Locally Adaptive Bilateral Clustering for Image Denoising and Sharpness Enhancement

Barjinder Singh Saini, Ravi Raj, and Indu Saini

***Abstract*—The purpose of denoising is to remove the noise while retaining the edges and other detailed features as much as possible. This paper, present a method for both image denoising and sharpness enhancement. We approach the problems of denoising and sharpening by first adaptively segmenting the image into clusters based on features that represent the underlying local image structures (e.g., image details, edges, and textures). The key idea behind this approach is denoising and sharpening according to the local image feature, so that noise amplification, undershoots, and overshoots can be effectively avoided. The parameters which are used to test the performance of the proposed method are i) Peak Signal to Noise Ratio (PSNR) and ii) Mean Absolute Error (MAE). Further the results which are obtained using the proposed method in term of PSNR and MAE were compared with the earliest published works. The results clearly confirm the superiority of our proposed method for sharpness enhancement and image denoising.**

***Index Terms*—Bilateral filtering, clustering, denoising, sharpness enhancement.**

I. Introduction

During acquisition and transmission, images are often corrupted by noise usually modeled as Gaussian type. The goal of image denoising is to recover the true or original images from such a distorted / noisy copy. Since the early 1990's the wavelet theory has been well developed and widely introduced into many fields of application. In order to reduce the affect of the noise, many wavelet based denoising methods have been developed over the past year, in which the wavelet threshold is one of the most popular approaches[1]. The main problem of wavelet-based method [2] is that they are prone to produce salient artifacts such as the low frequency noise and the edge ringing which are related to the structure of the underlying wavelet.

The two most common form of degradation an image suffers are loss of sharpness or blur and noise. The degradation model we use consists of a linear, shift-invariant blur followed by additive noise. The problem is in two fold. First we seek to develop a sharpening method, which sharpens an image by enhancing the high-frequency components lead to overshoot and undershoot around edge, which causes objectionable ringing or halo artifacts. Our aim is to develop a sharpening algorithm that increase the slope of edges without producing undershoots and overshoot, thereby improving the overall appearance of the image. The second aspect of the problem is to noise removal.

In this paper, we present a unified solution to both image denoising and sharpness enhancement. We approach the problems of denoising and sharpening by first adaptively segmenting the image into clusters based on features that represent the underlying local image structures. For our work, we choose the bilateral radiometric (gray value) and spatial kernels [3] as the features. Then, we estimate the intensity of each pixel using weighted averaging by selectively considering the bilateral weights in the clusters formed.

Our major contribution in this paper is the robust framework that allows us to perform image denoising and sharpness enchancement with a single algorithm. In addition to detail improvement, denoising, and noise suppression, our algorithm has low computational complexity as compared to those of other existing methods. These advantages, to name a few, suggest its appropriateness and importance for application in consumer electronic products.

II. Bilateral Filter and Its Properties

The bilateral filter proposed by Tomasi and Manduchi in 1998 is a nonlinear filter that smoothes the noise while preserving edge structure [3]. The bilateral filter [4] is a combination of domain and range filtering. The domain filter, also called geometric component, average the nearby pixel values and acts thereby as a lowpass filter. The range filter, also called photometric component, represents the nonlinear component and plays an important part in edge preserving. The shift-variant filtering operation of the bilateral filter is given as in (1)

$$\hat{f}[m,n] = \sum_k \sum_l h[m,n;k,l] g[k,l] \quad (1)$$

where $\hat{f}[m,n]$ is the restored image, $h[m,n;k,l]$ is the response at [m, n] to an impulse at [k, l], and g[m, n] is the degraded image. The bilateral filter is given as in (2)

$$h[m_0,n_0;m,n] = r_{m_0,n_0}{}^{-1} \exp\left(-\frac{(m-m_0)^2 + (n-n_0)^2}{2\sigma_d{}^2}\right) \times \exp\left(-\frac{(g[m,n]-g[m_0,n_0])^2}{2\sigma_r{}^2}\right), [m,n] \in \Omega_{m_0,n_0} \quad (2)$$

$[m_0,n_0]$ is the center pixel of the window, Ω_{m_0,n_0} = $\{[m,n]:[m,n] \in [m_0-N, m_0+N] \times [n_0-N, n_0+N]\}$, σ_d and σ_r are the standard deviations of the domain and range

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B. S.Saini, Ravi Raj, and Indu Saini are with Dr. B. R. Ambedkar National Institute of Technology, Jalandhar, 144011, India. (e-mail: sainibss@gmail.com, ravirajm4u@yahoo.co.in, sainii@nitj.ac.in).

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Gaussian filters, respectively in (3)

$$r_{m_0,n_0} = \sum_{m=m_0-N}^{m_0+N} \sum_{n=n_0-N}^{n_0+N} \exp\left(-\frac{(m-m_0)^2+(n-n_0)^2}{2\sigma_d^{\,2}}\right) \times \exp\left(-\frac{g[m,n]-g[m_0,n_0]^2}{2\sigma_r^{\,2}}\right) \quad (3)$$

is a normalization factor that assures that the filter preserves average gray value in constant areas of the image.

Bilateral filter as an alternative to wavelet thresholding for image denoising. It applies spatial weighted averaging without smoothing edges. This is achieved by combining two Gaussian filters; one filter works in spatial domain, the other filter works in intensity domain. Therefore, not only the spatial distance but also the intensity distance is important for the determination of weights.

One weakness of the bilateral filter is its inability to remove salt-and-pepper type of noise. The second drawback of the bilateral filter is its single resolution nature. Unlike the wavelet filter, the bilateral filter may not access to the different frequency components of a signal. Although it is effective in removing high frequency noise, the bilateral filter fails to remove low frequency noise.

III. The Adaptive Bilateral Filter (ABF)

The bilateral filter [4] presents a new sharpening and smoothing algorithm. The response at $[m_0, n_0]$ of the proposed shift-variant ABF to an impulse at [m, n] is given as in (4)

$$h[m_0,n_0;m,n] = r_{m_0,n_0}^{\;-1} \exp\left(-\frac{(m-m_0)^2+(n-n_0)^2}{2\sigma_d^{\,2}}\right) \times \exp\left(-\frac{(g[m,n]-g[m_0,n_0]-\zeta[m_0,n_0])^2}{2\sigma_r^{\,2}}\right), \text{ for [m, n]} \; \varepsilon\Omega m_0 n_0 \quad (4)$$

where $[m_0, n_0]$ and Ω_{m_0,n_0} are defined as before, and the normalization factor is given as in (5)

$$r_{m_0,n_0} = \sum_{m=m_0-N}^{m_0+N} \sum_{n=n_0-N}^{n_0+N} \exp\left(-\frac{(m-m_0)^2+(n-n_0)^2}{2\sigma_d^{\,2}}\right) \times \exp\left(-\frac{(g[m,n]-g[m_0,n_0]-\zeta[m_0,n_0])^2}{2\sigma_r^{\,2}[m_0,n_0]}\right). \quad (5)$$

Compared with the conventional bilateral filter given in [3], ABF contains two important modifications: First, an offset ζ is introduced in the range filter. Second, both ζ and the width of the range filter σ_r in the ABF are locally adaptive. If ζ =0 and σ_r is fixed, ABF will degenerate into a conventional bilateral filter. The combination of a locally adaptive ζ and σ_r transforms the bilateral filter into a much powerful filter that is capable of both sharpening and smoothing.

IV. Locally Adaptive Bilateral Clustering Filter

In the proposed approach of segmenting pixels into clusters [6] of similar local structure, the first step is a signal augmentation process. Let $W(y_i, y_j; x_i, x_j)$ be the local kernel representing the radiometric samples y_i and y_j at respective spatial locations x_i and x_j with the i-th pixel centered in $W(\,)$. We define the j neighboring pixels as the neighbor gram in (6) is

$$N = \{(y_j, x_j) \| j \| \le L\} \quad (6)$$

where $L > 0$ defines the local kernel support size with odd $(2L+1)\times(2\;L+1)$ dimensions. More precisely, N in the vectorized format represents the spatial and radiometric quantities of the j neighboring pixels.

Next, we sort N based on y_j as $\{y_1 \le y_2 \le y_3 \le \ldots \le y_{(2L+1)^2-1}\}$ in ascending order. Without losing the spatial information, the spatial locations x_j correspond to y_j are vectorially indexed to their sorted counterparts $\{y_1, y_2, y_3, \ldots, y_{(2L+1)^2-1}\}$. Hence, we denote the sorted neighborgram in (7) as:

$$N_s = \{(y_1, x_j), (y_2, x_j), (y_3, x_j), .., (y_{(2L+1)^2-1}, x_j)\} = \{N_s(1), N_s(2), \ldots N_s((2L+1)^2-1),\} \quad (7)$$

Similarly, N_S represents the pair of sorted pixel intensity y_j and the interrelated vectorially indexed spatial position x_j. Now, we compute the variational series V by taking the absolute difference between the adjacent sorted pixel intensities is given as in (8)

$$V(m) = | y_{m+1} - y_m |; \quad m=1, 2, 3, \ldots, (2L+1)^2-2 \quad (8)$$

Subsequently, we augment the variational series $V(m)$ with the aid of the Huber influence function $F(m)$, given as in (9)

$$F(m) = \begin{cases} 0.0 & : V(m) \le T_L \\ \dfrac{V(m)-T_L}{T_H - T_L} & : T_L \le V(m) < T_H \\ 1.0 & : V(m) \ge T_H \end{cases} \quad (9)$$

$F(m)$ provides us with a "soft" augmenting approach by two data driven parameter T_L and T_H. Since $V(m)$ inherently contains a high level of ambiguity.

Based on the augmented variational series, we adaptively segment the sorted neighborgram N_s into cluster of similar local structure. Agglomeratively segments N_s according to (10) is given as

$$z \longleftarrow z+1 \Leftrightarrow V_A(m) > T_C \quad (10)$$

where T_C is a clustering threshold Intially the first cluster $C_z(1)$ is composed of its fixed member $N_s(1)$, i.e. $C_z(1) =$

{ $N_s(1)$ }. Then the condition $V_A(1) > T_C$ is evaluated. If the condition is valid, then a second cluster is formed and the subsequent sorted neighborgram member $N_s(2)$ fall under the membership of $C_z(2)$ .If the condition does not hold , $N_s(2)$ will accept the membership of $C_z(1)$ i.e., $C_z(1)$ ={ $N_s(1)$, $N_s(2)$ }.This process is repeated. When the clustering process end, then we take the pixel data from the dominant cluster C_D into a higher dimensional cluster C_D into a higher dimensional space by associating each pixel with spatial and radiometric weights. Now we compute the spatial weights using the spatial similarity kernel is given as in (11)

$$S(n) = \exp\left[\frac{-\| N_{S,x}(n) - x_i \|_2^2}{2\sigma_s^{\,2}}\right], n \in C_D \tag{11}$$

where $\|\cdot\|_2$ represents the Euclidean distance between the spatial position and the central pixel.

The radiometric weights can be computed using the radiometric similarity kernel in (12) is given as

$$R(n) = \exp\left[\frac{-| N_{S,y}(n) - y_{(i)} - \xi(n) |^2}{2\sigma_r^{\,2}}\right], \; n \in C_D \tag{12}$$

Similarity $N_{S,y}(n)$ represents the sorted intensity of the *n-th* member in N_s , σ_r is the radiometric smoothing scalar, and $\xi(n)$ is an offset function for local gradient estimation is given as in (13) is

$$\xi(n) = \begin{Bmatrix} MAX(y_j) - y_i & : \delta > 0 \\ MIN(y_j) - y_i & : \delta < 0 \\ 0 & : \delta = 0 \end{Bmatrix} \tag{13}$$

where $\delta = MIN(y_j) - y_i$, and MIN, MAX and MEAN are operator for taking the minimum, maximum, and average intensity of the pixels. The restored pixel intensity is given as the weighted average of pixels is given as in (14)

$$\bar{y}_i = \frac{\sum_{n \in C_D} R(n) \cdot S(n) \cdot N_{S,y}(n)}{\sum_{n \in C_D} R(n) \cdot S(n)} \tag{14}$$

In (11), the rationale of combining the spatial and radiometric similarity weight is that two pixels are related not only if they occupy nearby spatial location, but also if they have similarity in the radiometric range.

V. Results and Discussion

In this work, the experiments were conducted on six images i.e. i) Barbara ii) Boats iii) Goldhill iv) Peppers v) House vi) Lena by adding white Gaussian noise of three values of standard deviation i.e. i) 10 ii) 20 and iii) 30. The parameters which are used and test the performance of the proposed method are i) Peak Signal to noise ratio (PSNR) and ii) Mean Absolute Error (MAE) are defined as follows

A. Peak Signal to Noise Ratio (PSNR)

The performance of the proposed algorithm is tested quantitatively based on the parameter PSNR [8] using (15) for various standard deviations of Gaussian noise level.

$$PSNR = 10 \log_{10}\left[\frac{255^2}{\frac{1}{MN}\sum_i \sum_j (Y_{ij} - X_{ij})^2}\right] \tag{15}$$

where Y_{ij} and X_{ij} denotes pixel values of restored image and original image respectively and M, N are the size of the image.

B. Mean Absolute Error (MAE)

The MAE is mathematically defined in (16) as

$$MAE = \frac{\sum_{i=1}^{M \cdot N} | y_i - o_i |}{M \cdot N} \tag{16}$$

where y_i and o_i is the i-th pixel gray value of the restored and original images, respectively[9].

These noisy images were then denoised using proposed algorithm and the PSNR and the MAE results were calculated which is shown in Table I and Table II in the form of comparison between proposed method and earlier published work.

Qualitative analysis is performed by visual comparison, Fig.1 gives the visual comparison of denoised Barbara image using the bilateral filter and the proposed method with PSNR value.

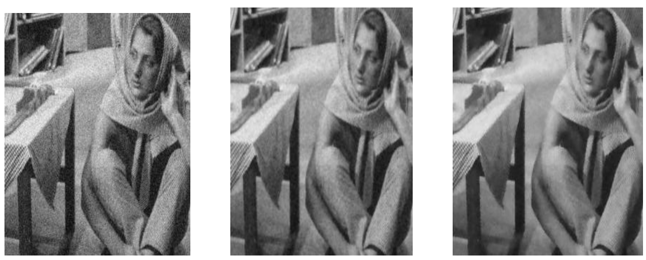

Fig. 1. Barbara Image denoising results in terms of PSNR (a) Noisy image (σ=30) [18.6 dB] (b) Bilateral Filter [24.69 dB] (c) Proposed Method [30.61 dB]

Table I demonstrate the results in terms of PSNR values obtained using our proposed method in comparison to earlier published works [7], implemented on the same set of images. As shown in Table I, the PSNR values which are obtained using our proposed method are quite higher for all the images when compared to earlier publish works. This proves the superiority of our proposed method. Further Table II demonstrate the result in terms of MAE values obtained using our proposed method in comparison to earlier published works, implemented on Lena Image for the noise standard deviation of 20. As shown in Table II, the MAE value which is obtained using our proposed method are quite low compared to earlier publish works. This again proves the superiority of our proposed method.

TABLE I: PSNR VALUES OBTAINED USING THE PROPOSED METHOD IN COMPARISON OF PUBLISHED WORK

Input Image	σ_n	Bayes Shrink [2]	Bilateral Filter [3]	Bayes Shrink Followed by Bilateral Filter [7]	New Sure [10]	DCF [11]	Proposed Method
	10	31.25	31.37	30.92	32.18	34.98	35.56
Barbara	20	27.32	27.02	27.16	27.98	31.78	32.14
	30	25.34	24.69	25.23	25.83	29.81	30.61
	10	31.98	32.02	31.81	32.90	33.92	34.77
Boats	20	28.55	28.40	28.43	29.47	30.88	31.28
	30	26.71	26.57	26.66	27.63	29.12	29.73
	10	31.94	32.08	31.93	32.69	33.62	35.56
Goldhill	20	28.69	28.90	28.80	29.52	30.72	34.33
	30	27.13	27.50	27.34	27.83	29.16	31.73
	10	31.49	32.98	31.89	33.18	34.68	36.77
Peppers	20	27.85	29.07	28.01	29.33	31.29	34.01
	30	25.73	27.02	26.07	27.13	29.28	31.84
	10	33.07	33.77	33.09	34.29	36.71	37.23
House	20	29.83	29.63	29.79	30.93	33.77	35.80
	30	27.12	28.11	28.10	28.98	32.09	33.77
	10	33.38	33.65	33.39	34.45	35.93	35.97
Lena	20	30.27	30.33	30.29	31.33	33.05	33.74
	30	28.60	28.54	28.62	29.55	31.26	31.53

TABLE II: COMPARISON OF MAE VALUES OBTAINED USING PROPOSED METHOD IN COMPARISON TO PUBLISHED WORKS ON LENA IMAGE

Methods	MAE
Proposed method	3.14
ABF [5]	5.92
BF [3]	5.57
SRHE [12]	6.09
FIET [13]	11.63
UM [14]	8.97
FUM [10]	7.98

VI. CONCLUSION

In this paper, we propose a simple but effective adaptive bilateral clustering filter for image denoising and sharpness enhancement. In this method the bilateral radiometric and spatial similarity kernels are used to capture the underlying geometric features before performing necessary denoising on the input image. The adaptive bilateral clustering filter outperforms the bilateral filter in noise removal. The results which are obtained using our proposed method clearly outperform the earlier published works in terms of both PSNR and MAE.

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Barjinder Singh Saini was born in Jalandhar, India, in 1970. He received his B.Tech and M.Tech.degree in Electronics & Communication Engineering in 1994 and 1996 respectively. He then obtained his PhD degree in Engineering on "Signal Processing of Heart Rate Variability" in 2009 from Dr. B. R. Ambedkar National Institute of Technology, Jalandhar. He is working as Associate Professor in Electronics & Communication Engineering Department at NIT Jalandhar since 1997. He supervised more than 20 M.Tech dissertations and presently guiding 06 Ph. D research scholars. He has published more than 20 research papers in internationally reputed Journals and Conference proceedings. He has accomplished research projects from government departments. He has also conducted several courses, workshops and international conferences for the benefit of faculty and field engineers. His areas of interest are Medical Image Processing, Digital Signal Processing and Telemedicine and embedded systems. Dr.

Saini holds membership of many professional bodies like IEEE, IEEE EMBS. He is a life member of the IETE.

Ravi Raj was born in Patna, India, in 1984. He received his B.Tech in Electronics & Communication Engineering in 2007 from Cochin University of Science and Technology, India. He then did his M.tech Degree in the Department in Electronics & Communication Engineering from NIT Jalandhar, India in 2012. His research interest includes Image Processing.

Indu Saini was born in Ferozepur, India, in 1971. She received her B.Tech degree in Electronics & Communication Engineering from Guru Nanak Dev University, India in 1994 and then obtained her M.Tech(by Research) degree in Electronics & Communication Engineering from National Institute of Technology Jalandhar. Presently, she is pursuing her Ph.D. in the area of Biomedical Signal Processing from Dr. B. R. Ambedkar National Institute of Technology Jalandhar, where she is also serving as Assistant Professor in Electronics & Communication Engineering Department since 2002.