2017 International Conference on circuits Power and Computing Technologies [ICCPCT]

Image Denoising Based on Weighted Regularized Least Square Method

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***Abstract*—Noise in an image is caused due to various reasons. Removal of noise in an efficient way is a big challenge for researchers. In this paper, one dimensional signal denoising based on weighted regularized least square method is mapped to two dimensional image denoising. The proposed technique of image denoising based on least square is experimented on standard images sub-jected to different noises with varying noise levels. The effectiveness of the proposed method of image denoising is compared against the recently pro-posed sparse banded filter based image denoising technique. The comparison is done based on standard metric called peak signal to noise ratio(PSNR). The experimental result analysis shows that the proposed technique of least square image denoising outperforms the recently proposed sparse banded fil-ter based image denoising. The advantages of the proposed method are sim-ple computation and fast processing.**

Keywords*— Salt and Pepper noise, Gaussian noise, Speckle noise, PSNR (peak signal to noise ratio), image denoising, least square.

I. Introduction

The digital images are potentially degraded by noise through various sources such as background illuminations, image acquisition and transmission [4]. The image can be affected by many kind of noises, in which the respective noise level may vary from low level to high level. Depending upon the level of noise and the type of noise, the image denoising technique [9] can be applied. Image denoising is the process of improving the quality of the image by removing the noise content. The domains which require efficient noise removal are medical diagnosis [1], image segmentation, pattern recognition, image restoration, object recognition and video analysis [2].

A. Significance of Image Denoising

The fundamental aspect of image processing is image denoising. Traditionally, noise removal from an image data involves spatial filters. These spatial filters are classified into linear and non-linear filters. Spatial filter helps in noise re-moval at the cost of blurring the image [6]. Many researchers proposed various theories like wavelets which results in superior performance due to the proper-ties such as sparsity and multi-resolution structure. The popularity of the wavelet transform [8] led to formulating various algorithm for the past decades. Achieving such a leap, wavelet domain replaced the Spatial and Fourier domain. Several algorithms are proposed by wide area of research for image denoising. The challenges for researchers in image denoising introduces artifacts and causes image blurring [3]. The achievement of optimum value of threshold is done by data adaptive thresholds [5]. This paper describes the in-sights of least square weighted regularization algorithm used to find the reliable original image data given its degraded version of the original image. The advantage of the proposed method over other methods is its simplicity and fast processing.

II. Mathematical Background

In this section, we discuss the least square weighted regularization algorithm for signal denoising. The one dimensional signal denoising using least square approach was proposed by Ivan.W. Selesnick [7]. In our proposed work, the approach for one dimensional signal denoising is mapped to two dimensional image denoising. The problem formulation is given by

$$min_x \|y - x\|_2^2 + \|\mathbf{D}x\|_2^2 \tag{1}$$

where D is the second order difference matrix given by

$$D = \begin{bmatrix} 1 & -2 & 1 & & & \\ & 1 & -2 & 1 & & \\ & & \ddots & & \ddots & \\ & & & 1 & -2 & 1 \end{bmatrix}$$

The basic idea formulated in eqn. (1) is to generate a signal similar to the information present in the noisy signal, except the noise. This corresponds to the first term in eqn. (1). The second term in the eqn. (1) $\|\mathbf{D}x\|_2^2$ represents the L2-norm squared of second order derivative of output denoised signal. The L2-norm squared energy of the derivative captures the degree of smoothness which in turn reduces the level of noise present in the signal. The minimization of first term in objective function in eqn. (1) forces the output y to be similar to input signal. The minimization of the second term in eqn. (1) leads to smoothing of the noisy input signal which results

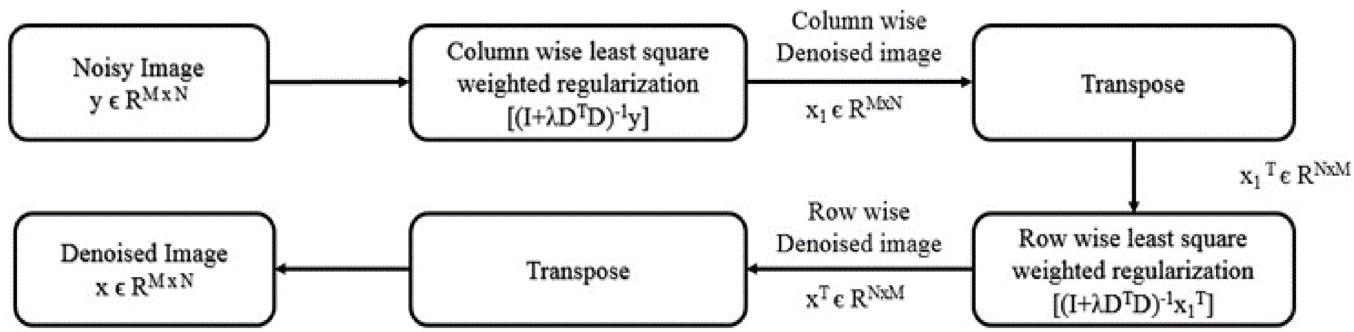

Fig. 1. Block diagram of proposed method for denoising

in denoised output signal. Let's consider y as the input noisy signal and x is the desired denoised signal. $\lambda > 0$ is the control parameter for the least square weighted regularization algorithm. The minimization of the sum in eqn. (1) results in achieving x to be smooth and similar to y. This achievement of the x to be smooth and similar to y is traded with the λ value. The least square formulation for the signal denoising is given by,

$$x = (\mathbf{I} + \lambda \mathbf{D}^T\mathbf{D})^{-1}y \quad (2)$$

The observations to be made in this least square weighted regularization algorithm is, (λ=0) results in the solution to be a noisy data (i.e. x=y). The proposed least square weighted regularization algorithm will fail to achieve the smoothness. If the smoothness is not achieved, it tends to result in failure of denoising of the signal.

III. Methodology

In the proposed method, the least square weighted regularization is applied for two dimensional image denoising. The block diagram of the proposed method-ology for image denoising is shown in Fig.1

1. Let us consider an input noisy image $y \in R^{M\times N}$, which is to be denoised.
2. The noisy image $y \in R^{M\times N}$, is passed as an input to the eq. (2) for applying column wise least square weighted regularization.
3. The image obtained from the above mentioned process is the column wise denoised image $x_1 \in R^{M\times N}$.
4.The column wise denoised image $x_1 \in R^{M\times N}$ is transposed to obtain $x_1{}^T \in R^{N\times M}$
5.Row wise least square regularization is applied on $x_1{}^T \in R^{N\times M}$ to obtain row wise denoised image $x^T \in R^{N\times M}$.
6.The row wise denoised image is transposed to obtain denoised output image $x \in R^{M\times N}$.

IV. Experimental Results and Analysis

In our proposed method, the least square weighted regularization method is used for image denoising. The experiment is performed on various standard images namely Cameraman, House, Lena, Peppers, Pirate. The different noise types used are Gaussian, Salt and Pepper and Speckle with various noise levels. Gaussian noise is added to image with constant zero mean and different variance values such as 0.01, 0.025, 0.05, 0.075, 0.1. Salt and Pepper noise is added to image with different mean values such as 0.05, 0.075, 0.1, 0.25, 0.5. Speckle noise is added to image with different mean values such as 0.04, 0.075, 0.1, 0.25, 0.5.

The experiment is performed for various image sizes such as 256×256, 512×512 and 1024×1024. The results obtained for all the image sizes are similar. The denoised output images obtained by our proposed technique for various standard images of size 1024×1024, with maximum noise level for Gaussian, Salt and Pepper, Speckle noise set as 0.1, 0.5, 0.5 respectively is shown in Fig.2-Fig.6.

The visual effect of the proposed method for image denoising is aided by the quality metric measurement. The Peak-Signal-to-Noise Ratio (PSNR) computed for Gaussian, Salt and Pepper, Speckle noise with maximum noise level of 0.1, 0.5 and 0.5 respectively on standard images are tabulated in Table. I. The λ for which the PSNR is maximum is tabulated in Table. I. Fig.7-Fig.9 shows the relationship between λ and PSNR computed for Gaussian, Salt and Pepper, Speckle noise with maximum noise level of 0.1, 0.5 and 0.5 respectively. While comparing the PSNR of noisy image with PSNR of denoised image, it is evident that the proposed denoising technique reduces various types of noise. The PSNR improvement for various standard images is around 12.5db for Gaussian noise and 10dB for Salt and Pepper noise and 12db for Speckle noise. Table. II shows the comparison of PSNR values obtained from sparse band matrix filter technique [2] and least square weighted regularization technique. It is evident that the least square weighted regularization technique proposed in this paper produces higher PSNR values than the sparse band matrix filter technique.

Table 1. Peak Signal to Noise Ratio (PSNR) of denoised image (DI PSNR) and noisy image (NI PSNR) for various noises on standard test images

Image	Noise Type	Noise Level	λ	DI PSNR(dB)	NI PSNR(dB)
Cameraman	Gaussian	0.1	20	**23.01**	11.51
	Salt & pepper	0.5	35	**17.36**	8.10
	Speckle	0.5	20	**22.88**	10.14
House	Gaussian	0.1	35	**24.74**	11.54
	Salt & pepper	0.5	50	**18.07**	8.21
	Speckle	0.5	50	**19.58**	9.77
Lena	Gaussian	0.1	20	**24.71**	11.35
	Salt & pepper	0.5	35	**19.24**	8.46
	Speckle	0.5	35	**22.29**	10.07
Peppers	Gaussian	0.1	20	**23.98**	11.44
	Salt & pepper	0.5	50	**18.35**	8.31
	Speckle	0.5	35	**22.57**	10.42
Pirate	Gaussian	0.1	20	**24.32**	11.38
	Salt & pepper	0.5	50	**18.89**	8.41
	Speckle	0.5	20	**23.52**	10.64

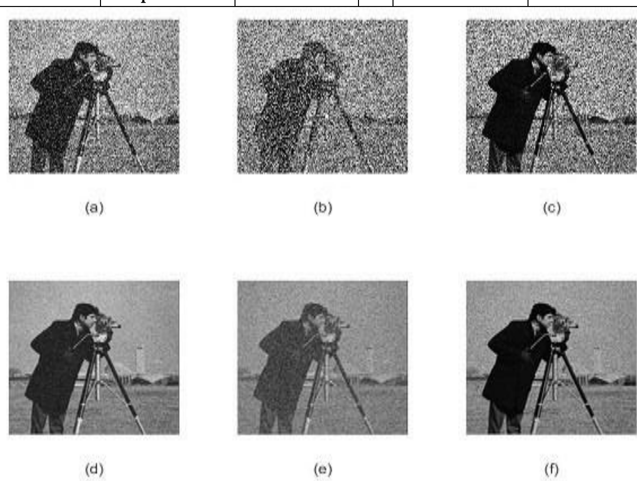

Fig. 2. (a) Input image with Gaussian noise (b) Input image with Salt and Pepper noise (c) Input image with Speckle noise. (d), (e), (f) Output denoised images

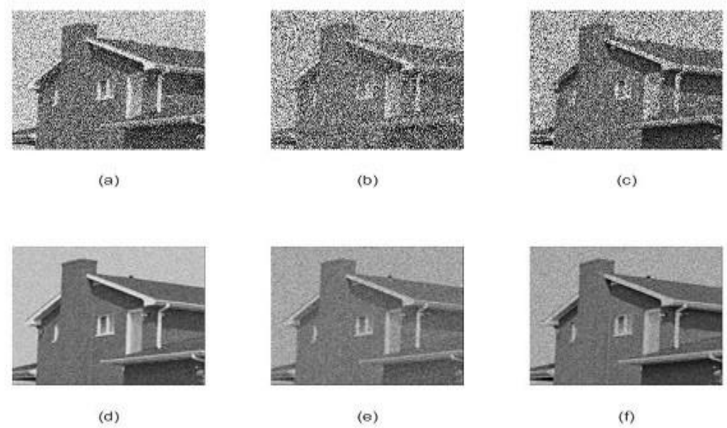

Fig. 3. (a) Input image with Gaussian noise (b) Input image with Salt and Pepper noise (c) Input image with Speckle noise. (d), (e), (f) Output denoised images

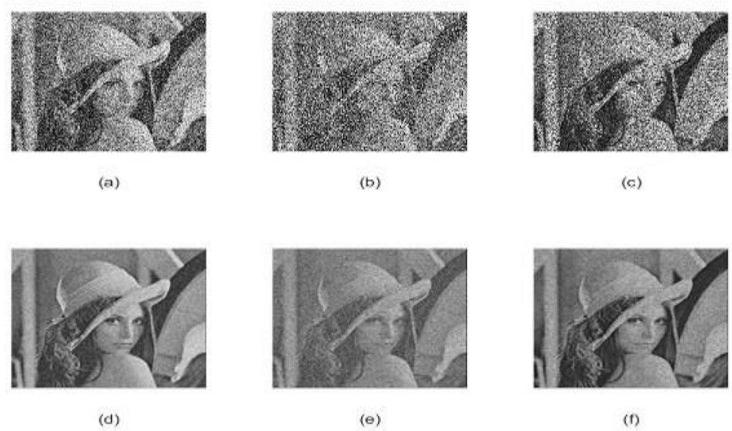

Fig. 4. (a) Input image with Gaussian noise (b) Input image with Salt and Pepper noise (c) Input image with Speckle noise. (d), (e), (f) Output denoised images

Table 2. Comparision of PSNR values obtained from (a) sparse band matrix filter techinque [2] and (b) least square weighted regularization technique.

Noise type	Cameraman		House		Lena		Peppers	
	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)
Gaussian	19.09	23.01	19.43	24.74	19.02	24.71	19.24	23.98
Salt & Pepper	25.17	26.69	23.84	27.53	24.57	27.14	24.09	26.65
Speckle	20.9	28.39	23.89	27.59	22.72	27.99	23.16	28.04

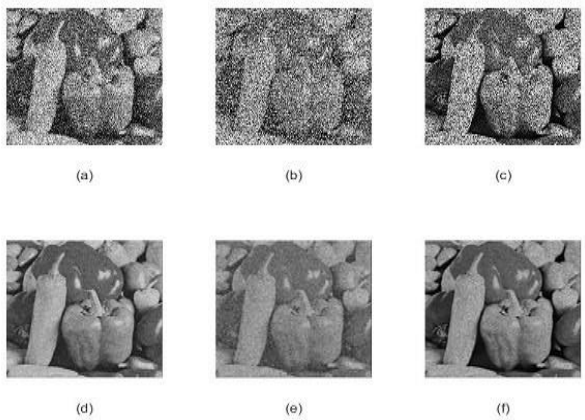

Fig. 5. (a) Input image with Gaussian noise (b) Input image with Salt and Pepper noise (c) Input image with Speckle noise. (d), (e), (f) Output denoised images

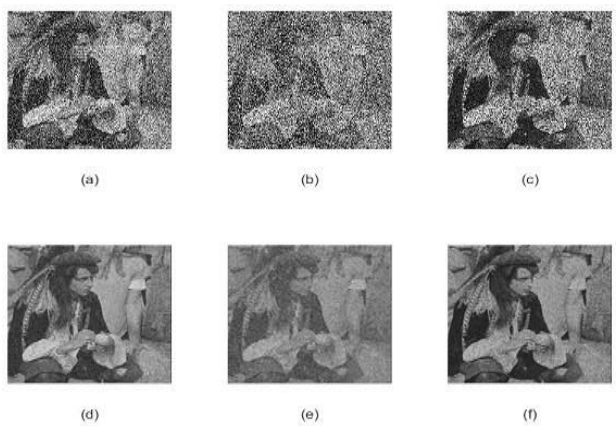

Fig. 6. (a) Input image with Gaussian noise (b) Input image with Salt and Pepper noise (c) Input image with Speckle noise. (d), (e), (f) Output denoised images

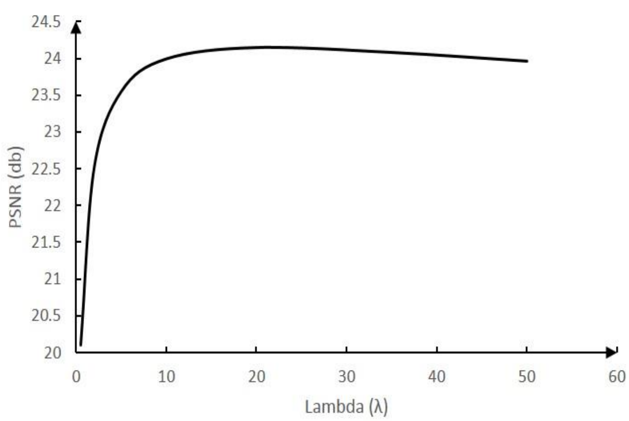

Fig. 7. Relation between Lambda and PSNR when Gaussian noise is set as 0.1

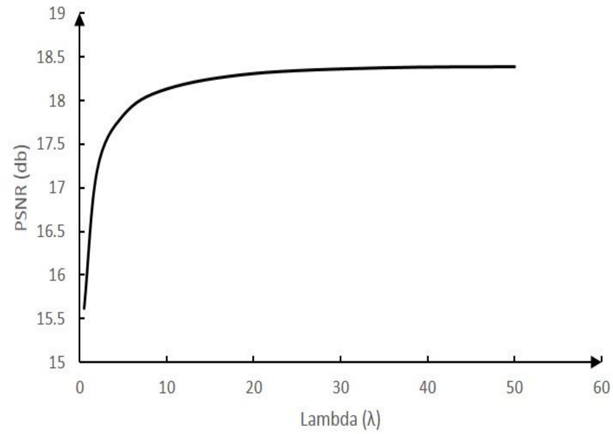

Fig. 8. Relation between Lambda and PSNR when Salt and Pepper noise is set as 0.5

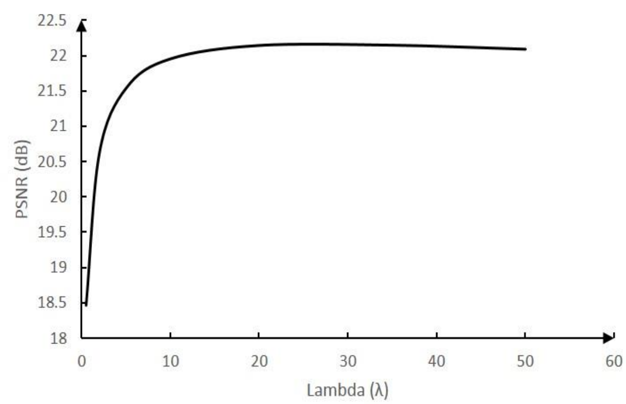

Fig. 9. Relation between Lambda and PSNR when Speckle noise is set as 0.5

V. CONCLUSION

Image denoising based on weighted regularized least square method is proposed in this paper. The least square weighted regularization is applied column-wise and row-wise to denoise the image. The proposed technique is experimented on standard test images subjected to different noises with different noise levels. The effectiveness of denoising by our proposed technique is proved by the significant improvement in image quality metric PSNR, which is aided by the visual analysis.

VI. References

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