

IMAGE CORRELATION WAVELET THRESHOLDING IMAGE DENISING OVER TRADITIONAL WAVELET THRESHOLDING

MONIKA RITU SHARMA ASHOK SAINI

ECE,B.M.I.E.T., Sonipat, India^{1,2},

Monika.hooda1@gmail.com¹

Abstract— Edge-preserving denoising is of great interest in image processing. This paper presents a wavelet-based multiscale products thresholding scheme for noise suppression of the images. A dyadic wavelet transform (A Canny edge detector-) is also employed. In the result we can see that the with the decay in noise rapidly it evolve the high magnitude across wavelet scale. To take advantage of the wavelet interscale dependencies we multiply the adjacent wavelet sub bands to enhance edge structures while weakening noise. In the multiscale products, edges can be effectively distinguished from noise.

An adaptive scale correlation wavelet thresholding technique is then proposed. In which the adaptive threshold is calculated which is imposed on the products, instead of on the wavelet coefficients. This proposed scheme suppresses the noise effectively and preserves the edges features than other wavelet-thresholding denoising methods. In the result we can see the better visual quality and increment in the signal to noise the last node will die in the network is to be discussed. In which round ratio as compare to the traditional technique.

Keywords:

SWT (stationary wavelet transform), RF radio frequency,

,WT(wavelet Transform)

1.1 Introduction To Wavelets And Wavelet Transforms

Wavelets are used to transform the signal under investigation into another representation which presents the signal information in a more useful form. When working with signals, the signal itself can be difficult to interpret. Therefore the signal must be decomposed or transformed in order to see what the signal actually represents.

The continuous wavelet transform is the most general wavelet transform. The problem is that a continuous wavelet transform operates with a continuous signal, but since a computer is digital, it can only do computations on discrete signals. The discrete wavelet transform has been developed to accomplish a wavelet transform on a computer.

Wavelets and wavelet transforms are used to analyze signals. The transformed signal is a decomposed version of the original signal, and can be converted back to the original signal. No information is lost in the process. When studying a musical tone, one of the features that is interesting is the frequency. The frequency for a clean A is 440Hz, see top plot in Figure 1.1. To determine the frequency of the signal one must measure the period of each wave, and calculate the frequency. The period of one wave is the time it takes from it is at one point in the wave, until it reaches the same position again. For example the time between two wave tops.

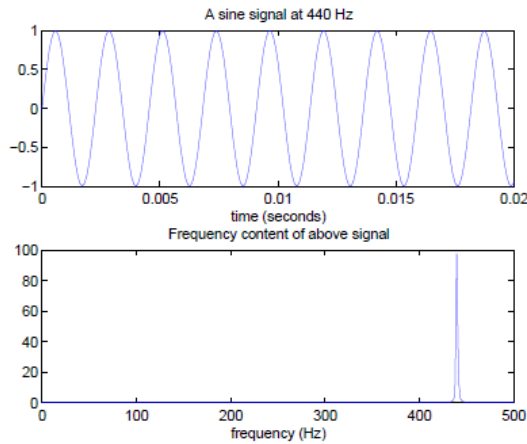


Figure 1.1: A sine wave at 440 Hz, and its Fourier transform

Using different transforms, the signal can be transformed into other representations. For this example, instead of having amplitude as a function of time, it would be better to have the amplitude as a function of frequency. This can be done by using the Fourier transform. Once one knows what frequencies are present, one can easily determine which tones the signal consists of, in the case of a musical signal. The bottom part of Figure 1.1 shows that it is easy to determine that the signal in the upper part of Figure 1.1 actually is an A when you perform the Fourier transform. Wavelet transforms can do the same, but they can also tell you when the tone A appeared in time, effectively giving you amplitude, time and frequency, all in one.

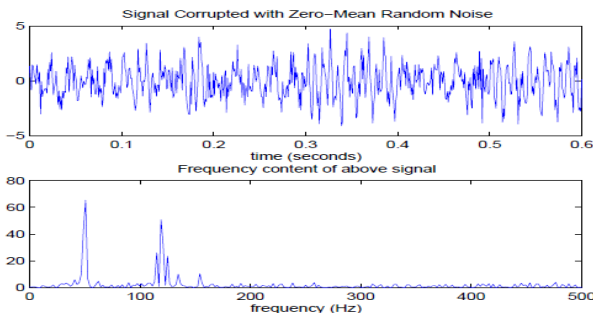


Figure 1.2: A noise input signal, and corresponding Fourier transform.

Wavelet Transform Plot

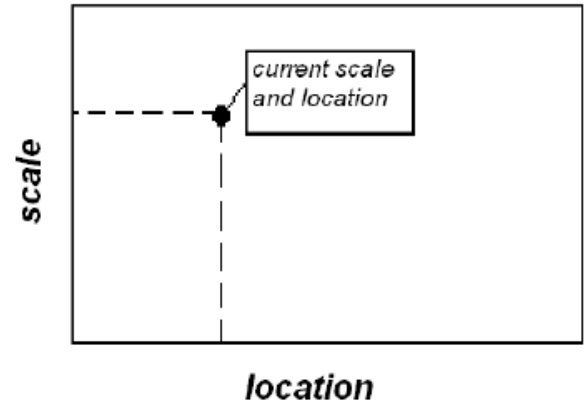


Figure 1.3: Wavelet Transform Plot

1.2 Present Work:

It was analyzed that previous traditional thresholding techniques are not giving satisfactory result for image denoising. Disadvantage of this technique is that the SNR ratio decreases with the increase in image size and this technique is time variant. So we proposed a new method named Scale Correlation Wavelet thresholding method with the help of 2D dyadic wavelet. Advantage of 2D dyadic wavelet is that it is time invariant, also changes only scale parameter. So using this, an adaptive wavelet can be designed to enhance instantaneous feature of the image.

A New sure approach to Image Denoising: Interscale Orthonormal Wavelet Thresholding beyond the point wise approach, more recent investigations have shown that substantially larger denoising gains can be obtained by considering the intra- and interscale correlations of the wavelet coefficients. In addition, increasing the redundancy of the wavelet transform is strongly beneficial to the denoising performance. We have selected three such techniques reflecting the

state-of-the-art in wavelet denoising, against which we will compare our results.

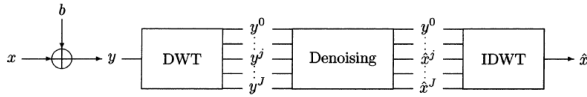


Figure 4.1-Principle of wavelet denoising.

1.3 Proposed Work:

In “Adaptive Wavelet Thresholding for Image Denoising and Compression” On a seemingly unrelated front, lossy compression has been proposed for denoising in several works [6], [5], [21], [25], [28]. Other works [4], [12]–[16] also addressed the connection between compression and denoising.

STEPS INVOLVED IN THIS WORK

In this paper, an adaptive scale correlation wavelet thresholding technique is promoted over traditional wavelet thresholding. For this paper the following steps are involve-

1. Taking original image
2. Calculate original SNR from the image
3. Create a noisy image.
4. 2D dynamic wavelet transform
5. Compute the coefficient of correlation.
6. Do the traditional thresholding on the image.
7. Calculate the SNR after traditional thresholding
8. Apply the scale correlation thresholding on the image now.
9. Calculate the SNR after scale correlation thresholding.
10. Measure the effect of use of scale correlation thresholding over traditional thresholding.

1.6 RESULTS AND DISCUSION

In this section, the performances by the proposed scheme on some INPUT images are compared with the traditional wavelets thresholding technique. We

made a comparison by using parameter i.e. signal to noise ratio and visual quality.

(a). **VISUAL QUALITY** : When we compare these techniques on the basis of visual quality the result is very clear that adaptive scale correlation wavelet thresholding technique give the best quality picture in the result. Figure (1.4) show the original image which is further made noisy by adding the random

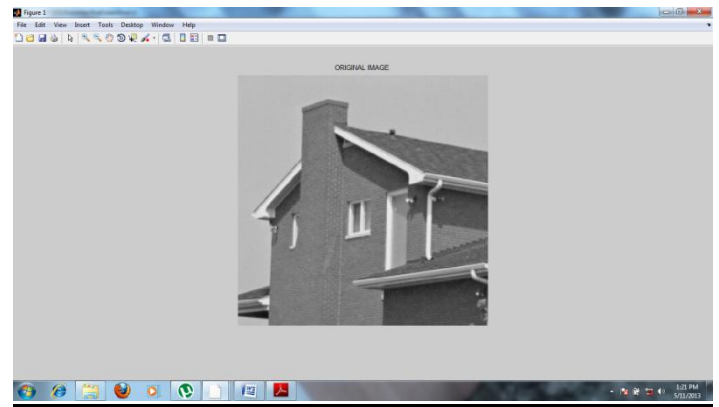


Figure 1.4 : ORIGINAL IMAGE

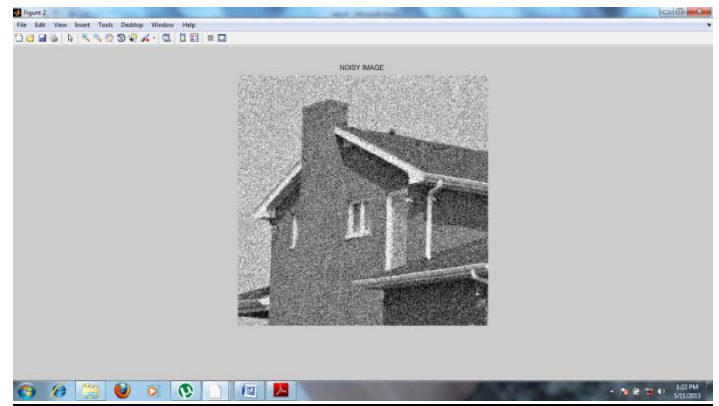


Figure 1.5 : NOISY IMAGE

Noise in the input image figure(1.5). Then after this by applying the traditional wavelet thresholding the output image is shown in figure(1.6).

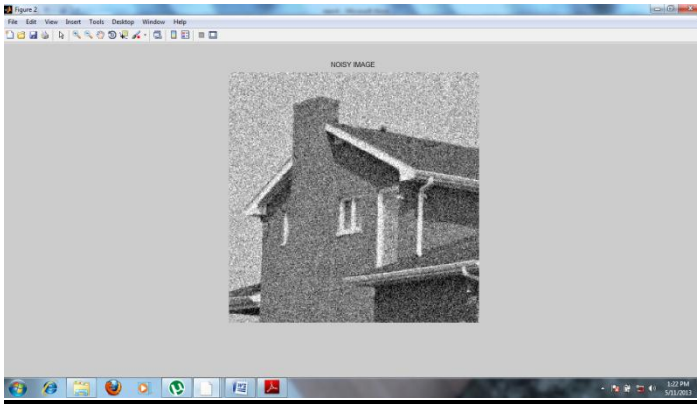


Figure 1.6 : Image After Traditional Wavelet Thresholding

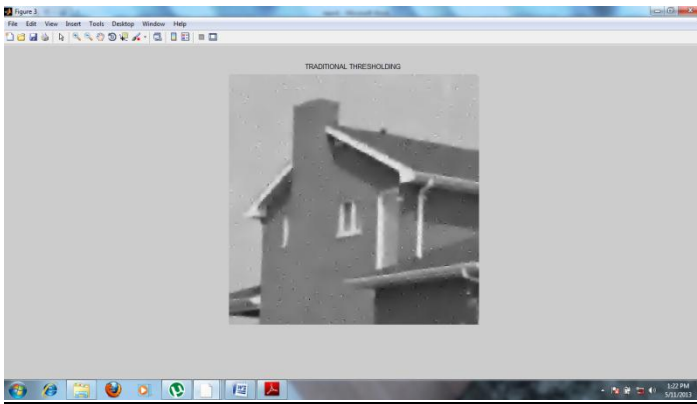


Figure 1.7 : Image after SCALE CORRELATION WAVELET THRESHOLDING

Finally the figure (1.7) show the result of adaptive scale correlated wavelet thresholding image from where it is clear that the image quality is far better in this case as compare to traditional wavelet thresholding.

(b) SIGNAL TO NOISE RATIO: We calculated the value of signal to noise ratio at three different point though which we can compare the both technique. The signal to noise ratio for the input or we can say original image is

$$\text{snr}_o = 14.3144 \text{ dB}$$

Then apply the traditional wavelet thresholding and calculate the signal to noise ratio, which is

$$\text{snr}_{ft} = 23.5478 \text{ dB}$$

The value for signal to noise ratio after adaptive scale correlation wavelet thresholding is

$$\text{snr}_f = 24.7967 \text{ dB}$$

From the above calculated value for signal to noise ratio we can conclude that the scale correlation wavelet thresholding technique give the best result over traditional wavelets thresholding.

1.4 Conclusion And Future Scope

This paper proposes an image denoising scheme using an adaptive scale correlation wavelet thresholding technique. Unlike traditional schemes that directly threshold the wavelet coefficients, the proposed scheme multiplies the adjacent wavelet subbands to amplify the significant features and then applies the thresholding to the multiscale products to better differentiate edge structures from noise. The distribution of the products was analyzed and an adaptive threshold was formulated to remove most of the noise. Experiments on the input images show that the proposed scheme not only achieves high SNR and VISUAL QUALITY measurements but also preserves more edge features.

By this adaptive scale correlation wavelet thresholding technique we get high quality of image and better value for the signal to noise ratio. This can be used in the medical images because edge features preserving nature. We can also design the further effective technique by forwarding this for getting more clear visuality and better in signal to noise ratio. By getting more correctively threshold value get the better in the output which is further beneficial in many areas.

References

- [1]. Yaobin Zou, Fangmin Dong, Bangjun Lei , Lulu Fang , Shuifa Sun, “Image thresholding based on template matching with arctangent Hausdorff distance measure” *Optics and Lasers in Engineering* 51 (2013) 600–609
- [2]. S. Tsantis, N. Dimitropoulos , M. Ioannidou , D. Cavouras , G. Nikiforidis, “Inter-scale wavelet analysis for speckle reduction in thyroid ultrasound images” *Computerized Medical Imaging and Graphics* 31 (2007) 117–127
- [3]. Kai-qi Huang, Zhen-yang Wu, George S.K. Fung, Francis H.Y. Chan, “Color image denoising with wavelet thresholding based on human visual system model” *Signal Processing: Image Communication* 20 (2005) 115–127
- [4]. Graeme K. Ambler and Bernard W. Silverman, “Perfect simulation for Bayesian wavelet thresholding with correlated coefficients”
- [5]. Z. Azimifar P. Fieguth E. Jernigan, “WAVELET SHRINKAGE WITH CORRELATED WAVELET COEFFICIENTS”
- [6]. Florian Luisier, Thierry Blu, Michael Unser, *Fellow*, “A New SURE Approach to Image Denoising: Interscale Orthonormal Wavelet Thresholding” *IEEE TRANSACTIONS ON IMAGE PROCESSING*, VOL. 16, NO. 3, MARCH 2007
- [7]. A. T. Walden, D. B. Percival & E. J. McCoy,” *Spectrum Estimation by Wavelet Thresholding of Multitaper Estimators*”
- [8]. Huiyue Yi, “ Robust Wavelet Transform-based Correlation Edge Detectors Using Correlation of Wavelet Coefficients” *International Journal of Signal Processing, Image Processing and Pattern Recognition* Vol. 4, No. 4, December, 2011
- [9]. PRATHIBHA.O.M, SWATHIKUMARI. N. S & SUSHMA P, “IMAGE FORGERY DETECTION USING DYADIC WAVELET TRANSFORM” *International Journal of Electronics Signals and Systems (IJESS)* ISSN: 2231- 5969, Vol-2, ISS-2,3,4, 2012
- [10]. Pankaj Hedao and Swati S Godbole, “WAVELET THRESHOLDING APPROACH FOR IMAGE DENOISING” *International Journal of Network Security & Its Applications (IJNSA)*, Vol.3, No.4, July 2011
- [11]. Wajdi Ghezaiel, Amel Ben Slimane Rahmouni, and Ezzedine Ben Braiek, “Evaluation of a Multi-Resolution Dyadic Wavelet Transform Method for usable Speech Detection” *World Academy of Science, Engineering and Technology* 79 2011
- [12]. S. Grace Chang, Bin Yu, and Martin Vetterli, *Fellow*, “Adaptive Wavelet Thresholding for Image Denoising and Compression” *IEEE TRANSACTIONS ON IMAGE PROCESSING*, VOL. 9, NO. 9, SEPTEMBER 2000
- [13]. David L. Donoho & Iain M. Johnstone, “Adapting to Unknown Smoothness via Wavelet Shrinkage “,*Journal of the American Statistical Association*
- [14]. Xiaobo Qu , Weiru Zhang , Di Guo , Congbo Cai , Shuhui Cai & Zhong Chen, “Iterative thresholding compressed sensing MRI based on contourlet transform” *Inverse Problems in Science*

and Engineering Vol. 18, No. 6, September 2010, 737–758

[15]. James S. Walker, “Wavelet-based image processing” *Applicable Analysis* Vol. 85, No. 4, April 2006, 439–458

[16]. Mohamed Allali, “Linear algebra and image processing”, *International Journal of Mathematical Education in Science and Technology*, Vol. 41, No. 6, 15 September 2010, 725–741

[17]. Donghoh Kim a , Youngjo Lee b & Hee-Seok Oh, “A fast wavelet approach for recovering damaged images” *Journal of Applied Statistics* Vol. 35, No. 8, August 2008, 927–938

[18]. Sam Efromovich, “Multiwavelets: Theory and Bioinformatic Applications” *Communications in Statistics—Theory and Methods*, 38: 2829–2842, 2009, Taylor & Francis Group, LLC ISSN: 0361-0926 print/1532-415X online DOI: 10.1080/03610920902947170

[19]. RAJESH GANESAN, TAPAS K. DAS & VIVEKANAND VENKATARAMAN, “Wavelet-based multiscale statistical process monitoring: A literature review” *IIE Transactions* (2004) **36**, 787–806 Copyright C _ “IIE” ISSN: 0740-817X print / 1545-8830 online DOI: 10.1080/07408170490473060

[20]. Maarten Jansen and Adhemar Bultheel, “Empirical Bayes Approach to Improve Wavelet Thresholding for Image Noise Reduction” 2001 American Statistical Association Journal of the American Statistical Association June 2001, Vol. 96, No. 454, Theory and Methods

[21]. L. Evers and T. J. Heaton, “Locally Adaptive Tree-Based Thresholding” © 2009 American Statistical Association, Institute of Mathematical Statistics, and Interface Foundation of North America *Journal of Computational and Graphical Statistics, Volume 18, Number 4, Pages 961–977 DOI: 10.1198/jcgs.2009.07109*

[22]. Selvaraju Murugesan and David B. H. Tay, “Design of Almost Symmetric Orthogonal Wavelet Filter Bank Via Direct Optimization” *IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 21, NO. 5, MAY 2012*

[23]. C.K. LEUNG and F.K. LAM, “PERFORMANCE ANALYSIS FOR A CLASS OF ITERATIVE IMAGE THRESHOLDING ALGORITHMS”

[26]. J. Baudewig, P. Dechent, K.D. Merboldt, J. Frahm, “Thresholding in correlation analyses of magnetic resonance functional Neuroimaging” *Magnetic Resonance Imaging* 21 (2003) 1121–1130

[27]. Changwei Hu, Xiaobo Qu, Di Guo, Lijun Bao, Zhong Chen, “Wavelet-based edge correlation incorporated iterative reconstruction for undersampled MRI” *Magnetic Resonance Imaging* 29 (2011) 907–915

[28]. Pierre Duchesne, Linyuan Li, Jill Vandermeersch, “On testing for serial correlation of unknown form using wavelet thresholding” *Computational Statistics and Data Analysis* 54 (2010) 2512_2531

[29]. H.D. Cheng, X.H. Jiang, Jingli Wang, “Color image segmentation based on homogram thresholding

and region merging” *Pattern Recognition* 35 (2002) 373–393

[30]. Lei Zhang, Paul Bao, Xiaolin Wu, “Hybrid inter- and intra-wavelet scale image restoration” *Pattern Recognition* 36 (2003) 1737 – 1746

[31]. H.D. Cheng, Xiaopeng Cai, Xiaowei Chen, Liming Hu, Xueling Lou, “Computer-aided detection and classification of microcalcifications in mammograms: a survey” *Pattern Recognition* 36 (2003) 2967 – 2991

[32]. Yakoub Bazi, Lorenzo Bruzzone, Farid Melgani, “Image thresholding based on the EM algorithm and the generalized Gaussian distribution” *Pattern Recognition* 40 (2007) 619 – 634

[33]. Yaobin Zou, Hong Liu, Enmin Song, Zhiyong Huang, “Image bilevel thresholding based on multiscale gradient multiplication” *Computers and Electrical Engineering* 38 (2012) 853–861

[34]. Tao Wu, Kun Qin, “Data field-based transition region extraction and thresholding” *Optics and Lasers in Engineering* 50 (2012) 131–139

[35]. Paul Bao and Lei Zhang, “Noise Reduction for Magnetic Resonance Images via Adaptive Multiscale Products Thresholding” *IEEE TRANSACTIONS ON MEDICAL IMAGING*, VOL. 22, NO. 9, SEPTEMBER 2003

[36]. Javier Portilla, Vasily Strela, Martin J. Wainwright, and Eero P. Simoncelli, “Image Denoising Using Scale Mixtures of Gaussians in the Wavelet Domain” *IEEE TRANSACTIONS ON IMAGE PROCESSING*, VOL. 12, NO. 11, NOVEMBER 2003

[37]. Stephane Mallat and Wen Liang Hwang, “Singularity Detection and Processing

with Wavelets” *IEEE TRANSACTIONS ON INFORMATION THEORY*, VOL. 38, NO. 2, MARCH 1992

[38]. Stephane Mallat and Sifen Zhong, “Characterization of Signals from Multiscale Edges” *IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE*, VOL. 14, NO. 7, JULY 1992