. In a low-density noise environment, the pixel values have very less difference and as a result NDP does not work accurately. Solution for this problem is through a threshold which acts as a prejudgement to make Dissimilar pixel definition stricter. Therefore, the pixels once proved similar need not be checked with the neighbours. A guidance matrix which consists of 0 and 1 is maintained to identify uncorrupted and noisy pixel respectively. It helps not only to identify noisy pixel but also to distinguish between the type of noise as different noise needs to be treated differently. An iterative framework is preferred so that during subsequent iteration the missed pixel can be detected correctly leading to better accuracy.

In this paper the Trilateral Filter with change in parameters is used. when RVIN is present in the image smaller values of σ_i and σ_j are used and on the other hand to smooth the Gaussian noise a larger value of σ_i and σ_j are used. One pass is capable of removing almost noise even in a very high impulse noise corrupted image.

3.2 Empirical Mode Decomposition and Adaptive Bilateral Filter Approach for Impulse Noise Removal [4]

In this paper, two stages are provided, first stage is for noise pixel identification and the second stage is for noise pixel correction. In the first step, the image is transformed and the intrinsic mode function are derived without leaving the time domain from the empirical mode decomposition.

$$S(t) = \sum_{i=1}^{N-1} S_i(t) + S_{res}(t)$$

Without considering the residual IMF (Intrinsic mode function) signal the mean of the Local Absolute difference (LAD) of $n-1$ signal are considered and checked against a predefined threshold. If the MLAD (Mean Local Absolute difference) is less than the threshold the pixel is identified as a noisy pixel else it is considered noise free pixel. The first stage results in a binary map stating whether a pixel is noisy or uncorrupted. After the identification of the corrupted pixel, in the second stage Adaptive bilateral filter is applied on the corrupted pixel.

$$y(m, n) = \frac{\sum_{s=-w}^w \sum_{t=-w}^w w_G(s, t) w_R(s, t) \eta(m+s, n+t)}{\sum_{s=-w}^w \sum_{t=-w}^w w_G(s, t) w_R(s, t)}$$

Where for a restored image y w_G and w_R are spatial and radiometric weights respectively. Sometimes Adaptive bilateral filter provides less accuracy for random valued impulse noise. Another concern for this method is that for a smoother or blur region it fails to yield better

solution. Also, in this method the parameters like edge and range detector are selected manually on trial and error basis.

3.3 An Adaptive Dynamically Weighted Median Filter For Impulse Noise Removal [5]

An Adaptive weighted median filter is used for noise removal in images. According to the algorithm it extends window size when current window does not have any noise-free pixel and Assigns 0 to a pixel suspected as noisy within the window. There are two stages in this experiment namely Noise pixel detection and noise pixel removal. In the first stage of noise pixel identification algorithm for a selected window the pixels are ranked in ascending order where first and the last pixels are considered as noisy pixel. Second stage is the final selection of noisy pixels, a 11x11 window is considered across all the noisy pixels computed in first stage. The distance vector is computed for each pixel with respect to the centre pixel. The distance vectors are sorted in ascending order. If a pixel lies outside this range then it is finally considered as a noisy pixel. The second stage of the algorithm is for noisy pixel correction using dynamically weighted median filter (DWMF). The input to this algorithm becomes the noisy image and the binary image obtained from the previous step where 1 represents a noisy candidate and 0 for uncorrupted pixel. The binary image helps to assign weights only to a noise pixel and the noise free pixel will get a weight 0 and thus remain unchanged. Pixels in the window gets weight by a Gaussian function, it will assign lesser weights as the intensity decreases with the processing pixel. These algorithm works for low and high-density noise and performs well for uneven noise distribution. Thresholds for changing window are set after extensive simulations. There are also chances of False detection of noise free pixel.

3.4 An improved non-local means filter for color image denoising[6]

Non-local means filter are a type of nonlinear filter which effectively removes Gaussian noise and also retains original image edge and texture details. A non-local mean filter uses dissimilarity measure and performed on a non-local patches. NLM filter are effective but computationally expensive, and also some blurring effect is produced. Texture information are added as weights, this method aims to benefit from NLM and bilateral filter advantages. Patch texture information is shown through the value of mean square deviation. A larger value of MSD indicates an edge and when the MSD tends to 0 it shows the smooth surface. The MSD for a patch window is given by

$$S = \frac{1}{\sqrt{3}p} \sum_{p=0}^{p-1} \|fk(x,y) - gk\|_2 \quad fk(x,y) \in PatchWindow$$

For a P number of pixels g shows the average of a patch window. The algorithm states that first calculate the MSD using the above formula for each patch window. Then calculate the weights using Gaussian function as described in bilateral filter for every patch window. Weights are then normalized to get the weighted average value for a pixel. NLM is used to assign weights to central region patch and neighborhood patch based on their similarity.

$$w_1(x, y, x_0, y_0) = e^{-\frac{(s_{x,y} - s_{x_0,y_0})^2}{h_1}}$$

$$w_2(x, y, x_0, y_0) = e^{-\frac{(x-x_0)^2 + (y-y_0)^2}{h_2}}$$

$$w(x, y, x_0, y_0) = e^{-\frac{\sum_{p \in P} \|f_k(x+p,y+p) - f_k(x_0+p,y_0+p)\|_2^2}{h}} w_1(x, y, x_0, y_0) w_2(x, y, x_0, y_0)$$

The final weight w is based on w1 and w2 where w1 denotes how similar are pixel and its neighbor mean squared deviation and w2 denotes the spatial proximity of the pixel with its neighbors. In the experiment the h1, h2, h parameters are 100, 50, 60 respectively. Experiment shows that this method works well for low density noise.

IV. CRITICAL SUMMARY

Table 1: Critical Summary of various non-linear filters

Sr. no	Name	Description	Features	Drawbacks
1.	Bilateral Filter [1]	Pixel replaced by normalized weight based on spatial and radiometric distance	Spatial and radiometric weighting function, Gaussian noise removal	Can't preserve edges and texture information.
2.	Trilateral Filter [2]	ROAD statistic incorporated to detect impulse pixel, Joint impulsivity parameter as a switch to assign impulsive weight only to impulse pixel.	ROAD statistics, Impulse detector, mixed noise removal	Need iteration when noise is more than 20%, parameters are varied locally after exhaustive experiment.
3.	DPC and Trilateral Filter [3]	Average difference to calculate dissimilar pixel and Trilateral filter for noise removal	Trilateral parameters σ_i and σ_j are set based on type of noise, mixed noise removal	If noise < 30% high miss and false rate in noise pixel detection.
4.	EMD and Bilateral Filter [4]	Decompose signal into intrinsic mode function without leaving the time domain.	Intrinsic mode function signal and Adaptive Bilateral Filter	Adaptive bilateral filter sometimes provides less accuracy for random valued impulse noise. Need to manually set parameters, fails for smoother and blur region.
5.	ADWM Filter [5]	Dynamically assigns weights	Adaptively assigns weights based on noisy pixel present in the window	Threshold needs to be set manually. False detection of noise free pixel
6.	NLM and BLF [6]	Non local means filter and Bilateral Filter	NLM used to weight when the pixels are radiometrically similar and BLF used to assign weights for a spatially similar pixel. Thus, it helps to add texture information as a weighting function.	Computationally expensive as it takes NLM in searching windows and it considers central region patch and the neighboring patch to compute similarity.

V. CONCLUSION

This paper presents an analytical assessment of nonlinear filter namely bilateral, trilateral filter and non-local mean filter. Originally Bilateral Filter was developed [1] as an enhancement of Gaussian filter as Gaussian filter tends to blur the images. Thereafter, trilateral filter [2] is an extension to bilateral filter used to efficiently remove Impulse noise, Gaussian noise and the mixture of impulse and Gaussian noise. ROAD statistic was developed for impulse pixels. This filter limits its usage for a noise until 25%, when the noise percentage increases the algorithm needs to be applied iteratively. Also, it has to set range and edge detectors parameter on trial and error basis. A statistical based method can be used which helps to derive the standard deviation for a given grayscale range. Impulse pixel detector [3] scheme has been developed to identify an impulse pixel and then use the extension of trilateral filter as the noise removal algorithm. This method also works for the removal of mixture of Gaussian and impulse noise. The main concern with this method is that for a low-level noise in the image it gives high miss and false rate for noise pixel identification. A new strategy can be developed for low level noise as it was mistaken as edge and texture information. In [4] it fails to provide good result for blur and smooth region and also the level of random valued impulse noise for which the filter provides less accuracy should be identified. In [5] some pixels are falsely detected as a corrupted pixel and thus modified which leads to decrease in accuracy. In [6] if for a low-density noise, it is computationally

expensive, what happens in case of high-density noise is not clearly stated. To measure similarity between patches texture feature can be added as the future work. Thus, parameters need to be varied greatly based on type of noise and level of noise. The statistical study of such parameters can lead to better accuracy and better visual results.

Acknowledgment I owe a great many thanks to great many people who helped and supported me during the completion of this paper. My deepest thanks to internal guide at L.D. Engineering College prof. Shital Solanki for guiding and rectifying several actions and steps and documents with attention and care. She has presented a decent amount of attention during the course of the process and made necessary correction as and when needed.

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