Efficient Wavelet Decomposition Based Hybrid Image Denoising

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Abstract - Image denoising is the fascinating research area among researchers due to applications of the images in everywhere, social networking sites, High Definition videos and stills. The need of it is to enhance the facility to imaging devices and the processing devices for denoising and enhancement of images. In this work, multi level reverse bi-orthogonal (RB) wavelet filter followed by hard thresholding are used to allow for possible accurate restoration near such boundaries. The proposed novel formulation of parametric threshold on noise levels from σ = 0.2 to analyze performance of denoising of images. The experimental outcomes of proposed methodology are usually compared in terms of peak-signal-to-noise ratio (PSNR) and structural similarity index(SSIM). These are image processing figure of merits that take care of noise power level in the whole image as well as shows the efficiency of the denoising algorithm.

Keywords - Wavelet, Decomposition, Hard Thresholding, PSNR, SSIM.

I. INTRODUCTION

One of the most common types of pollution on images is the noise. Noise arises during the acquisition of the image and depends on the quality of the components used in the acquisition device, on the type of signal detected, the exposure time, the detector sensitivity, and many other factors.

Noise is a random variation of brightness information in images. Usually noise is produced by the sensor or circuitry of imaging devices, i.e., scanner or digital camera. There are many variants of image noise. A brief introduction of some noise variants is given below.

- Additive White Gaussian Noise

Additive noise refers to the noise signal which is independently added to the image signal. If y(x) is a original signal where $x \in X$ is a 2D spatial coordinate that belongs to the image domain and η(x) is the noise signal.

- Salt and Pepper Noise

Salt and pepper noise refers to a wide variety of processes that result in the same basic image degradation: only a few pixels are noisy, but they are very noisy. The effect is similar to sprinkling white and black dots—salt and pepper—on the image. One example where salt and pepper noise arises is in transmitting images over noisy digital links.

- Speckle Noise

Speckle noise is a granular noise that inherently exists in and degrades the quality of images. Speckle noise is a multiplicative noise, i.e. it is in direct proportion to the local grey level in any area. The signal and the noise are statistically independent of each other.

- Poisson Noise

Fundamentally, most image acquisition devices are photon counters. Let 'a' denote the number of photons counted at some location (a pixel) in an image. Then, the distribution is usually modeled as Poisson with parameter λ. This noise is also called Photon noise or Poisson counting noise.

II. SYSTEM MODEL

The wavelet concepts for one dimensional signals can trivially be extended to two dimensional images. Instead of creating wavelet and scaling functions of two variables one can treat a picture row-by-row and column-by-column. This gives a very cost effective and simple method to expand wavelet theory into several dimensions.

A wavelet decomposition of a digital image is performed by first going through an image row- by-row and decomposing each row like it was a standard one dimensional signal. After having gone through all the lines a new image can be build where the left side represents the low frequency part of each row while the right side shows the high frequency parts of each row. The same steps can next be repeated column-by-column which at the end gives an image which is arranged of four quadrants.

The square on upper-left only consists of low frequencies while the lower-right square only shows the very high frequency details. The other two subbands display a mixture of low and high frequency data. The decomposition can be iterated where one for example further divides the low frequency part into four new quadrats.

in figure 2.1 $L: f(x, y)$ and $R: w(x, y)$ are the decomposition of a two dimensional image .

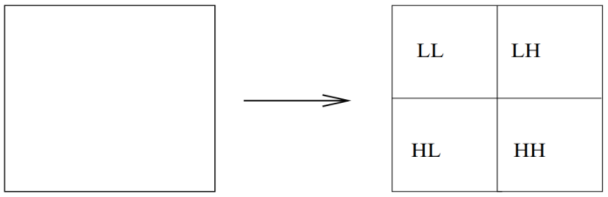

Fig. 2.1 Image decomposition

Over the years wavelets have become very popular for image compression as well as image denoising. After a wavelet decomposition most of the energy of a picture is found in the low-low frequency zone while the other parts only contain some limited amount of it, as most images do not contain a lot of high frequency details. In case of lossy compression the high frequency parts can be quantized heavily before being entropy coded. Unlike standard JPEG compression where an image is treated and quantized in blocks, a wavelet decomposition smears out any negative effects over the whole image giving improved outcomes at the same compression rates. Wavelet decom position also has other advantages due to the very nature of basis functions which generally give good decorrelation of data.

III. PROPOSED METHODOLOGY

The proposed image denoising approach is carried out using the efficient multi-stage multi-level hybrid filtered image denoising. The Implementation and simulation of proposed work has done on Matlab. Figure 3.1 represents block diagram of proposed work there are three separate blocks of there are noise standard deviation, multilevel reverse bi-orthogonal filtering, Adjustive normal filtering. The flow chart of proposed work has been given in figure.3.2

Orthogonal filters prompt orthogonal wavelet premise capacities; thus, the subsequent wavelet transform is energy saving. This reduce the mean square error (MSE) presented at the time of the quantization of the DWT coefficients is equivalent to the MSE in the reproduced signal. This is desirable since it implies that the quantizer can be designed in the trans- form domain to take advantage of the wavelet decomposition structure. For orthogonal filter banks, the synthesis filters are transposes of analysis filters. Be that as it may, on account of biorthogonal wavelets, the premise functions are not orthogonal and subsequently not energy efficient.

Biorthogonal filters characterize a superset of orthogonal wavelet filters and have discovered their utilization in for all intents and purposes all domains where wavelets are used. There are, however, certain parts of the biorthogonal wavelet transform which can be interesting to investigate. Since biorthogonal wavelet transforms obviously are not orthogonal, it should be possible to explore the aliasing and energy shifts which occur do to the non- orthogonality of the filters.

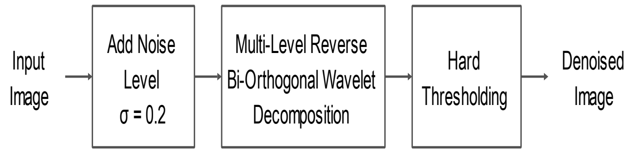

Fig. 3.1 Block Diagram of Proposed Denoising Algorithm.

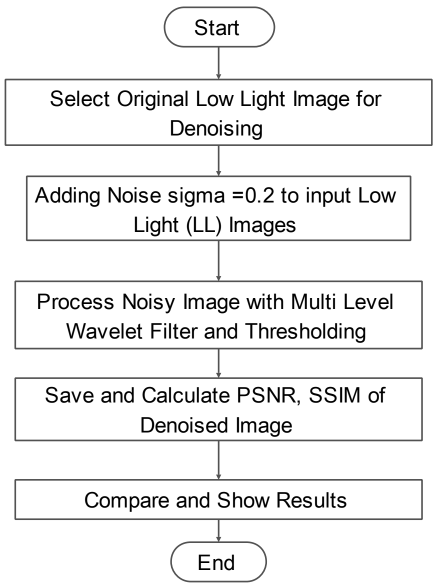

Fig. 3.2 Flow Chart of Proposed Denoising Algorithm.

Process Flow :

Compare with previous and show results.

Formula Used - MSE, PSNR, SSIM:

Mean Square Error (MSE)

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i,j) - K(i,j)]^2$$

Peak Signal to Noise Ratio (PSNR)

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

Structural SIMilarity (SSIM) index is a method for measuring the similarity between two images. The SSIM index can be viewed as a quality measure of one of the images being compared, provided the other image is regarded as of perfect quality.

$$S(x, y) = f(l(x, y)^{\alpha}, c(x, y)^{\beta}, s(x, y)^{\gamma})$$

IV. EXPERIMENTAL OUTCOMES

The implementation and simulation of proposed work has done on MATLAB. Proposed image denoising algorithm has been tested on a standard image set with noise standard deviation σ for additive white gaussian noise. The proposed strategy has been contrasted and the current image denosing algorithm and its variations. The correlation and examination of results has done based on the PSNR and the SSIM measures.

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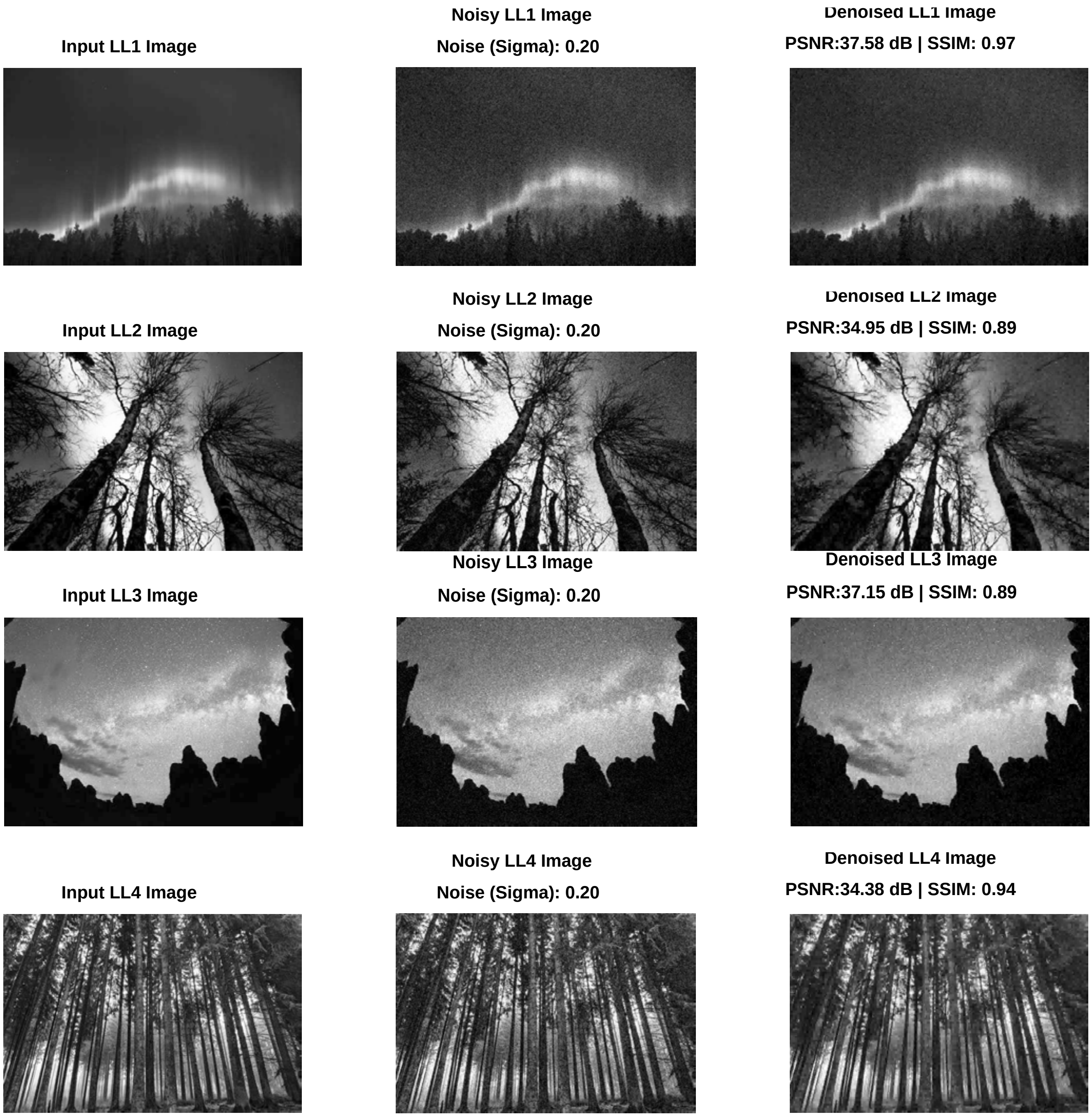
To assess the execution of proposed denoising approach Peak Signal to Noise Ratio (PSNR) and the Structural Similarity (SSIM) measure has been utilized. These are broadly utilized target measures for assessing the execution of image denoising algorithms. Fig. 4.1 shows the Simulation outcomes of PSNR and SSIM for different low light images (a) Original Image (b) Noisy Image and (c) Denoised Image on noise levels σ = 0.2 for *LL1, LL2, LL3* and *LL4 images* respectively.



(a) (b) (c)

Fig. 4.1 Simulation outcomes of PSNR and SSIM for (a) Original Image (b) Noisy Image and (c) Denoised Image on noise level σ = 0.2 for different low light images *LL1, LL2, LL3* and *LL4*

The peak signal to noise proportion (PSNR) refers to the ratio between the greatest power of a signal to the noise which debases the first image. This measure is based on the Mean Squared Error (MSE) which evaluates the contrast between the first image information and the corrupted image information.

The basic similarity index is utilized to discover similitude between two images. Comparable pixels have solid between functions when they are nearer. The accompanying equation measures SSIM.

Table 1 has given performance analysis of proposed work based on PSNR and SSIM. Fig. 4.2 shows the comparison of PSNR for All Images on Noise Level σ = 0.2. Fig. 4.3 shows the comparison of SSIM for All Images on Noise Level σ = 0.2.

Table 1: Performance Comparison of PSNR and SSIM for Noise Level σ = 0.2 for Different Low Light Images

Images	***Peak Signal to Noise Ratio (PSNR) in dB***		***Structural Similarity Index (SSIM)***	
	Previous Wavelet+TV	***Proposed (Wavelet Decomposition + Thresholding)***	***Previous Wavelet + TV***	***Proposed (Wavelet Decomposition + Thresholding)***
LL1	32.72	*37.58*	0.78	*0.97*
LL2	26.81	*34.95*	0.70	*0.89*
LL3	31.27	*37.15*	0.81	*0.89*
LL4	27.03	*34.38*	0.71	*0.94*

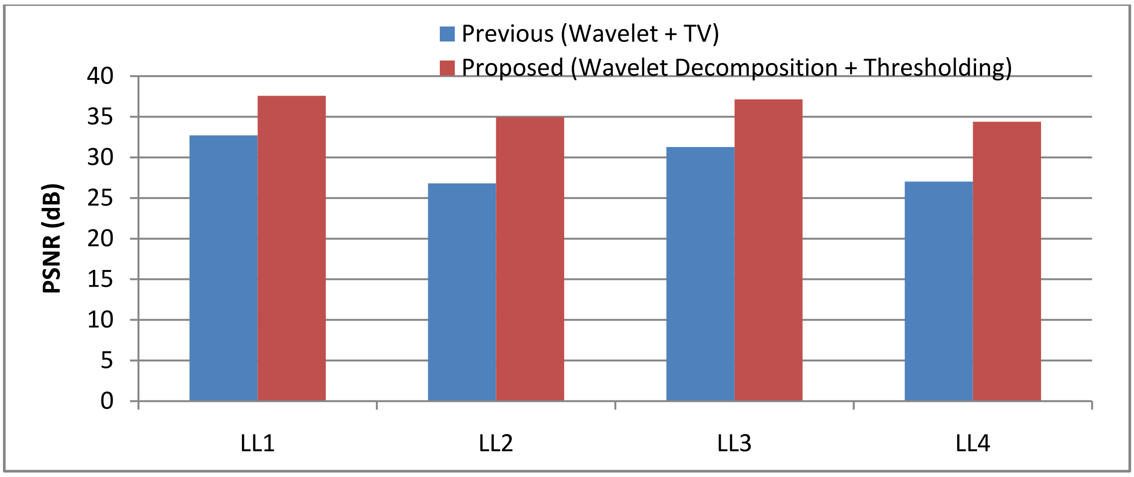


Fig. 4.2 Comparison of PSNR for *LL1*, *LL2*, *LL3* and *LL4* Images on Noise Level σ = 0.2

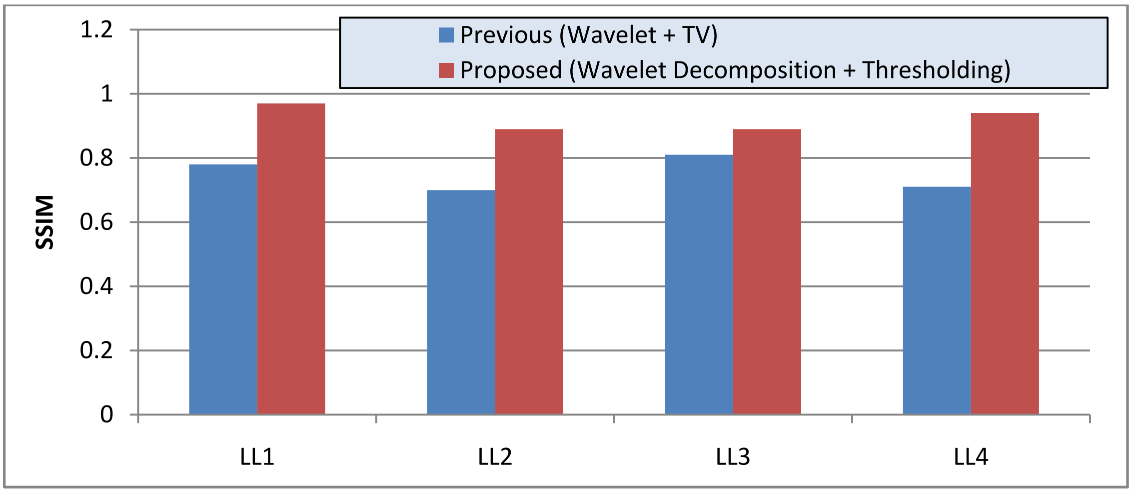


Fig. 4.3 Comparison of SSIM for *LL1*, *LL2*, *LL3* and *LL4* Images on Noise Level σ = 0.2

V. CONCLUSION AND FUTURE SCOPES

The key of this enhancement is to reduce the noise, which diminishes the patch similarity measurement time and expands the general denoising execution. The optimized parameters are used in our proposed method to improve the performance of the denoising scheme. Proposed image denoising approach shown in this work proves the efficiency of algorithm for various images and also for various noise densities of Noise Level. The Effectiveness of the proposed approach is contrasted and the current work as far as Peak Signal to Noise Ratio (PSNR) and Structural Similarity Index (SSIM). Experimental results are compared and shown in previous section in different visual aspects. The reverse bi orthogonal approach can be improved by integrating with or replacing with multiple structures of wavelet decomposition filters and levels to achieve optimum outcomes along with that adaptive filter can be modified with the integration of other filters for future perspectives. The following algorithms can be extended for colour image denoising or video denoising applications which can also be considered as a future work.

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