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Natural Image Denoising and Enhancement Based On Iterative Bilateral Filter

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ABSTRACT

Natural images tend to get corrupted by impulse noise and other noises due to the abnormalities in the optical and imaging system. In this paper the author propose an iterative algorithm based on bilateral filter to remove impulse noise preserving the edges and fine details preferably in natural images. The dynamic bilateral filter parameter selection for individual iterations make this approach more efficient in terms of edge preserved denoising of natural images. To prevent over-smoothing of image while denoising, the gradient of the image is calculated and compared with the previous iteration. The proposed algorithm efficiently denoises the image within a maximum of 3 iterations for highly corrupted image.

KEY WORDS: Image filter, Impulse Noise, Iterative Bilateral Filter, Noise Detector.

1. INTRODUCTION

Random valued impulse noise occurs in the imaging system due to the corrupted pixels in the camera or during the transmission of pixel data. Many linear and non-linear image filters are proposed which improves the image quality by estimating the pixel values of the corrupted one. To have a good performance of denoising algorithm, the noise level has to be estimated earlier to applying the noise removal technique. So far, median filter took the centre stage in the design of such nonlinear filter for removing impulse noise because of its good denoising characteristics and computational efficiency. However, it is not effective on images of higher noise density that results in significant information loss. The different variant of switching median filter that have been proposed like the adaptive median filter, the multistate median filter. These switching filters first locate the corrupted pixel and then replace them by using the local variant leaving other pixels unchanged.

The media and adaptive median filter based on the intensity of noise-free pixels in the neighborhood presented in is a two stage filtering scheme which was used for robust denoising. Following that switching median filters along with local median filter is employed to estimate the nature of the pixel. Fuzzy logic techniques is proposed for detail-preserving restoration of digital images corrupted by impulse noise. A new framework for reducing impulse noise from digital colour images is presented, in which a fuzzy detection phase is followed by an iterative fuzzy filtering technique.

Impulse noise detectors, which is based on the differences between the current pixel and the surrounding pixels are used for noise detection and it is combined with the weighted median filter to get a new directional weighted median (DWM) filter. Switching-based adaptive weighted mean filter is proposed to remove salt-and-pepper noise from the corrupted images which used an adaptive weighted mean filter to remove the detected impulses by replacing each noisy pixel with the weighted mean of its noise-free neighbor's in the filtering window. A high performance detection (HPD) filter proposed in for impulse noise removal in images detects the noisy pixel iteratively through several phases, based on a set of unique similarity criteria. A turbulent particle swarm optimization (PSO) (TPSO)-based fuzzy filtering approaches to remove impulse noise from highly corrupted images.

A novel operator proposed acts as a hybrid filter obtained by appropriately combining a median filter, an edge detector, and a neuro-fuzzy network and the most distinctive feature of the proposed operator over most other operators is that it offers excellent line, edge, detail, and texture preservation performance while, at the same time, effectively removing noise from the input image. A new filtering scheme based on contrast enhancement within the filtering window is proposed and it filters the image iteratively till the stopping criteria. A novel filtering scheme based on threshold Boolean filtering, where the binary slices of an image is implemented. A modified boundary discriminative noise detection (BDND) is a powerful class of filters which effectively filters the image corrupted by impulse noise. To make an accurate decision, an iterative switching median is used along with two robust and reliable decision criteria. A switching bilateral filter (SBF) with a texture and noise detector for universal noise removal is proposed and the sorted quadrant median vector (SQMV) scheme includes important features such as edge or texture information.

Bilateral Filter: Bilateral filter (BF) is an efficient edged preserving smoothing filter. It is used for removing noise and other editing techniques on texture of the image and to modify the tone of the image. The bilateral filter is simple in its function as each pixel can be replaced by the weighted mean of the neighborhood pixels. The two parameters of the filter indicates the features of the image which should be preserved. Basically it is a non-iterative filter but it

can be used iteratively depending on the application. Various numerical methods makes the efficient computation of the bilateral filter which makes it suitable for implementation.

The bilateral filter combines the degree of similarity in geometry and photometry simultaneously and it was proposed by Tomasi initially. The mathematical equation which governs both the degree is given by;

$$h(x) = k^{-1}(x) \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(\xi) c(\xi, x) s(f(\xi), f(x)) d(\xi) \quad (1)$$

And, after the normalization,

$$k(x) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} c(\xi, x) s(f(\xi), f(x)) d(\xi) \quad (2)$$

The parameters defined in the equation are: h(x) - output pixel; f(x) - input pixel; $c(\xi,x)$ - Geometric closeness between the neighbourhood centre pixel x and a nearby pixel ξ; $s(f(\xi),f(x))$ - photometric similarity between the pixel at the neighborhood centre x and that of a nearby point ξ; $k(x)$ - ensures that the weights for all the pixels add up to one.

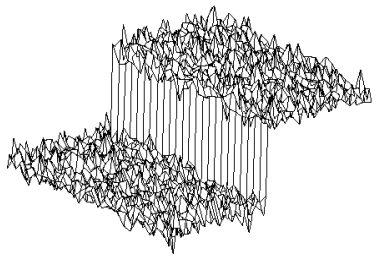

Figure.1. (a) A 100-gray-level step perturbed by Gaussian noise with σ = 10 gray levels

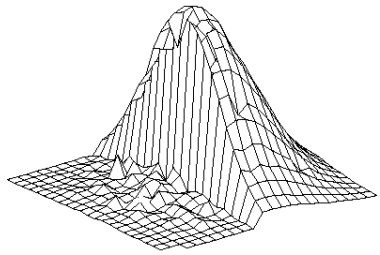

Figure.1. (b) Combined similarity weights for a 23x23 neighborhood

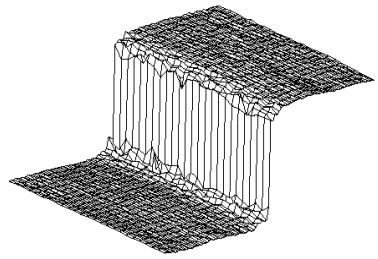

Figure.1. (c) The step in (a) after bilateral filtering

The bilateral filter and it is a smoothening filter but preserves the edges in the image. It performs the domain filtering and range filtering. The domain filter is a low pass filter and it takes the average of the neighbourhood pixel and it is also called geometric filter or geometric component. The second filter is the photometric component which represent the nonlinear filter and it preserves the edges of the image while removing the noise.

The bilateral filter enables to denoise the image for various kinds of noises which are common during the image acquisition and transmission. Each pixel of interest are replaced by a weighted average of the surrounding pixel of a *(2N+1) X (2N+1)* space. Perhaps the bilateral filter smooth the image and the degree of smoothness depends on the weights and the radiometric distance considered, thus preserving the edges in the image.

More precisely, let x be the location of the pixel of interest, and let $\Omega = \Omega_x(N)$ be the pixels in *(2N+1) X (2N+1)* neighbourhood of x. The weight of each pixel with respect to x is the product of two components, one spatial and one radiometric:

$$w(x, y) = w_S(x, y) w_R(x, y) \quad (3)$$

$$w_S(x, y) = e^{-\frac{|x - y|^2}{2\sigma_S^2}} \quad (4)$$

$$w_R(x, y) = e^{-\frac{|u_x - u_y|^2}{2\sigma_R^2}} \quad (5)$$

The weights must be normalized, so the restored pixel $\tilde{u}_x$ is given by

$$\tilde{u}_x = \frac{\sum_{y \in \Omega} w(x, y) u_y}{\sum_{y \in \Omega} w(x, y)} \quad (6)$$

When the spatial distance between x and y increases, the weighting function $w_s(x,y)$ decreases and when the radiometric distance between the intensities of the pixels (i.e.) u_x and u_y increases, the weighting function $w_R(x,y)$ decreases.

Impulse Noise Model: Understanding the nature of noise helps in constructing a suitable filter for efficient noise estimation and removal. The two commonly used impulse noise models are Fixed-Valued Impulse Noise (FVIN) and the Random-Valued Impulse Noise (RVIN). As the name indicates, the FVIN will have two extreme fixed values of pixel with either dark or white and it is 0 or 255 for 8-bit representation.

The FVIN is given by

$$y_{ij} = \begin{cases} \{0, 255\} & \text{with probability p} \\ x_{i,j} & \text{with probability 1 - p} \end{cases} \quad (7)$$

Where x i, j is the original pixel value and yi,j denotes the resulting pixel being corrupted with a probability p at the location (i, j).

But an interesting noise model is considered as Fixed Range Impulse Noise (FRIN) uses two fixed range of pixel values instead of two fixed pixel values. The noise model is described as;

$$y_{ij} = \begin{cases} [0, m) & \text{with probability } p_1 \\ x_{ij} & \text{with probability 1 - p} \\ (255 - m, 255 & \text{with probability } p_2 \end{cases} \quad (8)$$

Where p = p1 + p2.

But in general, the corrupted pixel can take any random pixel value and hence we go for a RVIN model and using a robust noise detector, the corrupted pixel with random value can be detected.

Proposed Iterative Bilateral Filter (IBF): The bilateral filter can be imposed several times on the same image till the desired output is obtained. Iteration of bilateral filter preserves the edges when the range and spatial or domain parameters are chosen carefully. In general, to have a better filtering effect, the range parameter should be increased in connection with the spatial parameter. But a higher value of range parameter tends to over smooth the image and the minute details and the borders will be lost. In order to preserve the edges and strong details, the bilateral filter can be iterated rather than increasing the range and spatial parameters which leads to over smoothing sometimes.

In this paper we propose an iterative bilateral filter which will adjust its range and domain filter coefficients based on the estimated noise intensity. Spatially closer pixel will have more impact rather than the other surrounding layers and also weights are given based on the range of the surrounding pixels. The range filters preserves edges as their weights are adjusted according to the image intensity.

Algorithm:

1. Initialize the acquired noisy image
2. Estimate the noise intensity using robust noise estimator
3. Calculate the gradient of the image
4. Compute the σ_d and σ_r using the formula σ_d=1.8 and σ_r= σ X 1.7
5. Apply the bilateral filter with the above range and domain coefficients.
6. Recompute the noise intensity from the resulting image.
7. Recompute the gradient of the filtered image.
8. Go to step 4 in the change in noise intensity is more than 5% or the change in gradient is significant (greater than 5%).
9. Stop and store the resulting denoised image.

By adapting the above mentioned algorithm several standard test images are denoised with wide range of corrupted noise pixels from 10% to 80%. The performance of adaptive bilateral filter based denoising algorithm performs well in the experiment. The figure.2b and 3b shows the lena image corrupted with 15% and 80% additive RVIN. The corresponding denoised image for every iteration is also shown.

Figure.2. Bilateral Filtered Lena image corrupted with 15% of RVIN for successive iterations, (a) Original image; (b) Noisy image; (c) Denoised image on Iteration 1; (d) Denoised image on Iteration 2; (e) Denoised image on Iteration 3

Figure.3. Bilateral Filtered Lena image corrupted with 80% of RVIN for successive iterations, (a) Original image; (b) Noisy image; (c) Denoised image on Iteration 1; (d) Denoised image on Iteration 2; (e) Denoised image on Iteration 3

The figure.2, does not show much improvement in the iteration 2 and 3 as majority of the noise pixels are estimated in the first iteration itself as the image is corrupted with less noise. While figure 3 shows a considerable improvement in the successive iterations thus denoising the image further. The figure 4b and 5b show the peppers image corrupted with 15% and 80% additive RVIN. The corresponding denoised image for every iteration is also shown.

Figure.4. Bilateral Filtered Peppers image corrupted with 15% of RVIN for successive iterations, (a) Original image; (b) Noisy image; (c) Denoised image on Iteration 1; (d) Denoised image on Iteration 2; (e) Denoised image on Iteration 3

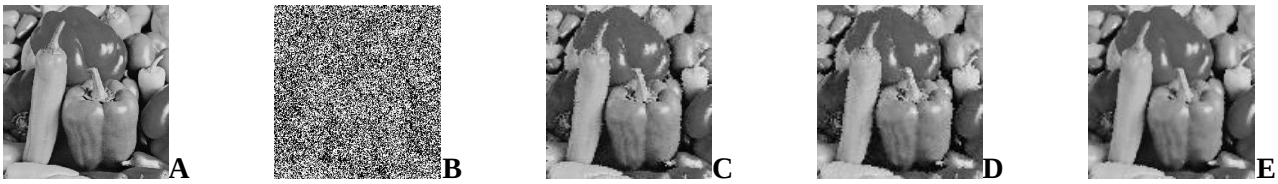

Figure.5. Bilateral Filtered Peppers image corrupted with 80% of RVIN for successive iterations, (a) Original image; (b) Noisy image; (c) Denoised image on Iteration 1; (d) Denoised image on Iteration 2; (e) Denoised image on Iteration 3

The figure.4, does not show much image quality improvement in the iteration 2 and 3 as majority of the noise pixels are estimated in the first iteration itself as the image is corrupted with less noise. While figure 5 shows a considerable improvement in the successive iterations thus denoising the image further.

Further to avoid over smoothing of image while going for iterations, the gradient of the image is calculated at every stage and the iteration is stopped if there is a significant change in the gradient while noise estimation is minimum. There is a tradeoff between denoising and the smoothness of the image. Calculating the gradient at every iteration helps in concluding the algorithms if there is no significant change in the estimated noise.

Image Quality Assessment: The quality of reconstructed image is evaluated using quality metrics (PSNR) and distortion metrics (MSE).

Quality Metrics: Peak Signal To Noise Ratio (PSNR): PSNR in decibels (dB) between the original (X) and reconstructed ($\hat{X}$) image of size MXN is defined as:

$$PSNR = 20\log_{10}\left(\frac{2^B - 1}{\sqrt{MSE}}\right) \tag{9}$$

Where, B represents bits per pixel (bpp).

Distortion Metrics: Mean Square Error (MSE): MSE between the original (X) and reconstructed ($\hat{X}$) image is defined as:

$$MSE = \frac{\left\| X - \hat{X} \right\|^2}{MN} \tag{10}$$

An MSE=0 in a reconstructed image indicates that $\hat{X}$ is a perfect reconstruction of X . Increasing values of MSE correspond to increasing error.

2. EXPERIMENTS AND RESULTS

As an example of how the algorithm works for different noise level, the lena image is considered. The table.1, compares the output of conventional bilateral filter and the proposed iterative bilateral filter based denoising algorithm. Table.1, shows the PSNR and MSE for the denoised Lena image corrupted with additive RVIN ranging from 5% to 80%. The proposed filter works well compared to the existing bilateral filter for a maximum iteration of 3 beyond which the algorithm over smooth the image.

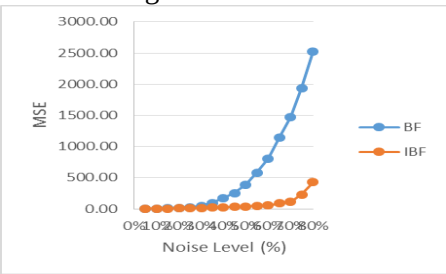

Figure.6. Comparison of MSE between BF and IBF for the denoised Lena image for noise level ranging from 5% to 80%

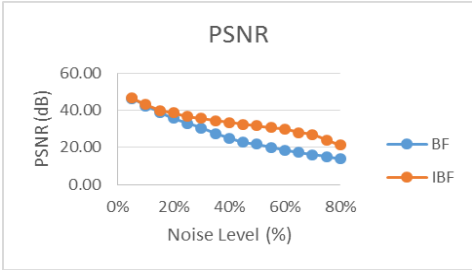

Figure.7. Comparison of PSNR between BF and IBF for the denoised Lena image for noise level ranging from 5% to 80%

Table.1. Bilateral Filter and Iterative Bilateral Filter for various Noise Densities (lena)

Noise density	Bilateral Filter		Iterative Bilateral Filter	
	MSE	PSNR	MSE	PSNR
5 %	1.14	46.27	1.04	46.65
10%	2.81	42.46	2.43	43.07
15%	6.36	39.01	5.13	39.92
20%	14.54	35.57	7.12	38.54
25%	27.12	32.91	10.90	36.75
30%	47.45	30.55	13.79	35.76
35%	96.01	27.40	18.76	34.46
40%	175.56	25.04	23.52	33.51
45%	253.15	22.79	29.59	32.54
50%	389.82	21.64	37.34	31.56
55%	579.14	20.01	46.41	30.65
60%	804.28	18.63	56.36	29.83
65%	1139.80	17.16	90.16	27.85
70%	1474.65	16.08	111.67	26.95
75%	1936.92	14.93	232.13	23.86
80%	2525.15	13.81	425.52	21.31

An exhaustive comparison of PSNR (dB) is shown in table.2 and various state of the art techniques discussed in the current literature are considered.

Table.2. Comparison of PSNR (dB) with the existing state of the art denoising algorithms for Lena image

Noise density	BDND	ABDND	LOFBDND	NASMF	BF	IBF
5%	42.27	43.22	45.24	45.96	46.27	46.65
10%	37.32	38.72	39.83	41.24	42.46	43.07
15%	35.90	36.33	37.43	37.91	39.01	39.92
20%	31.69	32.65	34.65	35.48	35.57	38.54
25%	31.03	31.76	32.25	33.23	32.91	36.75
30%	28.11	30.14	30.01	32.52	30.55	35.76
35%	25.88	26.92	26.79	29.29	27.40	34.46
40%	24.20	24.83	25.54	28.60	25.04	33.51
45%	22.18	23.29	23.04	25.99	22.79	32.54
50%	19.61	21.21	21.93	24.91	21.64	31.56
55%	19.65	22.04	21.19	24.61	20.01	30.65
60%	18.74	19.14	20.31	22.52	18.63	29.83
65%	17.77	18.20	19.30	21.76	17.16	27.85
70%	16.50	16.68	18.27	20.75	16.08	26.95
75%	14.15	14.79	15.48	18.62	14.93	23.86
80%	12.55	12.87	14.19	15.78	13.81	21.31

The figure.8, plots the PSNR of the denoised lena image while being corrupted by RVIN with densities ranging from 5% to 80%. As the noise density increases, the reconstruction or denoising efficiency goes down which is plotted in the figure.8.

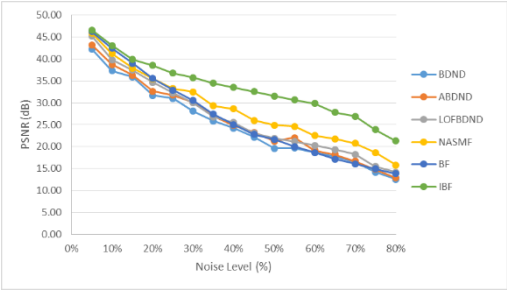

Figure.8. Comparison of PSNR of state of the art denoising algorithms for Lena image with noise level ranging from 5% to 80%

3. CONCLUSION

The implemented iterative bilateral filter based denoising algorithm works well for natural images and it has been tested with the standard images available. It is suitable for images corrupted by wide range on noise densities of RVIN. The usage of gradient operator to prevent smoothing of images had an important role when the number of iteration increases for removing the corrupted pixels while preserving sharp edges and transitions. The PSNR and MSE values of the sample test images show that this algorithm performs well with robust noise removing characteristics and preserving fine details of the image.

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