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Multi Wavelet Based Image Denoising With Hard And Soft Threshold In Bone Cancer Images

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Abstract
Medical Imaging is playing the vital role in diagnosing and treatment of diseases such as locating the tumours in brain, tumours in bones, detection of cancer cells in early stages etc. For gettingcompletely correct results, the images acquired by various medical imaging modalities must be free from noise. So in Medical image analysis, Image denoising is act as an important pre-processing activity. Developing the denoising algorithms is a difficult task because diagnostic information must be preserved while removing the noise. Earlier the denoising algorithms were designed in the spatial domain such as median filtering, harmonic filtering, and weiner filtering etc. by directly working on the pixel values, these methods will remove noisewhile introducing the blur in the denoised images. Wavelet algoirthms are helpful instrument for signalprocessing, for example, image compression and denoising. Wavelet thresholding is a signal estimation strategy that adventures the capacities of wavelet transform for signal denoising. In this paper, we proposed and implemented a fixed form with soft and hard threshold with various coefficients (i. e. scaled and unscaled with white noise, non-white noise). Visu shrink threshold is used for estimating threshold.

Keywords: denoising, fixed form threshold, visu shrink,

Introduction

TThe image more often than not has commotion which is not effectively dispensed with in image processing. As per real image trademark, noise statistical property and frequency spectrum distributionrule, individuals have created numerous strategies for taking out noises, which roughly are partitioned into space and transformation fields. The space field is information operation carried on the original picture, and procedures the picture grey quality, similar to neighborhood average strategy, wiener filter, center value filter etc. The transformation field is administration in the change field of pictures, and the coefficients after change are prepared. At that point the point of dispensing with commotion is accomplished by inverse transformation, similar to wavelet transformation [1], [2]. Fruitful misuse of wavelet transformation may decrease the commotion impact or even overcome it totally [3]. There are two principle sorts of wavelet transformation - continuous and discrete [2]. In view of PCs discrete nature, PC projects utilize the discrete wavelet transform.

The discrete transform is exceptionally proficient from the computational perspective. In this paper, we will basically manage the displaying of the wavelet transform coefficients of regular pictures and its application to the picture denoising issue. The denoising of a characteristic picture ruined by Gaussian noise is an excellent issue in signalprocessing [4]. The wavelet transform has turned into a vital apparatus for this issue because of its vitality compaction property [5]. In reality, wavelets give a system to flag disintegration as an arrangement of signs known as estimate signs with diminishing determination supplemented by a succession of extra touches called points of interest [6][7]. Denoising or estimation of capacities, includes reconstituting the sign and in addition conceivable on the premise of the perceptions of a helpful sign undermined by commotion [8] [9] [10] [11]. The systems in view of wavelet representations yield extremely basic calculations that are regularly more effective and simple to work with than customary routines for capacity estimation [12]. It comprises of deteriorating the watched sign into wavelets and utilizing edges to choose the coefficients, from which a sign is combined [5]. Picture denoising calculation comprises of few stages; consider an information signal x(t) and boisterous sign n(t). Add these segments to get uproarious informationy(t) i. e.

$$y(t) = x(t) + n(t)$$

Here the noise can be Gaussian, Poisson‟ s, speckle andSalt and pepper, then apply wavelet transform to get w(t).

$$y(t) \xrightarrow{\text{Wavelet Transform}} w(t)$$

Modify the wavelet coefficient w(t) using different threshold algorithm and take inverse wavelet transform to get denoising image $\hat{x}(t)$.

$$w(t) \xrightarrow{\text{Inverse Wavelet Transform}} \hat{x}(t)$$

Image quality was expressed using signal to noise ratio of denoised image.

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Related Work
Wavelet thresholding de-noising system taking into account discrete wavelet transform (DWT) proposed by Donoho and Johnstone is frequently utilized as a part of de-noising of ECG signal [1, 15]. Sayadi O and Brittain J. S. have utilized Wiener filtering and Kalmanfiltering strategies to uproot the added substance commotions [16, 17]. Harishchandra T. Patil gave another strategy for edge estimation for ECG signal de-noising utilizing wavelet decomposition, where, threshold is registered utilizing most extreme and least wavelet coefficients at every level [18].

Wavelet Based De-Noising
Wavelet de-noising systems manages wavelet coefficients utilizing a suitable chosen threshold value ahead of time. The wavelet coefficients at diverse scales could be acquired by taking DWT of the noisy signal. Typically, those wavelet coefficients with littler extents than the preset threshold are brought about by the noise and are supplanted by zero, and the others with bigger sizes than the preset limit are created by original signal basically and kept (hard-thresholding case) or shrunk (the softthresholding case). At that point the de-noised signal could be reproduced from the subsequent wavelet coefficients.

Soft And Hard Thresholding
A sort of signal estimation method called wavelet thresholding have signal de-noising capacities. Wavelet shrinkage operation is classified into two thresholding strategies hard and soft. Execution of thresholding simply relies on upon the sort of thresholding technique and the thresholding guideline utilized for the given application.

In hard thresholding, the coefficients that are littler than the limit are vanished and the others are kept unaltered. Be that as it may, the softthresholding makes a ceaseless circulation of the scaling so as to remain coefficients focused on zero them.
Soft thresholding [10] is given as follows:

$$\hat{X} = \begin{cases} y - sgn(y)T & if\ |y| \geq T \\ 0 & if\ |y| < T \end{cases}$$

The soft thresholding(whose transfer function is shown in Figure 1), shrinks coefficients above the threshold inabsolute value.

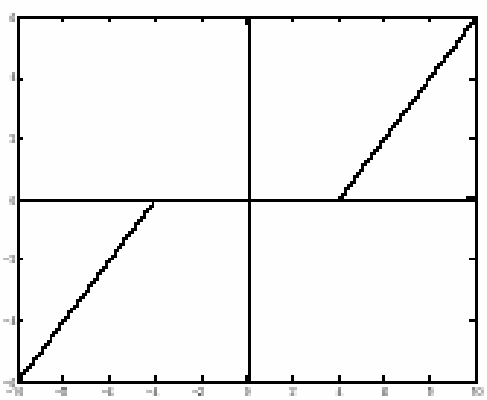


Figure 1: SoftThresholding

Hard thresholding is given as following:

$$\hat{X} = \begin{cases} y & if\ |y| \geq T \\ 0 & if\ |y| < T \end{cases}$$

The alternative, hard threshold is a "keep or kill" procedure and is more intuitively appealing. Thetransfer function of the same is shown in Figure 2.

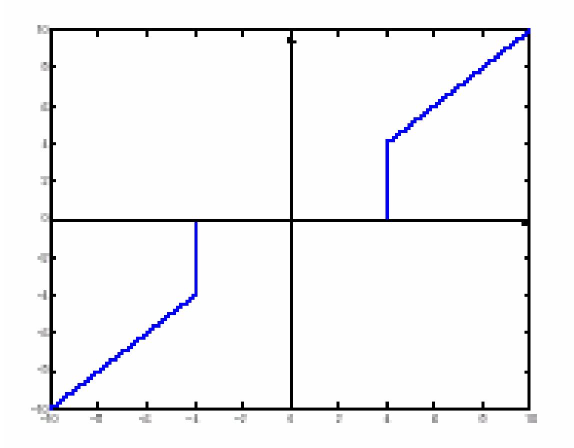


Figure 2: Hard Thresholding

While at first sight hard thresholding may appear to be normal, the coherence of softthresholding has a few points of interest. It makes calculations scientifically more tractable [13]. In addition, hard thresholding does not even work with a few calculations, for example, the GCV method [14]. Some of the time, immaculate noise coefficients may pass the hard threshold and show up as irritating "blips" in the yield. Softthresholding therapists these false structures.

Visu Shrink
Visu Shrink was presented by Donoho [13]. It utilizes a threshold value t that is corresponding to the standard deviation of the noise. It takes after the hard threshold rule. An appraisal of the noise level σ was characterized in view of the median absolutedeviation given by

$$\hat{\sigma} = \frac{Median(\{\ |g_{j-1,k}\ | : k = 0,1, \ldots\ 2^{j-1} - \})}{0.6745}$$

Where corresponds to the detail coefficients in thewavelet transform. VisuShrink does not deal with minimizingthe mean squared error. Another disadvantage is that it cannotremove speckle noise. It can only deal with an additive noise. VisuShrink follows the global threshold scheme, which isglobally to all the wavelet coefficients [9].

Proposed System
The input image is taken as a noisy image then that image is transformed into various levels with the help of wavelet

transform. Then transformed image is converted into noise free image i. e. de-noised image with the help of visu shrink threshold.

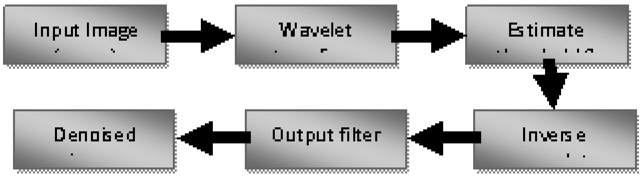


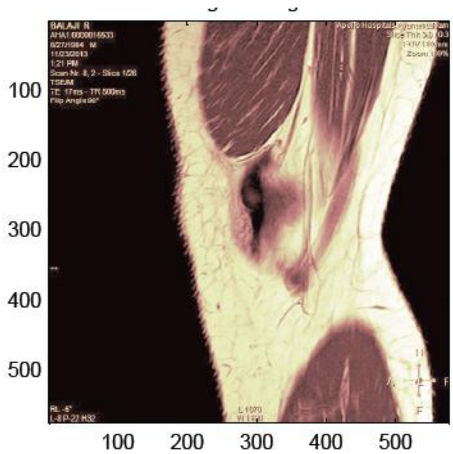
Figure 3: Block diagram of Image denoising using Wavelet Transform

Experimental Results

Wavelet De-noising using shrink thresolding was performed on the MRI scan image taken from Apollo hospital database. The outcomes are provided for thresholds chose by VisuShrink hard and soft strategies and thresholds chose of course general limit for hard and soft thresholding.

FIXED FORM THRESHOLDING

Threshold Selection byVISU Shrink



Original Image

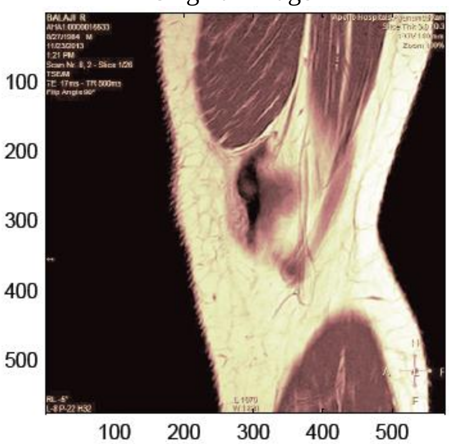


Figure. 4. Denoised Image using Haar at level 5 obtainedby wavelet coefficients thresholding using fixed form HARD threshold and scaled white noise structure

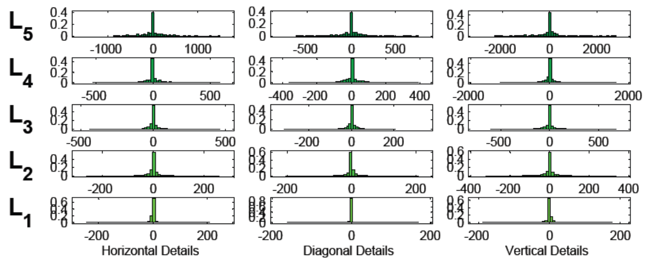


Figure. 5. Hard thresholding applied to MRI bone image at level 1 to level 5

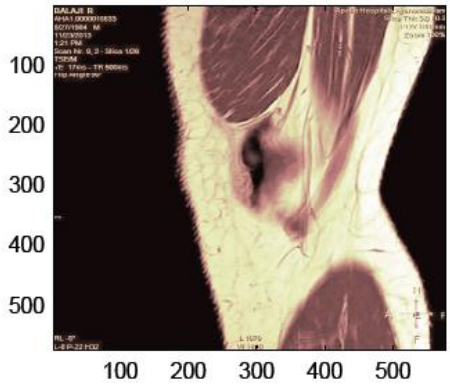


Figure. 6. Denoised Image using Haar at level 2 obtainedby wavelet coefficients thresholding using fixed form HARD threshold and unscaled white noise structure

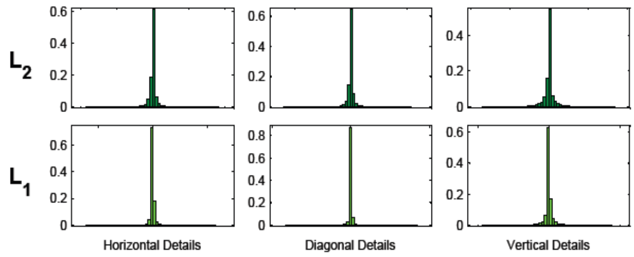


Figure. 7. Histogram of original and denoised image based onfixed form HARD threshold and unscaled white noise structure

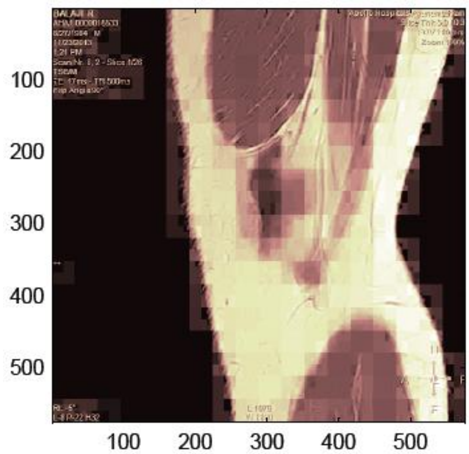


Figure. 8. Denoised Image using Haar at level 5 obtainedby wavelet coefficients thresholding using fixed formSOFT threshold and non- white noise structure

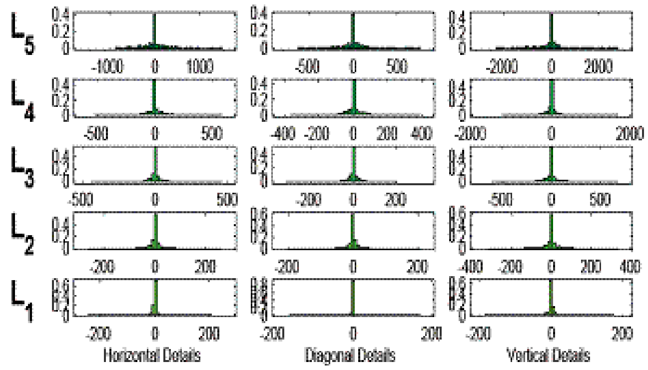


Figure. 9. Softthresholding applied to MRI bone image at level 1 to level 5

Conclusion

In this paper we introduced the framework for recharging the sensor nodes by sensors. This approach increases the longevity of the network. Simulation are performed to

Conclusion

After experimentation it can be concluded that hardthreshold not always gives better denoising performance;it depends on which wavelet thresholding algorithm waschosen. Wavelet denoising is a powerful tool for image enhancement. In this paper, we have seen that wavelet thresholding is a successful strategy for denoisingnoisy signals. We initially tried hard and soft on noisy versions of the standard 1-D signals and discovered the best threshold. In future we can utilize same threshold function for medical images and in addition surface pictures to get denoised picture with enhanced execution parameter.

References

[1] Donoho. D. L, Johnstone. I. M, “Ideal spatial adaptation via waveletshrinkage”, Biometrika, Vol. 81, pp. 425-455, 1994.

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

[3] AglikaGyaourovaUndecimated wavelet transforms for image denoising, November 19, 2002.

[4] Bart Goossens, Aleksandra Piˇzurica, and Wilfried Philips, “ImageDenoising Using Mixtures of Projected Gaussian Scale Mixtures”, IEEETransactions On Image Processing, Vol. 18, No. 8, August 2009, Pp. 1689-1702

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

[6] C Sidney Burrus, Ramesh A Gopinath, and HaitaoGuo, “Introduction towavelet and wavelet transforms”, Prentice Hall1997. S. Mallat, AWavelet Tour of Signal Processing, Academic, New York, secondedition, 1999.

[7] R. C. Gonzalez and R. Elwood‟ s, Digital Image Processing. Reading, MA: Addison-Wesley, 1993.

[8] M. Sonka, V. Hlavac, R. Boyle Image Processing , Analysis , AndMachine Vision. Pp10-210 & 646-670.

[9] Raghuveer M. Rao. , A. S. Bopardikar Wavelet Transforms: IntroductionTo Theory And Application Published By Addison-Wesley 2001 pp1-126.

[10] Arthur Jr Weeks , Fundamental of Electronic Image Processing PHI2005.

[11] JaidevaGoswami Andrew K. Chan, “Fundamentals Of WaveletsTheory, Algorithms, And Applications”, John Wiley Sons.

[12] Donoho, D. L. and Johnstone, I. M. (1994) Ideal spatial adaptation viawavelet shrinkage. Biometrika, 81, 425-455.

[13] David L Donoho. De-noising by soft thresholding. IEEE Transactions on InformationTheory, 41(3):613–627, May 1995.

[14] Maarten Jansen. Noise Reduction by Wavelet Thresholding, volume 161. SpringerVerlag, United States of America, 1 edition, 2001.

[15] Donoho, “De-noising by soft thresholding”, IEEE Trans. Trans. Inform. Theory, vol. 41, pp. 613-627, 1995.

[16] Sayadi O. , Shamsollahi M. B. , ECG denoising and compressionusing a modified extended kalman filter structure, IEEE Trans. on Biomedical Engineering, (2008) vol. 55, no. 9, pp. 2240-2248.

[17] Lu G. , Brittain J. S. , Holland P. , Yianni J. , Green A. L. , SteinJ. F. , Aziz T. Z. , Wang S. , Removing ECG noise from surfaceEMG signals using adaptive filtering, Neuroscience Letters, (2009), vol. 462, no. 1, pp. 14-19.

[18] Harishchandra T. Patil, R. S. Holambe, New approach ofthreshold estimation for denoising ECG signal using wavelettransform, India Conference (INDICON), 2013 Annual IEEEConference, Mumbai, India, 13-15 Dec. 2013.