INTERNATIONAL JOURNAL OF SCIENTIFIC PROGRESS AND RESEARCH (IJSPR) ISSN: 2349-4689
Issue 109, Volume 38, Number 02, 2017

Hybrid Decomposition using Wavelets for Fast and Efficient Denoising of Images

Deepak Bharti[1], Prof. Akhilesh Bansiya[2], Prof. Raj Kumar Paul[3]

[1]Mtech Scholar, [2]Guide, [3]HOD

Department of Computer Science and Engineering, VIT, RKDF University, Bhopal

Abstract – Image denoising is the most essential step in any higher level image processing operations like image segmentation or object tracking, due to occurrence of undesirable noise is inherent to any physical image retrieval device. It is a fundamental process in image processing, pattern recognition, and computer vision fields. The main objective of image denoising is to enhance or restore a noisy image and help the other system (or human) to understand it better. To improve the performance of image processing in this work we proposed a an efficient image denoising approach based on hybrid decomposition utilizing wavelet to achieve fast and efficient denoising of images. on the basis of simulation result we have measured performance parameters such as efficiency and capability of wavelet transforms as a promising mathematical image processing tool in terms of image denoising.

Keywords: PSNR, Wavelet Decomposition, Symlet Filter, Thresholding and Gaussian noise.

I. INTRODUCTION

Images obtained from the real world are always mixed with noise. The noise brought in is derived from multiple sources. The imperfect instrument itself would produce a certain amount of noise when the image is taken. When transforming the optical signal into a digital signal, the pixel's value at specific location is dependent to the number of photons the corresponding captor has received. So the instability of the number of receiving photons can cause the production of noise. Moreover, during image's amplification and transmission, additional perturbations can be introduced by electronic devices and transmission lines.

There are several different types of noise in digital images. For instance, shot noise is generated by the random way photons are emitted from a light source especially when the light intensity is limited and it is usually characterized by Poisson distribution. Thermal noise, also known as dark current noise, is produced by thermal agitation of electrons at sensing sites and highly dependent on the sensor's temperature and the exposure time. Images with impulsive noise, which is generally caused by the malfunctioning of elements in the camera sensors or timing errors in the data transmission process, have bright pixels in dark areas and dark pixels in bright areas. And quantization noise often happens due to the errors when an analog signal is converted to a number of discrete digital values.

Among various transform domain denoising approaches, wavelet transform is increasingly considered as a powerful tool for its outstanding denoising performance.

A wavelet is a brief wave-form oscillation with amplitude that begins at zero, increases and decreases back to zero. It has small area, limited length and the average is zero. Wavelets can analyze a signal in detail based on different scales. To apply a wavelet transform, a particular wavelet, as known as mother wavelet, is chosen first. Then it is translated and diluted to meet a given scale and locate the specific position, while investigating its correlations with the analyzed signal. From alternated point of view, the wavelet analysis is a two channel digital filter bank consisting of a lowpass and a highpass filter. The lowpass filtering yields an approximation of a signal at a given scale, whereas the highpass filtering yields the details that constitute the differ-ence between the two successive approximations. The following figure 1.1 illustrates the wavelet decomposition of one scale.

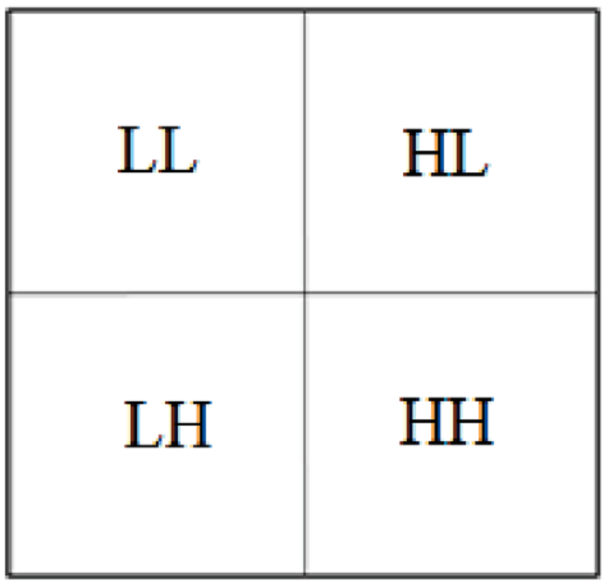

Figure 1.1 wavelet decomposition one scale.

The directions response the order in which the highpass (H) and lowpass (L) filters are applied along the orientations of the input image. For instance, Label LH refers to the subband in which the coefficients are the output of the lowpass filter in the horizontal direction and the highpass filter in the vertical direction. The subbands LH, HL, HH are details, which represents vertical, horizontal and diagonal details and structures, respectively. LL is the low resolution residual and can be further split at coarser scales.

II. Wavelet Transforms and Denoising

Wavelets are mathematical functions that analyze data according to scale or resolution [19]. They aid in studying a signal in different windows or at different resolutions. For example, if the signal is viewed in a large window, gross features could be noticed, but if viewed in a small window, only small features could be noticed. Wavelets provide some advantages over Fourier transforms. As they do a good job in approximating signals with sharp spikes or signals having discontinuities. The Wavelets could also for speech, music, video and non-stationary stochastic signals. Wavelets could be used in applications such as image compression, human vision, radar, earthquake prediction, etc. [19].

The term “wavelets” is used to refer to a set of orthonormal basis functions generated by dilation and translation of scaling function ϕ and a mother wavelet ϕ [15]. The finite scale multiresolution representation of a discrete function can be called as a discrete wavelet transform [18]. DWT is a fast linear operation on a data vector; length is an integer power of 2. Such transform is invertible and orthogonal, where as the inverse transform expressed as a matrix is the transpose of the transform matrix. The wavelet basis or function, different sines and cosines as in Fourier transform (FT), is quite localized in space. But similar to sines and cosines, the individual wavelet functions are localized in frequency.

A. Wavelet Thresholding

Donoho and Johnstone [17] pioneered the work on filtering of additive Gaussian noise using wavelet thresholding. The properties and behavior, wavelets play a major role in image compression and image denoising. Since our topic of interest is image denoising, the latter application has been discussed in detail. Wavelet coefficients calculated by a wavelet transform represent change in the time series at a exacting resolution. By taking into consideration the time series at different resolutions, it is then possible to filter out noise.

The term wavelet thresholding is explained as decomposition of the data or the image into wavelet coefficients, comparing with the detail coefficients with a given threshold value, and shrinking such coefficients close to zero to take away the effect of noise in from the data. The image is reconstructed from the modified coefficients. This process is also called as the inverse discrete wavelet transform. All through thresholding, a wavelet coefficient has been compared with a given threshold and is set to zero if its magnitude is less than the threshold; other then it is retained or modified depending on the threshold rule. Thresholding distinguishes the coefficients due to noise and the ones consisting of important signal information.

The choice of a threshold is an important point. Which plays a major role in the removal of noise in images because denoising most frequently produces smoothed images, dropping the image sharpness of the image. Care should be taken for preserving the edges of the denoised image. There exist many methods for wavelet thresholding, which rely on the option of a threshold value. Some usually used techniques for image noise removal include VisuShrink, SureShrink and BayesShrink [15, 16, 17].

Now let us focus on the three methods of thresholding mentioned earlier. For all these methods the image is first subjected to a discrete wavelet transform, which decomposes the image into may sub-bands. Graphically it can be represented as shown in Figure. 2.1.

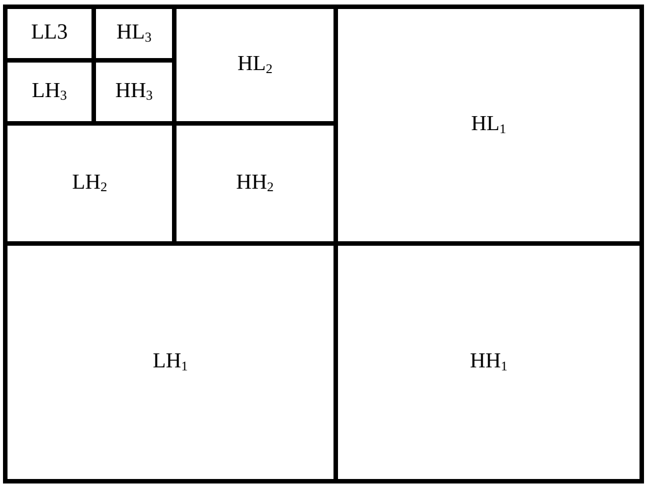

Fig. 2.1: DWT on 2-dimensional data

III. Proposed Methodology

The proposed methodology followed in this work is presented here with the block diagram and flow chart of algorithm execution. Proposed methodology significantly improves the results compared to previous work. Which is explained in the next section of the paper. In Fig. 3.1 shows the block diagram and Fig. 3.2 shows the flow chart of proposed methodology.

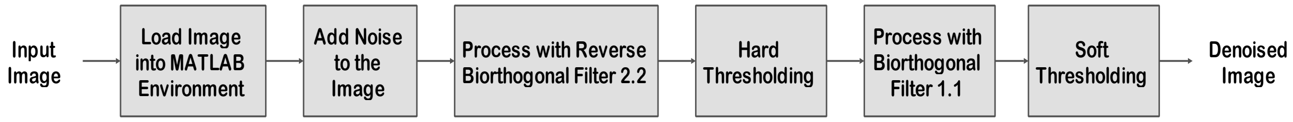

Fig. 3.1: Block Diagram of Proposed Methodology

In Fig. 3.1 block diagram of proposed methodology is displayed which has two main blocks i.e. first gaussian noise of values sigma=0.01 to 0.05 is added to original input image and then second block denoising using wavelet decomposition is applied with reverse bi orthogonal filter followed by hard thresholding. The second block has the series structure of wavelet decomposition with filters bi orthogonal filter followed by soft thresholding is applied, and denoised image as output of the system.

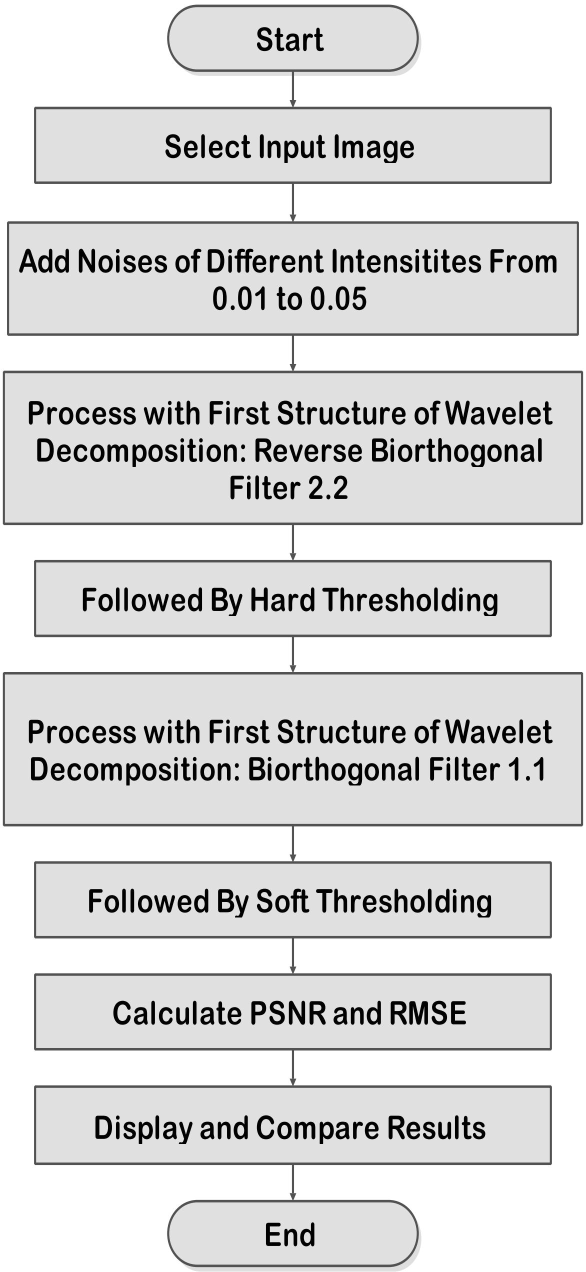

Fig. 3.2: Flow Chart of Proposed Methodology

In Fig. 3.2 flow chart of proposed methodology is shown. As the proposed denoising algorithm starts a original image should be given as input for processing. The original image is attacked with different intensities of gaussian noise (σ = 0.01 to 0.05) to checking the robustness and efficiency of denoising method. Then wavelet decomposition with two different values is applied one after another for optimum results and these are 'rbio2.2' filter with hard thresholding and then 'bior1.1' filter with soft thresholding.

After processing of noisy image with wavelet decomposition image is denoised and PSNR is calculate of denoised image which is improved than previous methods.

IV. SIMULATION RESULTS

The simulation of proposed methodology as explained in previous section is simulated and performed on different images to check the authenticity of results on various images. The images are Image Category1, lena, Image Category 2 vegetables are taken for simulation. During simulation we have calculated peak signal to noise ratio (PSNR), that shows the Fig. of merit for denoising algorithms, means large value of PSNR of denoised image, efficient the denoising method is. Among all the results we have displayed one here how denoising methodology is working and the Table I compares the PSNR values of proposed work with the previously applied methodologies, and found efficient in every manner of denoising.

Lena_256

Fig. 4.1 Lena Noisy Images with Different Noise Levels (a) 0.01, (b) 0.02, (c) 0.03, (d) 0.04, (e) 0.05

Noise Level: 0.01 | PSNR:32.8 dB| RMSE:5.86 | Time : 0.2190 Sec.

Noise Level: 0.02 | PSNR:30.5 dB| RMSE:7.62 | Time : 0.1361 Sec.

Noise Level: 0.03 | PSNR:29.1 dB| RMSE:9.03 | Time : 0.1352 Sec.

Noise Level: 0.04 | PSNR:28.0 dB| RMSE:10.19 | Time : 0.1236 Sec.

Noise Level: 0.05 | PSNR:27.2 dB| RMSE:11.15 | Time : 0.1335 Sec.

Table 1 has given 256x256 image PSNR comparison with previous work (existing work) with proposed work at noise level 0.01 , 0.03 and 0.05 three noise samples. PSNR value of proposed work is always batter then previous base work from [1].

It is observed form table 1 that PSNR vale of proposed work is better for same noise level it shows that proposed work is better as compared to existing base work [1]. The quality of demised image from figure 4.1 is visible better for different noise level on same dimension image of Lina 256x256 pixels.

Table 1: Lena 256x256 Image PSNR Comparison

Noise Level	Previous PSNR	Proposed PSNR
0.01	32.33 dB	32.8 dB
0.03	26.76 dB	29.1 dB
0.05	24.95 dB	27.2 dB

(a) (b) (c) (d) (e)

Fig. 4.1 Image category1 Lena Denoised Images with Size 256x256 and Different Noise Levels (a) 0.01, (b) 0.02, (c) 0.03, (d) 0.04, (e) 0.05.

V. CONCLUSION AND FUTURE SCOPE

The simulation of proposed work has been dome on Matlab Ra2011 . The performance of proposed work has been evaluated based on noise level PSNR value. The value of PSNR of proposed outcome has been compared to the value existing base for Lena image. The outcome of proposed work has better in terms of image quality noise and compression ratio. The denoising algorithm is applied on various gaussian noised images and the results of robustness are clear from table of PSNR compared with the previous values. From the results itcan be concluded that the denoising method of proposed algorithm is efficient than the previously applied methodologies. In future more series combination of wavelet filters will give better results, and this concept is also implemented with other decomposition techniques to get the better results.

REFERENCES

[1] S. Saxena, H. S. Khanduga, S. Mantri and S. Puri, "An efficient denoising method based on SURE-LET and Wavelet Transform," 2016 International Conference on Electrical, Electronics, and Optimization Techniques (ICEEOT), Chennai, 2016, pp. 918-923.

[2] F. Ayari and C. Ben Amar, "Image de-noising of a metal matrix composite microstructure using Sure-let wavelet and weighted bilateral filter," 2015 11th International Conference on Information Assurance and Security (IAS), Marrakech, 2015, pp. 146-151.

[3] S. Trambadia and H. Mayatra, "Endoscopic image restoration using truncated constrained least squares filter in frequency-domain and SURE-LET filter," 2015 5th Nirma University International Conference on Engineering (NUiCONE), Ahmedabad, 2015, pp. 1-5.

[4] W. Liejun and Y. Ting, "A new approach of image enhancement based on improved fuzzy domain algorithm," 2014 International Conference on Multisensor Fusion and Information Integration for Intelligent Systems (MFI), Beijing, 2014, pp. 1-5.

[5] M. Arora, S. Bashani, K. K. Gupta and A. M. Mohammed, "Wavelet denoising: Comparative analysis and optimization using machine learning," 2014 9th International Conference on Industrial and Information Systems (ICIIS), Gwalior, 2014, pp. 1-6.

[6] D. A. Huang, L. W. Kang, Y. C. F. Wang and C. W. Lin, "Self-Learning Based Image Decomposition With Applications to Single Image Denoising," in IEEE Transactions on Multimedia, vol. 16, no. 1, pp. 83-93, Jan. 2014.

[7] A. Mouton, G. T. Flitton, S. Bizot, N. Megherbi and T. P. Breckon, "An evaluation of image denoising techniques applied to CT baggage screening imagery," 2013 IEEE International Conference on Industrial Technology (ICIT), Cape Town, 2013, pp. 1063-1068.

[8] Donoho.D.L,Johnstone.I.M, “Ideal spatial adaptation via wavelet shrinkage”, Biometrika,81,pp.425- 455,1994.

[9] Gao Zhing, Yu Xiaohai, “Theory and application of MATLAB Wavelet analysis tools”, National defense industry publisher, Beijing, pp. 108-116, 2004.

[10] Aglika Gyaourova Undecimated wavelet transforms for image denoising, November 19, 2002.

[11] Bart Goossens, Aleksandra PEzurica, and Wilfried Philips, “Image Denoising Using Mixtures of Projected Gaussian Scale Mixtures”, IEEE Transactions On Image Processing, Vol. 18, No. 8, August 2009, Pp. 1689-1702

[12] Michel Misiti, Yves Misiti, Georges Oppenheim, Jean-Michel Poggi, “Wavelets and their Applications”, Published by ISTE 2007 UK.

[13] J. Xu, K. Zhang, M. Xu, and Z. Zhou. An adaptive threshold method for image denoising based on wavelet domain. Proceedings of SPIE, the International Society for Optical Engineering, 7495:165, 2009.

[14] J. Portilla, V. Strela, M.J. Wainwright, and E.P. Simoncelli. Image denoising using scale mixtures of Gaussians in the wavelet domain. Image Processing, IEEE Transactions on, 12(11):1338-1351, 2003.

[15] F. Luisier, T. Blu, and M. Unser. A new SURE approach to image denoising: Interscale orthonormal wavelet thresholding. IEEE Transactions on Image Processing, 16(3):593-606, 2007.

[16] B.A. Olshausen and D.J. Field. Sparse coding with an overcomplete basis set: A strategy employed by V1? Vision research, 37(23):3311-3325, 1997.