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A Review on Wavelet Transform Based SONAR Image Denoising using Wavelet Thresholding

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Abstract- *Devices which use underwater sound for communication or observation are generally mentioned to as SONAR system. Basic principle for SONAR image formation is transmission of pulse energy into water medium and subsequent reception of any returned energy reflected from objects or seabed. But during this image formation considerable amount of acoustic noise get added into sonar signals. The presence of acoustic noise distorts and degrades the accuracy of information extracted from sonar images. Thus it is very essential to eliminate or reduce noise from sonar images before using those images for various purposes. The main property of a good image denoising model is that it should completely remove noise as far as possible as well as preserve edges. Discrete Wavelet Transform(DWT) is most powerful tool in image denoising. One of the most popular method in wavelet domain is thresholding the wavelet coefficients (using the Hard threshold or the Soft threshold) as introduced by Donoho. This paper presents a review of wavelet domain denoising techniques in non-linear coefficient thresholding based methods. One of the key properties underlying the success of wavelet expansions tend to concentrate the signal energy into a relatively small number of large coeffcients. This energy compaction property of the wavelet transform makes the wavelet domain attractive for signal processing.*

Keywords –SONAR, Acoustic, DWT, Thresholding,Compaction

I. Introduction

Compared to radio waves, acoustic waves have become the most effective way in underwater wireless communication. It is because radio waves are highly reduced and spreading occurs due to high frequency. Hence, they can propagate only over very short distances. On the other hand if acoustic waves are used, long distance communication can be established[1]. However underwater wireless communication is still perplexing due to frequency band limitation and underwater channel disturbances in the form of ambient noise. The disturbance is generated by both natural (seismic, wind marine animals, rain, breaking waves etc.) andbymanmade sources (shipping, fishery, self noise of machines or ships itself etc.). The SONAR systems are used in a large spectrum of military, fishery or civil applications. This classification process issometimes very difficult, due to thepresence of the speckle. Speckle is of multiplicative nature, the use of anti-specklefilters isrequired beforethe application of a detection or classification procedure.

The rest of the paper is organized as follows. Noise Models are proposed in section II, Wavelet Transform and Wavelet Thresholding is explained in section III & IV resp. Concluding remarks are given in section IV.

II.NOISE MODELS

Noise is present in image either in additive or multiplicative form[2].

A. Additive Noise Model

Noise signal which additive in nature gets added to the original signal to generate a corrupted noisy signal and follows the following rule:

$w(x,y)=s(x,y)+n(x,y)$ (1)

where, in Equation (1)

$s(x, y)$ = original image intensity.

$n(x,y)$= noise introduced to produce the corrupted signal $w(x,y)$ at pixel location (x,y).

B. Multiplicative Noise Model

In this model, noise signal gets multiplied to the original signal. The multiplicative noise model follows [3] the following rule:

$w(x,y)=s(x,y)n(x,y)$ (2)

III WAVELET TRANSFORM

Wavelets are mathematical functions that analyze data according to scale or resolution. They aid in studying a signal in different windows or at different resolutions. The finite scale multiresolution representation of a discrete function can be called as a discrete wavelet transform [1]. DWT is a fast linear operation on a data vector**.** A set of denoising methods for additive noise act in the wavelets domain have three steps: the computation of a wavelet transform (WT), the filtering of the detail wavelet coefficients and the calculation of the corresponding inverse WT (IWT). Wavelet domain is advantageous because DWT make the signal energy focused in a smallnumber of coefficients, hence, the DWT of a noisy image consists of number of coefficientshaving high Signal to Noise Ratio(SNR) whilerelatively large number of coefficients is having shortSNR[2]. After removing the coefficients with low SNR, the image is reconstructed using inverse DWT. A first category of denoising methods applied in the wavelets domain is based on nonparametric techniques and uses the hard or the soft thresholding filters. Time and frequency localization is simultaneously provided by Wavelet transform.The sub-bands HH1, HL1, LH1, called the details Note, LL1is the low resolution component[4]. Thresholding is now applied to the detail components of these sub-bands to remove the undesirable coefficients, which contribute to noise[3]. And as a final step in the denoising algorithm, the inverse discrete wavelet transform is applied to compute back the modified image from its coefficients. It results in two level wavelet decomposition which is shown in Fig.1.

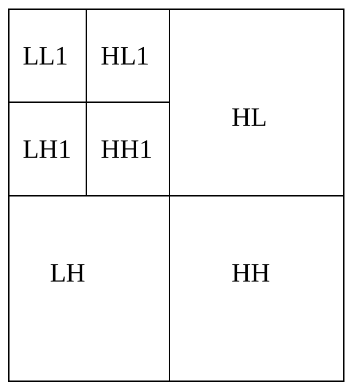

Fig.1 Two Level Wavelet Decomposition

IVWAVELET BASED THRESHOLDING

Wavelet thresholding is a signal assessment technique that exploits the abilitiesof Wavelettransform for signal denoising. It removes noise by killing coefficients that are unrelated to the data or into wavelet coefficients, likening the detail coefficients with a given threshold value, and shrinking these coefficients close to zero to eliminatethe effect of noise in the data. The choice of a threshold is an important point of interest. It plays an important role in the removal of noise in images[2]. There exist various methods for wavelet thresholding, which based on the choice of a threshold value. Some typically used methods for image noise removal include VisuShrink, SureShrink and BayesShrink[5]. Prior to the discussion of these methods, it is necessary to know about the two general class of thresholding. They are hard- thresholding and soft-thresholding[2].

A. Hard Thresholding:

The hard-thresholding T_H can be defined as in Equation (3)-

$$T_H = \begin{cases} x \, for \, |x| \geq t \\ 0 \text{ in all other regions} \end{cases} \qquad (3)$$

Thus, all coefficients whose magnitude is greater than the designated threshold value *t*remain same as they are and the others with magnitudes smaller than *t* are set to zero. It creates a region around zero where the coefficients are considered negligibleHere *t*is the threshold value. A plot of is shown in Fig.2

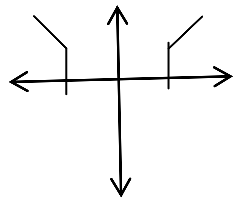
Fig.2 Hard Thresholding

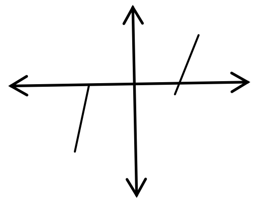
Fig.3 Soft Thresholding

B.Soft thresholding:

Soft thresholding is where the coefficients with greater than the threshold are shrunk towards zero after comparing them to a threshold value. It is defined as follows-

$$T_S = \begin{Bmatrix} sign(x)\ for\ |x| > t \\ 0 \text{ in all other regions} \end{Bmatrix} \qquad (4)$$

In practice, it can be seen that the soft method is much better and produces more visually pleasant images[7]. This is because the hard method is discontinuous and yields abrupt artifacts in the recovered images. Also, the soft method yields a smaller minimum mean squared error compared to hard form of thresholding. A plot is shown in Fig.3

Now, let focus on the methods of thresholding. For all these methods the image is first subjected to a discrete wavelet transform, which decomposes the image into various sub-bands, which is shown in Fig.(1).

1. **VisuShrink:**

VisuShrink was introduced by Donoho. It uses a threshold value tthat is proportional to the standard deviation of the noise. It follows the hard thresholding rule. It is also referred to as universal threshold and is defined in Equation (1)

$$t=\sigma\sqrt{2logn} \qquad (5)$$

σ^2=noise variance present in the signal

n = signal size or number of samples.

Disadvantage is that it cannot remove speckle noise. It can only deal with anadditive noise. VisuShrink follows the global thresholding scheme where there isa single value of threshold applied globally to all the wavelet coefficients

2.**SureShrink:**

A threshold chooser based on Stein's Unbiased Risk Estimator (SURE) was Proposed byDonoho and Johnstone [Do94] and is called as SureShrink. It is acombination of the universal threshold and the SURE threshold. This method specifies a threshold t_j value for each resolution level jin the wavelet transform which is referred to as level dependent thresholding [An01]. The goal of SureShrink is to minimize the mean
squared error. The SureShrinkthreshold t*is defined in Equation (6)

$$t^*=\min (t,\sigma\sqrt{2\log n} \qquad (6)$$

where,

t= value that minimizes Stein's Unbiased Risk Estimator

σ = noise variance

n = size of the image.

SureShrink follows the soft thresholding rule.

3. **BayesShrink:**

BayesShrink was proposed by Chang, Yu and Vetterli [Ch00]. The goal of this method is to minimize the Bayesian risk, and hence its name, BayesShrink. It uses soft thresholding and is subband-dependent, which means that thresholding is done at each band of resolution in the wavelet decomposition. Like the SureShrink procedure, it is smoothness adaptive. The Bayes threshold,t_B is defined as:

$$t_B=\frac{\sigma^2}{\sigma_s} \qquad (7)$$

Where, in Equation (7)

σ^2 = noise variance

σ_s= signal variance without noise

The noisevariance $\sigma^2$is estimated from the subband HH1.

V. CONCLUSION

This paper was presented in the particular case of SONAR images starting with the noise models and presenting in detail wavelet domain filtering methods based on thresholding techniques. Denoising of images using VisuShrink, SureShrink and BayesShrink

REFERENCES

[1] SorinMoga and AlexandruIsar,“SONAR Image Denoising Using a Bayesian Approach in the Wavelet Domain”,*Proceedings of the Romanian Academy, Series A*,Volume 7, Number 2/2006, pp.000 -000.
[2] Fu-tai wang, Jenny lee, hsiao-wen tin , shao-weileu, Chan-chuan wen, and shun-hsyungchang, “Novel fractal-wavelet technique for denoising side-scan sonarImages”,*wseas transactions on signal processing*, volume 10,2014.
[3] SaritaDangeti,“Denoising Techniques-A Comparison”,*AThesis*,Louisiana State University,May 2003.
[4] AlexandruIsar, IoanaFiroiu, Corina Nafornita1 and SorinMoga,” SONAR Images Denoising”,*Sonar System*.
[5] David L. Donoho and Iain M. Johnstone, “Adapting to Unknown Smoothness via Wavelet Shrinkage,”*Journal of American Statistical Association*, 90(432):1200-1224, December 1995.
[6] S. Grace Chang, Bin Yu and Martin Vetterli, “Adaptive Wavelet Thresholding for Image Denoising and Compression,” *IEEE Trans. ImageProcessing*, Vol 9, No. 9, Sept 2000, pg 1532-1546.
[7] David L. Donoho, “De-noising by soft-thresholding”, Department of Statistics, Stanford University, 1992.

