An Effective Method of Denoising of 2-D Data Using Adaptive Kernel Bilateral Filter

Lukka Sirisha, A.Geetha Devi, B. Surya Prasada Rao

Abstract-In this paper, adenoising scheme using bilateral filter with adaptive kernel bandwidth scheme is proposed. Here the image is divided into laplaciansubbands these are applied with adaptive kernel filter and bilateral filter to reduce the noise. The Gaussian filter is used to acquire a low band signal which is subtracted from original signal to obtainedhigh band signal. The low band signal is applied with conventional bilateral filter and for high band adaptive kernel bilateral filter is applied. The proposed scheme is further processed using gradient histogram method for edge sharpening. The proposed method performs better when compared with the results of bilateral filter and over complete wavelet expansion filters in terms of peak signal to noise ratio, Entropy, minimum mean square error, mean absolute error.

Index Terms:-Image De-noising, Adaptive kernel, Bilateral filter, Laplacian subbands, gradient histogram preservation, Edge detection.

1. INTRODUCTION

The addition of noise and loss of sharpness are the two most common degradations suffered by an image. There are various sources of noise in digital images some of which are: heat in the sensor, slow shutter speed and noise introduced via communication channel during the acquisition, signal amplification and transmission [10]. There are many existing filtering methods for image de-noising. Adaptive Kernel Bilateral Filtering is one of the effective filtering scheme [2]. The edge sharpening is the important topic in image processing which enriches the visual quality of an images. Suppressing the noise while preserving the edges uses the similarities of pixels locally or globally [6]. Edge pixels can be determined by thresholding [7, 11].

In this paper three methods were compared and are filter with adaptive kernel than bilateral filter and wavelet based linear minimum mean square error filters. It is an efficient method for suppressing high band noise with low computation time.The basic idea behind applying adaptive kernel bilateral filter [1] is the suppression of noise present in high band image which is not possible with the low band image denoising techniques like wavelet based LMMSE [3,4] and conventional BLF [5] methods. The adaptive kernel BLF [2] also processes the denoised high band image using gradient histogram pervasion method [12] for strengthening the filtered output.

Experiments on the images corrupted by additive white gaussian noise by estimating different parameters [8, 9]like PSNR, MSE, MAE [13] and Entropygives the best results thanotherdenoising techniques.Also,modification of the edge coefficients in the high band gives sharpened images with less noise amplification than the conventional edge-sharpening method in the Laplaciansubbands.

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2. REVIEW OF RELATED WORK

2.1 Bilateral Filter

A bilateral filter is a nonlinear, edge preserving, noise reducing and smoothing filter for images. The intensity value at each pixel in an image is replaced by a weighted average of intensity values from nearby pixels. This weight is based on a Gaussian distribution.

The bilateral filter output is defined as

$$V(x) = \frac{1}{z}\sum_{y\epsilon N_x} Z(x,y)I(y) \quad (2.1.1)$$

Where x and y denote pixel positions, Nxis the neighbour of x, I(y) is the intensity of input image at a pixel y, Z is the normalizing factor $Z = \sum_{y\epsilon N_x} Z(x,y)$, and Z(x, y) is the adaptive kernel of the BLF which can be defined as

$$Z(x,y) = \exp\left(-\frac{\|x-y\|^2}{2\sigma_d^2}\right)\exp\left(-\frac{\|I(x)-I(y)\|^2}{2\sigma_r^2}\right) \quad (2.1.2)$$

Here σ_d is the band width for the spatial distance and σ_r is the bandwidth for the normal distance. Hence for reducing noise variance while keeping the edges, it is important to find the balance between σdand σr and also to find an appropriate size of the neighbour.

2.2Laplacian Sub Bands

When a signal is low pass filtered and the filtered outputis subtracted from the original, then we obtain a highband signal. If this process is repeated for the low passfiltered signal, then we obtain a set of subband signals.The Laplacian pyramid for an image is constructed inthis manner, where the low pass filter is a Gaussian filterwith appropriate kernel bandwidth. More specifically,for a given image I, the Gaussian filter is applied iterativelywith downsampling at every step. This process canbe described as

G0 = I,

Gk+1 =↓2 for k = 0, . . , n −1(2.2.1)

Where ↓2 (·) denotes the down sampling by 2 and Gaussian(·) is the Gaussian filtering. Then, the Laplaciansubbands are defined as

Lk+1=Gk− ↑2 (Gk+1) for k = 0, . . . ,n – 1

Ln+1 =Gn (2.2.2)

Where n represents the level of pyramid. If n=1 then L1 denotes the high-frequency subband and L2 becomes G1 representing the low frequency sub band.

3. LAPLACIAN SUBBANDS IN THE KERNEL BILATERAL FILTER

3.1 Adaptive Kernel bilateral filter

For a given input image, we first perform sub band decomposition as Eqs. (2.2.1), (2.2.2) to obtain the low band signal L2 and high band L1. For the low band image L2, we apply the conventional BLF with σd=1.8 and σr=σ as suggested, where σ is the noise variance. As stated above, we concentrate on the filtering scheme for the high band image L1, especially at the edge area. The basic idea is to give larger weights to the pixels that have similar edge intensities. These objectives are concealed in Eq.(2.1.2) as

$$Z(x, y) = \exp\left(-\frac{\|x-y\|^2}{2\sigma_d^2}\right)\exp\left(-\frac{\|I(x)-I(y)\|^2}{2\sigma_r^2}\right)\exp\left(-\frac{\|h(x)-h(y)\|^2}{2\sigma_h^2(x)}\right) \quad (3.1.1)$$

Where σ_h^2 (x) is the pixel dependent bandwidth, and h(x) is the intensity of the pixel p in the histogram-equalized image of L1. Comparing this kernel with that of the original BLF in Eq. (2.1.2), the third term is our proposal which adaptively controls the weights near the edge areas. The adaptive bandwidth for the BLF has already been considered in [5], where the σris adjusted along with an offset parameter by the optimization method with some training images. Unlike this previous adaptive BLF, our method is quite a simple algorithm which adjusts σhin the new kernel depending on whether the pixel is on the edge or not.

The bandwidth in the new term is to be pixel dependent, i.e., the pixel difference in the high band ($\|h(x) - h(y)\|$) is considered in weight control. Precisely, our method adjusts σh(p) to 2√2σ or 4√2σ depending on the edge strength of given image. For these edge-dependent modifications, we extract edge information from the bilateral filter of low band image L2, which is denoted as $\widehat{L_2}$. For determining whether a pixel is an edge pixel or not, we apply the Laplacian of Gaussian filter and then thresholding. Specifically, we convolve $\widehat{L_2}$ with the kernel defined as

$$\mathrm{LoG}\ (p\ ,q)=-\frac{1}{\pi\sigma^4}\left(1-\frac{p^2+q^2}{2\sigma^2}\right)\exp\left(-\frac{p^2+q^2}{2\sigma^2}\right) \quad (3.1.2)$$

then the output pixels larger than 75 % of the mean value are considered the edge pixels. This gives an edge map E(x) which is 1 when the pixel x belongs to edge pixels, and 0 if not. For simplicity, the edge map is obtained from the approximate intensity component and this edge map is applied to all of colour components equally. With this edge map, the kernel bandwidth is determined as

$$\sigma_h(x) = \begin{cases} 2\sqrt{2}\sigma if E(x) = 1 \\ 4\sqrt{2}\sigma otherwise \end{cases} \quad (3.1.3)$$

It can be seen that the kernel bandwidth is small when the pixel is on the edge, so that the neighbouring pixels less contribute to the averaging and thus the edge intensities are less changed. Conversely, the pixels in the flat areas are more strongly filtered than the edge pixels. It is worth to mention that we use ($\|h(x) - h(y)\|$) instead of ($\|L_1(x) - L_2(y)\|$), because $L_1(x)$ can have negative value and its dynamic range is large. Denoting the output of proposed BLF of L1as$\widehat{L_1}$, the final denoised image is obtained as$\widehat{L_1}$+ $\widehat{L_2}$.

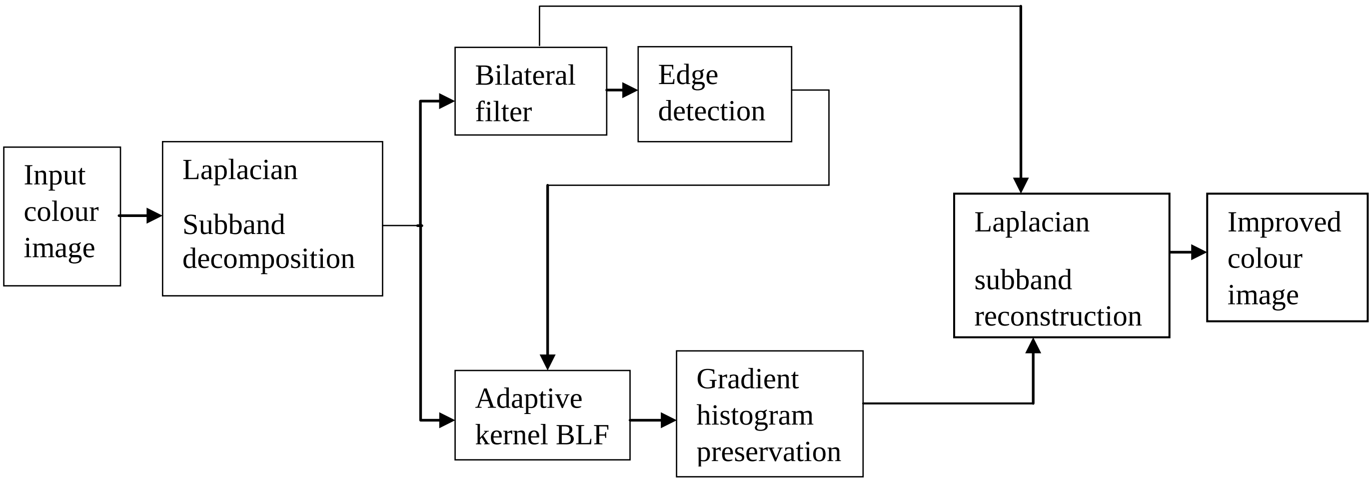

Figure 1: Block diagram of Adaptive Kernel Bilateral Filter

Throughout the experiments, it is found that the lowband (L2) filtering with a variety of parameter changes does not much affect the overall performance. Hence, we apply just the original BLF with σr= σ for the low-band filtering, and we have focused on the kerneldesign for the high-frequency subbandL1.The overall process is illustrated in Fig.1.The proposed adaptive kernel with laplaciansubbandsis explained above, and the edge enhanced results areexplained in the next section.

3.2 Histogram with Edge preservation

The edge enhancement can also be easily achieved by manipulating the denoised high band signal in the Laplaciansubbands. Since the edge components in the high band have been smoothed in the filtering process. Hence, we try to restore the edge strength of the high band image as strong as the original one, and then add these restored edges.For this, we consider the idea of gradient histogram preservation (GHP) in [12], which is to impose a constraint that the processed image has the same gradient histogram as the estimated original one. Specifically, for the noisy image model.

$$y = x + v \qquad (3.2.1)$$

Where x is the original image, v is the noise, and y is the observed noisy image, the processed image is constrained to have similargradient histogram as x.Note that the high band image L1 in our subband bilateral filter scheme is also a kind of gradient image, where the above gradient histogram preservationapproach can be applied. Applying the Laplaciansubband decomposition to Eq. (3.2.1), we have the high band relationship as

$$L1(y)=L1(x)+ L1(v) \qquad (3.2.2)$$

Where L1(·) is the operator that extracts high band signal of the input image, and hence L1(y) = L1 in our problem. Like the GHP approach, we wish to find the histogram of L1(x) so that we match the histogram of L^1 to this one. The edge enhanced image is obtained as

$$\widehat{L_1} = \lambda . \widehat{L_{1,f}} + (1-\lambda). \widehat{L_{1,}}edge \qquad (3.2.3)$$

4. ESTIMATION OF PARAMETERS

In bilateral filter the image de-noising occurs only for low band signal. For high bandsignal it cannot give noise reduced output image and moreover the run time also high when compared with other schemes. In linear minimum mean square error estimation noise reduction of image depends on wavelet transform. The process of wavelet transform in which the average weights of adjacent pixel values are estimated known as context modelling. Thus the context value is applied to wavelet transform to reduce noise. In this averaging is done for only near pixels values but not for all the pixel valuesin the image. So, in the image some noise will be present. It isnot suitable method for images that are weekly correlated. For such images the wavelet interscaledependency is typically very low, and the proposed model would be unable to take the advantage of interscale dependencies to yield reasonable gain for denoising. In wavelet LMMSE the time dependency is also more when compared to proposed system.

To overcome the above saiddrawbacks adaptive kernel bilateral filter is proposed. In this method the laplacian sub bands are divided into two bands low band and high band. For low band images bilateral filter is applied to reduce noise and for high band imagesit uses adaptive kernel bilateral filter for noise reduction. But in case of edge pixels after filtering operation the pixels get week. So we can apply histogram edge preserving method to get an effective noise reduced image output. This procedure can be seen from the above figure(1). This filter can be applied to all the images and it gives the best results

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in all the cases. The time requirement is also low and noise reduction is also more we can see the parameter valuesfrom the table (1) in the results.

From the enhance output image, performance of the proposed algorithm is calculated by using PSNR, MSE, MAE and Entropy. PSNR, MAE and MSE and Entropy is calculated [13] by using following equation (4.1),(4.2),(4.3)and (4.4).

Peak Signal to Noise Ratio (PSNR): It is the measure of quality of the image by comparing denoised image with original image. It is an expression used to depict the ratio of maximum possible power of image (signal) and the power of the corrupting noise that affects the quality of its representation.

$$PSNR = 10\log_{10}\left(\frac{MAX_I^2}{MSE}\right) \quad (4.1)$$

Mean Square Error (MSE):It is the cumulative squared error between the final de-noised image and the original image. This enables us to compare mathematically as to which method provides better results.

$$MSE = \frac{1}{mn}\sum_{y=1}^{n}\sum_{x=1}^{m}[I(x,y) - I'(x,y)]^2 \quad (4.2)$$

Mean Absolute Error (MAE):It is the absolute error between the original image and the de-noised image. It represents the average value of introduced deviation per pixel with respect to original image.

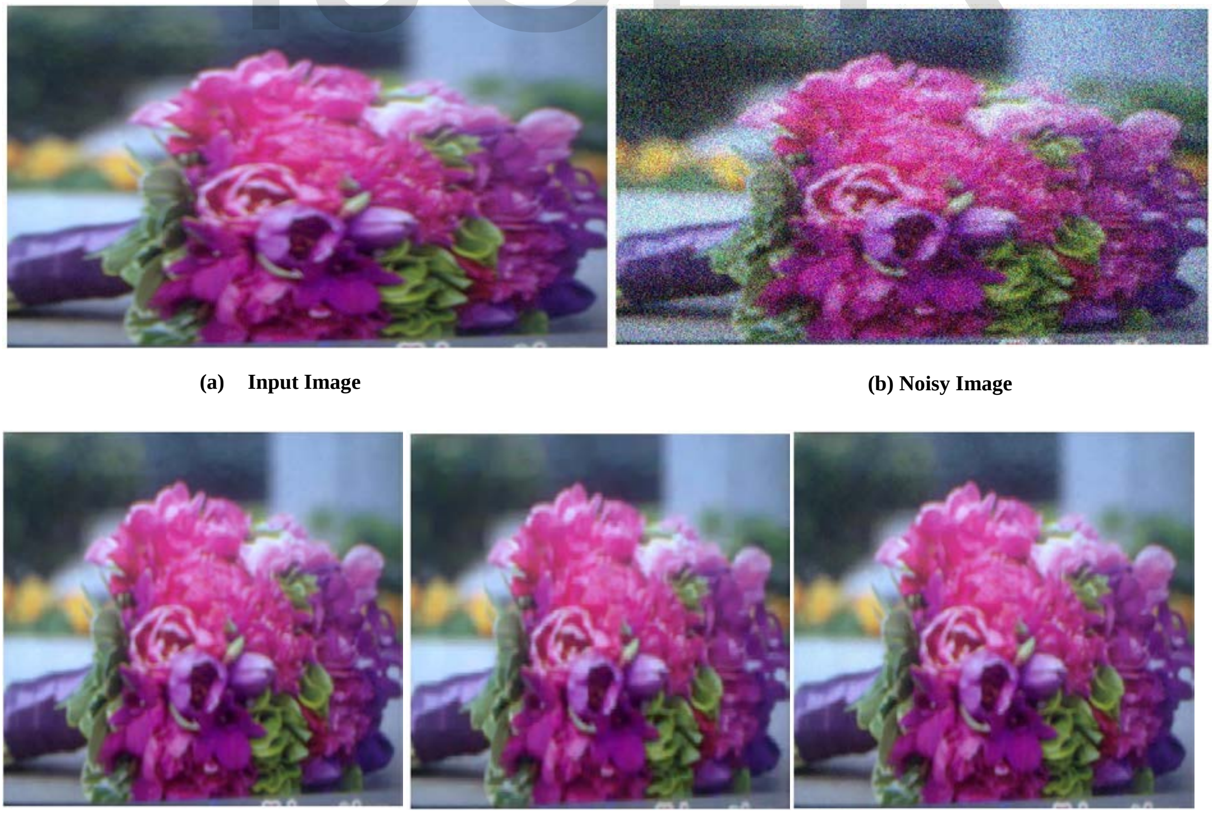
$$MAE = \frac{1}{mn}\sum_{y=1}^{n}\sum_{x=1}^{m}[I(x,y) - I'(x,y)] \quad (4.3)$$

Entropy: Image entropy is a quantity which is used to describe the amount of information which must be coded for by a compression algorithm. It represents the sum of probabilities of differences of adjacent pixels.

$$Entropy = -\sum_i P_{i\log_2 P_i} \quad (4.4)$$

5. RESULTS

In order to evaluate the performance of propose method, bouquet image in fig.2 is used. Bouquet image is corrupted by the Additive White Gaussian Noise.Comparison for the output imagesobtained from adaptive kernel bilateral filter method, the conventional bilateral filter and wavelet based linear minimum mean square error are depicted in fig.2. The figure below portrays (a) the original image, (b) the noise image, (c) the result of sequentially appliedbilateral filter, (d) wavelet based linear minimum mean square error denoised image and (e) is the proposed method imagesrespectively.



(a) Input Image (b) Noisy Image

(c) BLF (d) LMMSE (e) AKBLF

Figure 2: Enhancement of Noisy Image for Bouquet using BLF, LMMSE and AKBLF

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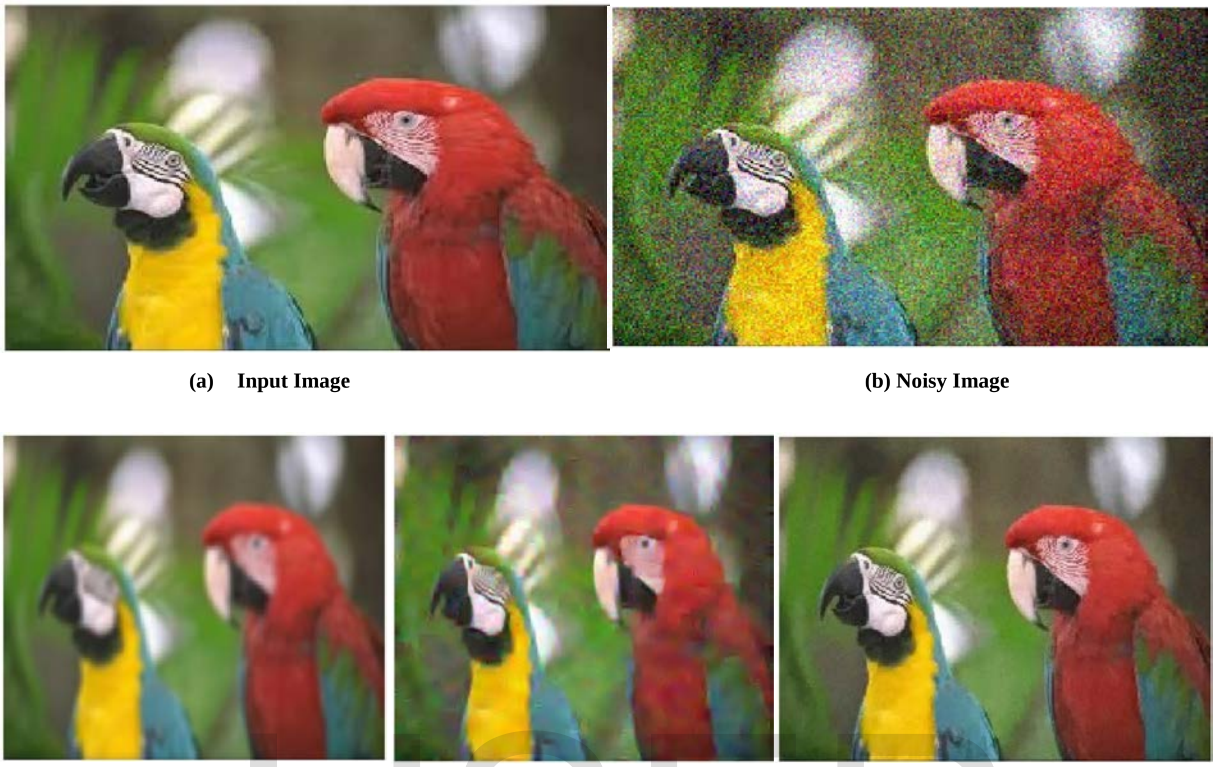
In figure 2 it can be observed that proposed method gives the best denoisied image than the bilateral filter and linear minimum mean square error. The visualquality is alsobetter than other methods.

TABLE 1: PARAMETER ESTIMATION FOR DIFFERENT NOISE

		NOISE DENSITY				
	PARAMETERS	10	20	30	40	50
BLF	MSE	0.102	0.107	0.027	0.026	0.030
	PSNR	92.09	91.59	89.63	85.45	80.63
	MAE	0.82	1.50	2.083	3.022	3.083
	ENTROPY	1.5	2.734	2.97	3.01	3.22
WAVELET BASED LMMSE	MSE	28.85	49.55	70.89	94.37	12.22
	PSNR	33.52	31.17	29.62	28.38	37.25
	MAE	0.047	0.114	0.023	0.070	0.014
	ENTROPY	0.042	1.05	1.39	2.63	3.71
AKBLF	MSE	6.799	9.166	12.75	18.30	4.787
	PSNR	39.80	38.50	37.07	35.50	41.32
	MAE	0.062	0.130	0.200	0.219	0.0194
	ENTROPY	1.39	2.55	3.85	4.01	5.03

Table1 shows the parameter estimation for different noise densities. In this table it can be observed that proposed adaptive kernel bilateral filter shows better performance than LMMSE and BLF. In bilateral filter the filtering occurs only for low band signals whereas, in the proposed method filtering is possible for both low and high band signals. Hence there is increase in PSNR value while the error values of MSE, MAE are low. The performance of entropy is also seemed to be better than Bilateral filter and linear minimum mean square error.

Figure3 is a sample image of restored images, which shows that the proposed method AKBLF provides better visual quality results than the BLF and LMMSE. The proposed method takes less computation time than the other methods. We present the results of the proposed method with overall process shown in fig.1 It first shows the decomposition of the laplacian subbands as low and high bands respectively. Then the applied filter i.e., adaptive kernel with bilateral filter denoised the images and enhanced the edges. Results of denoised images through BLF, LMMSE and AKBLF are finally portrayed.



(a) Input Image (b) Noisy Image

(c) BLF (d) LMMSE (e) AKBLF

Figure 3: Enhancement of Noisy Image for parrot using BLF, LMMSE and AKBLF

6. CONCLUSION

In this paper, we presented an adaptive kernel bilateral filter method with histogram edge preserving. The input image is decomposed into two subbands by the Laplacian of Gaussian, and the bilateral filter is applied to each of the subbands with appropriate filtering adaptive kernel bandwidth and parameters. The proposed method increase PSNR and shows batter performance in case of MAE, MSE and Entropy compared to the bilateral filter and wavelet based LMMSE schemes. The proposed method requires less computation time and edge preserving can be effectively performed along with the denoising.

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