THE NOISE REDUCTION AND COMPRESSION OF VERY LOW FREQUENCY (VLF) TRANSIENTS USING WAVELET BASED TECHNIQUES

Abstract

Noises in the signal were generated due to various natural and manmade causes like excess use of heavy machines, spacecraft and lighting and sometimes due to volcanic eruption and earthquakes. These noises degrade the quality of observed signals and responsible for the loss of information. To retrieve the information from these noisy signals various methods based on Linear Band Pass Filter (BPF) were used, but efficiency of BPF was compromised when dealing with Non-Gaussian like natural Very Low Frequency (VLF) signals. Here, we have used wavelet thresholding based denoising method for denoising of the VLF signal. It was found that wavelet the thresholding method denoise the signal without affecting it original shape.

Keywords: VLF signal, Wavelet Transform, wavelet thresholding, Filter bank

Authors

Dr. D. K. Sondhiya
School of Sciences
SAGE University
Bhopal, India

Dr. Preeti Singh
Department of Physical Science
Rabindra Nath Tagore University
Bhopal, India

Dr. S. K. Kasde
Department of Physics
Government College Bhainsdehi
Betul, India

I. INTRODUCTION

Noise in the signal were defined as unwanted frequency content in the signal and generally considered as undesired parts of the signal, which corrupt the important information associated with the signal. Retrieval of significant information from noisy signal is an important task in signal processing. Linear Band Pass Filter (BPF) were used to perform this tasks, which is based on phase properties. The Efficiency of BPF is reduce, when the signals were non stationary in nature [1]. Alternate solution of this problem is to use Weiger filter, which focus on minimizing mean square error between signal and denoised signals [2]. Weiger filter method was not used for VLF transients due to its non-stationary nature. To denoised the VLF signal wavelet based denoising [4] and compression [5] technique were used for the VLF transient noise reduction and compression.

II. WAVELET ANALYSIS

In wavelet analysis similarity is calculated between the signal and mother wavelet $\psi(t)$ for different time intervals and results were represented in a two or a three dimensional plot.

Criterion for mother wavelet

1. It contains finite energy

$$E = \int_{-\infty}^{\infty} |\psi(t)|^2 < \infty \tag{1}$$

2. The admissibility condition

$$C_\psi = \int_0^{\infty} \frac{|\hat{f}(\omega)|^2}{f} df < \infty \tag{2}$$

Where $\hat{f}(\omega) =$ Fourier transform Condition implies that mean of the wavelet $\psi(t)$ must be equal to zero.

The Fourier transform $\psi(f)$ of complex wavelets must be real and vanish for negative frequencies.

- **Wavelet transform:** There are two types of Wavelet transform

  - **Continuous Wavelet Transform (CWT)**

The CWT of a function $f(t)$ is given by [5]:

$$Wf(x,s) = \frac{1}{\sqrt{|s|}} \int_{-\infty}^{\infty} f(t)\psi^*\left(\frac{t-x}{s}\right) dt \tag{3}$$

Where $s =$ Scale factor

To normalize the energy of VLF signals at various scales the wavelet coefficients are divided by the factor $\sqrt{|s|}$. Increasing the value of s decrease the time resolution Δt and increases the frequency resolution Δf. It is well established that $\Delta t. \Delta f$ is constant, which gives:

$$\frac{\Delta f}{f} = c \quad (4)$$

Where c is constant

The scaling parameter s and translation parameter x, known as wavelet series were used to calculate the value of CWT. The constant relative frequency resolution (Q property) of wavelet analysis was defined as a ratio of center frequency f_c and bandwidth f_b [6]. The best choice for wavelet series construct is given by:

$$Wf_{m,n} = \int_{-\infty}^{\infty} f(t)\psi_{m,n}(t)dt, \text{ with } \psi_{m,n} = s_0^{-\frac{m}{2}}\psi(s_0^{-m}t - n\tau_0) \quad (5)$$

For a dyadic grid, $s_o = 0$ and $\tau_0 = 1$. The reconstruction of the original signal is possible, only if following condition was fulfilled

$$f(t) = \sum_{m=-\infty}^{\infty}\sum_{n=-\infty}^{\infty} Wf_{m,n}\psi_{m,n}(t) \quad (6)$$

CWT provides a good frequency resolution and a good time resolution for high frequencies (small scales) and low frequencies (large scales) respectively.

Morlet wavelet function, which was obtained by Guassian (bell shaped window) were generally used for the analysis:

$$\psi(t) = g(t)e^{-j2\pi f_c t}, \quad g(t) = \sqrt{\pi f_b}\, e^{\frac{t^2}{f_b}} \quad (7)$$

Here

f_c = center frequency

f_b = bandwidth parameter

In analyzing function f_c and f_b parameters determine the number of cycles. For the Morlet wavelet

$$f = \frac{f_c}{s} \quad (8)$$

- **Discrete wavelet transform:** The orthonormal bases for discrete time series was very easy to design using filter bank. The time frequency resolution of expanded filter bank is always same as wavelet transform.

Filter banks

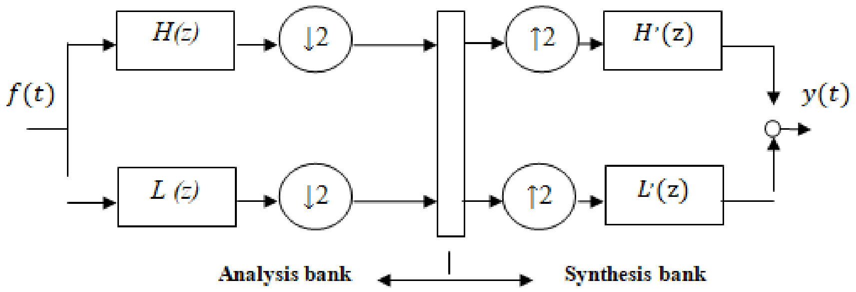


Figure 1: A filter bank of two channels

Figure 1 shows a filter bank of two channels, which is the collection of discrete filter with a common input and output. It separates the signal frequency content using low pass filter $L(z)$ and a high pass filter $H(z)$ known as sub-bands and the technique called sub-band coding. Each filter output contains equal amount of sample and half frequency contains, therefore number of output signal is double as compared to input signal. So, down sampling by factor two $(\downarrow 2)$ was applied at the output of filter bank.

Original signal is reconstructed by up-sampling the filter bank output by factor $(\uparrow 2)$ using synthesis filter bank and passes through $L^{'}(z)$ and $H^{'}(z)$ [7].

Down and up sampling: The down sampling operation is a non-invertible operation as, it saves only even numbered output components, which prevent the data loss. The loss of information should be reduced by using the Shannon sampling theorem according to this down sampling signal by a factor M constructed a signal, whose spectrum is estimated by dividing the signal into M equal bands.

$$x = \begin{bmatrix} \cdot \\ x(0) \\ x(1) \\ x(2) \\ x(3) \\ x(4) \\ \cdot \end{bmatrix} (\downarrow 2) = \begin{bmatrix} \cdot \\ x(0) \\ x(2) \\ x(4) \\ \cdot \end{bmatrix} \quad (\uparrow 2)(\downarrow 2) = \begin{bmatrix} \cdot \\ x(0) \\ 0 \\ x(2) \\ 0 \\ x(4) \\ \cdot \end{bmatrix} \qquad (9)$$

The transpose of $(\downarrow 2)$ is $(\uparrow 2)$
Hence,$(\uparrow 2)(\downarrow 2) = I$, since $(\uparrow 2)$
So it is possible to obtain an original signal.

Perfect reconstruction
Biorthogonal filter were used for perfect reconstruction of signal. For the perfect reconstruction of signal, the filter bank needs to be. Also for the perfect reconstruction of a signal, some designing criterion for preventing the aliasing and distortion should be fulfilled.

Two channel filter bank fragmented the signal into two frequency bands using the filter as illustrated in Figure 1, For perfect brick wall filter down sampling would not leads to loss of information, but is not possible to realized in practice as shown in Figure 2.

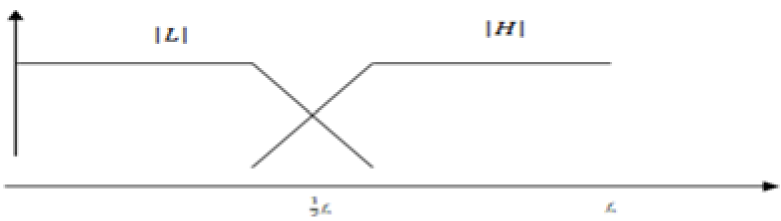


Figure 2: Phase Response of Two Channels Filter Bank

In a two channel filter bank aliasing can be reduced by using synthesis filter bank as:

$$L'(z) = H(-z) \quad (10)$$

$$H'(z) = -L(-z) \quad (11)$$

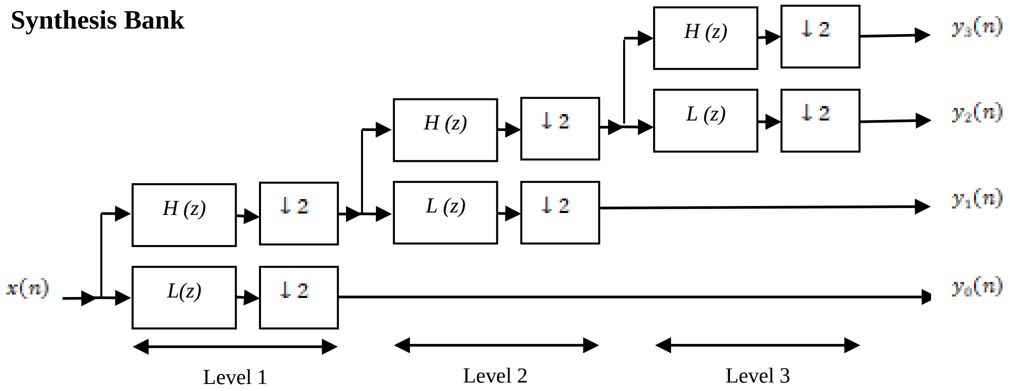
$P_0(z) = L'(z)L(z)$ is a products filter, which eliminate the distortion. Also, it is eluded if

$$H'(z)(z) - P_0(-z) = 2z^{-N} \quad (12)$$

Where N = overall delay in filter banks

Multiresolution Filter Banks

(a) Synthesis Bank



(b) Analysis Bank

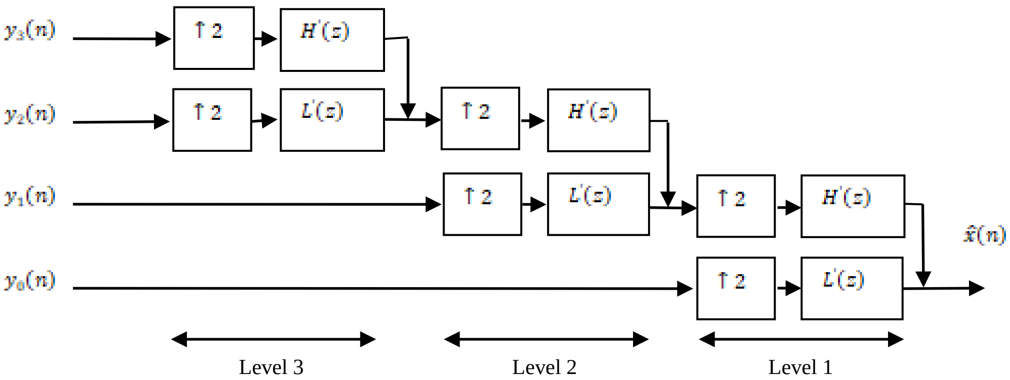


Figure 3: Three Channel Filter Bank

It is possible to obtained multiresolution of signal with the help of Discrete Wavelet Transform (DWT) at various frequency range. DWT filter bank produced a signal approximation and a details using a low and a high pass filter respectively. It is possible to find any desired level of resolution using filter bank of higher order. Figure 3 shows a three level filter bank in which coefficient $y_1(x)$ coefficient represents half lowest frequencies in $x(n)$. Also frequency resolution is double during the down sampling due to which only half numbers of samples are presents in $y_1(x)$.

Wavelet Filters

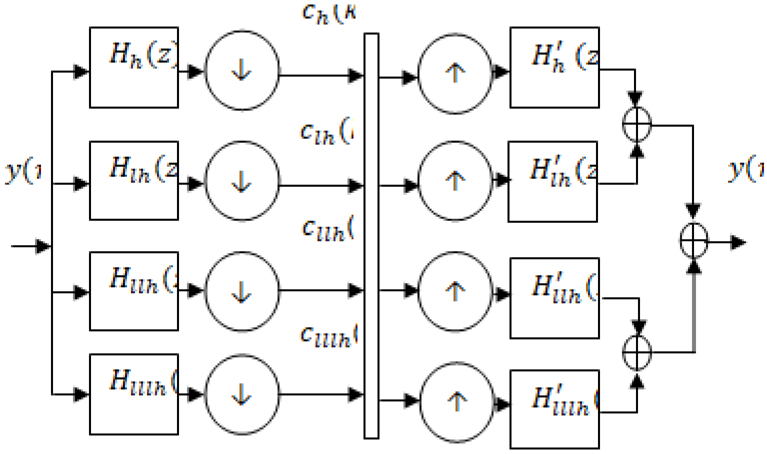


Figure 4: Equivalent of Figure 3

To compare the CWT and DWT filter bank of Figure 3 can be redrawn in Figure 4. An increase rate of down sampling provides large time scale for the lowest frequencies (or higher scale). At the higher level if impulse level of a particular filter is a stable waveform $L(z)$ and $H(z)$ are considered as wavelet filters and its subsequent scaled versions were known as regular [8]. The wavelet filter are further classified as orthogonal and biorthogonal filters. For the easiest construction of limit functions the impulse responses are calculated from the reconstruction path. Starting from the lower branch of synthesis bank (Figure 3 (c)), which consists of low-pass filters and up sampling in between. Both filters are FIR filters from the definition of Quadratic Mirror Filter (QMF). After several interaction, if impulse response converges to a final function $l(n)$ and satisfied the equation (13), then

$$\emptyset(t) = \sum_{n=0}^{N} l(n)\emptyset(2t - n) \quad (13)$$

Thus, this function is known as wavelet scaling function [9]. Similarly, it is also possible to obtain a final function for the band pass sequence by this method, except for high pass filter and this function h_c(t) is known as the wavelet $\psi(t)$:

$$\psi(t) = \sum_{n=0}^{N} h(n)\psi(2t - n) \quad (14)$$

For a wavelet c_{lll} sub band cA and cD is known as approximation and details, which contains the lowest frequencies and detail information of the signal respectively.

For a p-level decomposition, the highest approximation coefficients cA related with the sample frequency f_s can be calculated as:

$$= \frac{f_s}{2^{p+1}} \quad (15)$$

Also, the approximation cA and detail frequency bands cD can be calculated as:

$$f_{cA} = [0, \ \ 2^{-p-1} f_s] \tag{16}$$
$$= [2^{-p-1} f_{s,} \qquad 2^{-p} f_s] \tag{17}$$

Here

f_{cA} = approximation frequency band

f_{cD} = detail frequency band

The resolution of decomposition is strongly depends on a chosen wavelet filter and signal properties.

III. WAVELET BASED NOISE REDUCTION TECHNIQUES

The Wavelet decomposition of VLF transients gives a matrix, whose coefficients contains all the necessary information required for the signal reconstruction. The large coefficient have very good correlation with the input VLF transients and on the other hand small coefficient have comparably poor correlation. For signal noise reduction, it is important to choose the wavelet coefficient in order to preserve the complete shape of transients and remaining the coefficient associated with signal noise. There are two properties of wavelet transform which separate the noise coefficient from the rest are:

1. The significant choice of wavelet basis, matched with the signal characteristic.
2. The coefficient of transformation for input transients that are zero mean with uncorrelated sample (white noise). Also for Gaussian distributed transients wavelet coefficients will be Gaussian and independent.
3. For suitable basis applied to decomposed a noisy signal will produced a high degree of correlation and low degree of correlation with noise for suitable basis applied to decompose a signal.

The denoising process

- Decompose the signal using appropriate mother wavelet.
- The noise removable using suitable thresholding method.
- Signal reconstruction using inverse wavelet transform.

The noise estimation

The estimation of proper denoising level is most an important step in the noise reduction process. Generally, it is done by threshold the signal at a specified level.

If transformation coefficient were taken as a noisy observation series, then from normal decision theory, the observation $w = (w_i)_{i=1}^{n}$ were given according to:

$$w_i = \theta_i + \varepsilon z_i \qquad (i = 1, \ldots, n), \tag{18}$$

Where z_i are distributed independent and identically as $N(0,1), \varepsilon > 0$ was consider as noise level and $\theta = (\theta_i)$ is the quantity of interest.

Donoho and Jonhstone [10] estimates the value of ε as the ratio of coefficients and absolute median deviation E and 0.6745 at fine scale. If $X = \{x_i\}$ is independently and identically distributed variable then E is defined as:

$$E = \mathrm{median}|x_i - \mathrm{median}(X)| = \mathrm{median}|x_i| \tag{19}$$

As illustrated in Figure 3, the coefficients q_1 and q_2 were defined as two values of X as they bound 50% of the distribution of $X = \{x_i\}$ at center. From table of standard normal distributions $q_2 = -q_1 = 0.6745\varepsilon$. The absolute value of X will have 50% of its values bounded by $0 \leq X \leq q_2$, so that $\mathrm{median}|x_i| = q_2 = E = 0.6745\varepsilon$, or $\varepsilon = E/0.6745$.

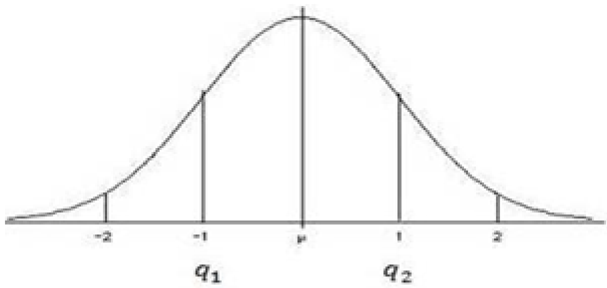


Figure 5: Normal distribution curve indicating center 50%

After determination of noise level, threshold value (T_u) is set by some constant multiple of noise standard deviation. **For Example:** (e.g., $T = m * \sigma$, where m typically lies in the interval $2 < m < 5$.

There are four methods for computation of a threshold value

1. **The universal threshold:** Leadbetter et al. [11] estimate the value of the universal threshold by statistical theorem given. Let us consider an independent and identical distribution $N(0, \varepsilon)$ of variables X_i, then as $N \to \infty$,

$$P(\max_i |X_i| \leq T_u) = 1 \tag{20}$$

Where T_u is given by

$$T_u = \sigma\sqrt{2\log(N)} \tag{21}$$

To understand the rationales for this threshold consider a VLF transient "s" as a vector of zeros, whose transformation coefficients $\left\{D_{j,t}^{(s)}\right\}$ are a part of an independent and identical distribution, Gaussian series $\{e_{j,t}\}$ with zero mean and variance σ_ε^2. If $N \to \infty$, then

$$P\left[\max\left\{\left|D_{j,t}^{(s)}\right| \le T_U\right\}\right] \equiv P[\max\{|e_{j,t}| \le T_U\}] \to 1 \quad (22)$$

Universal thresholding removes the noise therefore some time small signal coefficients are mistakenly set to zero. The value of σ_ε^2 is estimated by Median Absolute Deviation (MAD) standard deviation estimate by using coefficients in $D_1^{(s)}$ at $N/2$ level $j = 1$. so

$$\hat{\sigma}_{MAD} \equiv \frac{\text{median}\left\{\left|D_{1,0}^{(s)}\right|,\left|D_{1,1}^{(s)}\right|,\dots,\left|D_{1,\frac{N}{2}-1}^{(s)}\right|\right\}}{0.6745} \quad (23)$$

To make $\hat{\sigma}_{MAD}$ suitable estimator of standard deviation for Gaussian white noise the factor 0.6745 was rescaled. $\hat{\sigma}_{MAD}$ was estimated from the elements of $D_1^{(s)}$ because it is noise dominated with the possible exception of the largest values.

2. **Steins unbiased risk estimator (SURE) threshold:** Donoho and Johnstone [12] proposed a new method of threshold calculations known as SURE threshold based on the work of Stein [13].

3. **Hybrid threshold:** In case of signal with low energy SURE threshold (T_s) provides inaccurate results due to dominated noise, which produce inaccurate results. Therefore hybrid method threshold (T_H) is selected among (T_u) and (T_s) on the basis of significant detected signal energy.

4. **MiniMax threshold:** Donoho and Johnstone, [10] and Bruce and Gao [14] used this principal in wavelet thresholding. In this method MiniMax threshold values were tabulated as a function of sample size.

IV. WAVELET THRESHOLDING METHODS

Two different methods of thresholding are generally used in denoising problem known as hard and soft threshoding.

1. **Hard thresholding:** The non-linear hard thresholding function y_{hard} was analytically written as:

$$y_{hard} = \begin{cases} D_{j,t}^{(s)} & \left|D_{j,t}^{(s)}\right| > thr \quad thr \ge 0 \\ 0 & \left|D_{j,t}^{(s)}\right| \le \text{thr} \end{cases} \quad (24)$$

here "thr" is the threshold estimated by user [15]. It retained all the coefficient above the threshold value and set all other to zero. Main disadvantage of this method that it removes all fine details below threshold level and produce fictitious oscillations.

2. **Soft thresholding:** The non-linear hard thresholding function known as soft thresholding or "wavelet shrinkage" y_{soft} is defined as:

$$y_{soft} = \begin{cases} \mathrm{sign}\left(dD_{j,t}^{(s)}\right).\left(\left|dD_{j,t}^{(s)}\right| - \mathrm{thr}\right) & \left|D_{j,t}^{(s)}\right| > thr, thr \geq 0 \\ 0 & \left|D_{j,t}^{(s)}\right| \leq \mathrm{thr} \end{cases} \quad (25)$$

In soft thresholding method all the coefficient, whose coefficient is smaller than y_{soft} were set to zero and magnitude f remaining coefficient were modified as per threshold value [10].

Translational invariant denoising: Wavelet denoising with DWT can occasionally produce artefacts generated due to bad alignment of signal discontinuity with wavelet [15]. Cycle Spinning (CS) denoising algorithm based on wavelet denoising technique was proposed by Coifman and Donoho [15] to get rid of these difficulties. CS algorithm was designed to suppress artefacts around the discontinuities introduced by DWT. Data is shifted for a variety of delays and its DWT is computed as a result the outcome is unshifted. In order to create a quasi-shift-invariant DWT, this process is repeated for a variety of shifts, and the results are averaged. The number of shifts that this transform produces in the input signal directly relates to how redundant it is. In terms of all circular shifts of the input signal, CS and a translation-invariant WT are equal.

Let us consider s(i) and s(i-p) represents the original and threshold signal respectively, then:

$$s_B^p(\alpha) = \langle s(n-p), g_\alpha(n)\rangle = \langle s(n), g_\alpha(n+p)\rangle \quad (26)$$

The vectors $g_\alpha(n+p)$ are not in the basis $B = \{g_\alpha\}_{\alpha\in A}$. It yields an estimate $\widehat{u^p}$ for every translated version s^p of the original signal:

$$\widehat{u^p} = Ds^p = \sum_{\alpha\in A} a^p(\alpha) s_B^p(\alpha) g_\alpha \quad (27)$$

□

CS based Translation Invariant Wavelet Thresholding (**TIWT**) was achieved by averaging these estimations after translated in inverse sense:

$$\mathrm{TIWT}(s) = \frac{1}{|I|}\sum_{p\in I} \hat{u}^p(i+p) \quad (28)$$

V. DATA

Source: VLF whistlers and hiss transients signals were taken from French Micro satellite DEMETER during 2004-2010 for the mid latitude.

VI. WAVELET BASED NOISE REDUCTION

1. **DWT and universal thresholding:** The observed VLF signal consists of VLF transients with some type of atmospheric noises analytically written

$$s = x + \varepsilon \quad (29)$$

Where x is a VLF transient and ε represents independent and identically distributed (i.i.d) vector of dimension N (Gaussian noise).

For the purpose of denoising via thresholding Dohono and Johonstone, [10] recommended computation of partial DWT of level J_0 giving coefficient vectors $cD_1^{(s)}, \ldots, cD_{J_0}^{(s)}$ and $cA_{J_0}^{(s)}$. We have:

$$cD_{j,t}^{(s)} = d_{j,t} + e_{j,t} \qquad j = 1, \ldots, j_0; \quad t = 0, \ldots, N_j - 1 \qquad (30)$$

In thresholding process the coefficients of vector $cD_k^{(s)}$ are subject to change, but the coefficient of $c\,A_{J_0}^{(s)}$ were remain unchanged therefore the portion of s is automatically assign to signal X. After that threshold method must be selected and chosen thresholding rule were apply on $cD_{j,t}^{(s)}$ $j = 1, \ldots, J_0$ and $t = 0, \ldots, N_j - 1,$ to obtained the threshold coefficient $\{\widehat{cD}_{j,t}^{(s)}\}$ to form $\widehat{cD}_j^{(s)}, j = 1, \ldots, J_o$. D is estimated as $\hat{X}$ obtained by inverse transformation of $\widehat{cD}_1^{(s)}, \ldots, \widehat{cD}_{J_0}^{(s)}$ and $\widehat{cA}_{J_0}^{(s)}$.

VII. DENOISING ALGORITHM

Algorithm for signal denoising was illustrated in Figure 9.

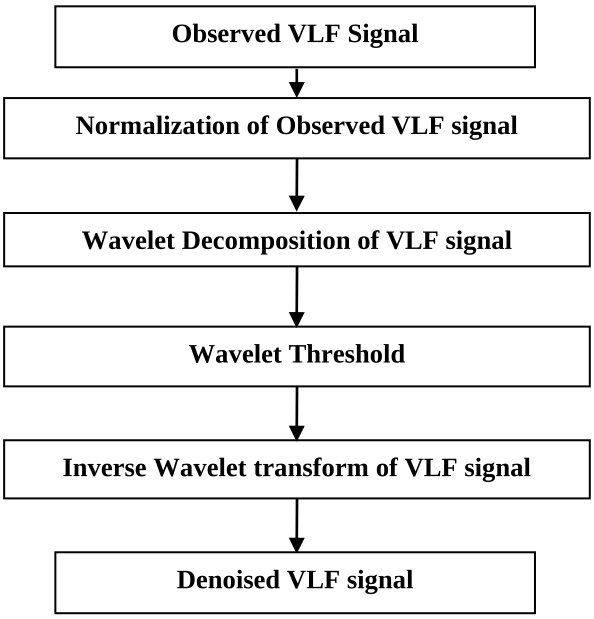


Figure 6: Denoising Algorithm Using Wavelet Thresholding

1. **Noise normalizing:** For Scaling of the input $N(0,1)$ noise is produced with the help of avelab.700 toolbox [16].

2. **Segmenting the VLF transients:** Segmentation the data into blocks prior to processing provides the opportunity to handle a large amount of stored data and allow the extension

of technique. In our case, the Sampling frequency of VLF signal recorded by DEMETER satellite was 40 kHz, hence 32768 sample approximately represents 0.81 sec of VLF signal.

3. **Signal decomposition:** Selection of a proper wavelet basis plays an important role in in overall performance of algorithm, but unfortunately there is no precise method to choose a proper wavelet basis. Primarily, it is done by comparison of results using various wavelet basis.

4. **Thresholding:** Soft thresholding with the modified universal threshold value T_u and level dependent the thresholding were used in this work.

5. **Reconstruction:** Segment of each denoised signal is transformed back to the signal domain where it is weighed and overlapped to allow for smooth reconstruction.

VIII. PERFORMANCE ANALYSIS OF PROPOSED DENOISING ALGORITHM BASED ON WAVELET THRESHOLDING

In proposed noise reduction algorithm Quadratic Mirror Filters (QMF) are used to smooth the signal observed at the normalization stage. In the next stage, transients were decomposed in various sub-bands using “Morlet” wavelet function with level of decomposition 5.

The value of threshold is estimated by modified universal threshold function given in equation (21). Finally, the estimated value is used with the soft thresholding method to reconstruct the signal. The waveform of transients observed with their denoised version is demonstrated in Figure 7 and Figure 8 upper and lower panel respectively shows observed and denoised signals.

SNR and crest factor (C.F) were used to test the performance of algorithm. The result is summarized in a Table 1 and Tables 2.

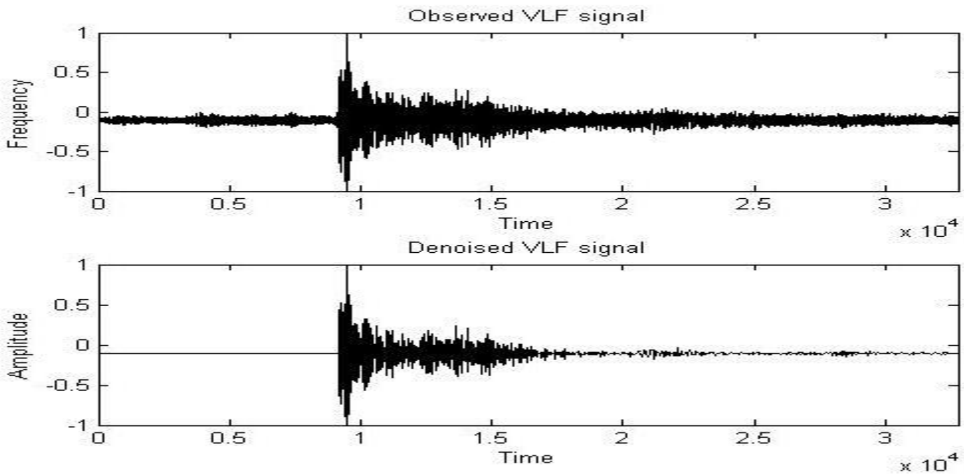


Figure 7: Observed and Denoised VLF Whistler Signal

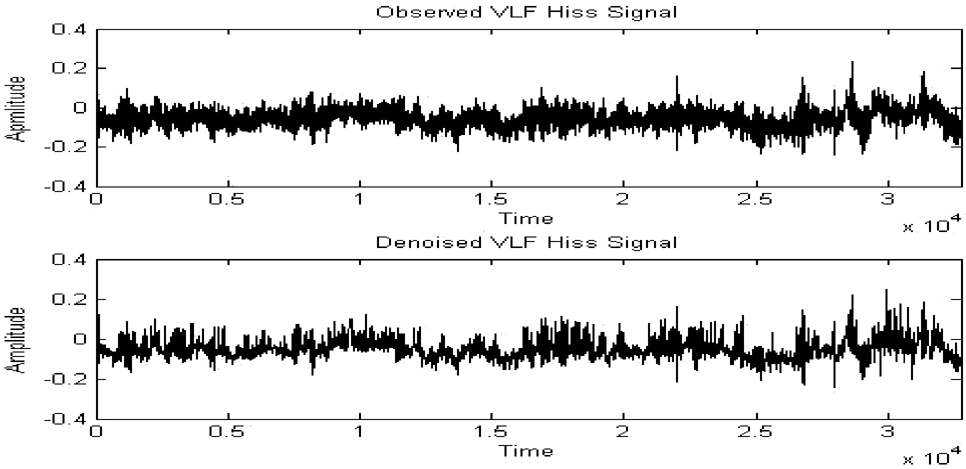


Figure 8: Observed and Denoised VLF Hiss Signal

Signal to Noise Ratio (SNR): SNR is defined as a ratio of signal power to noise and analytically, it is given by:

$$SNR = 10\log_{10}\left(\frac{P_{signal}}{P_{noise}}\right) = P_{signal} - P_{Noise}(\text{indb}) \qquad (31)$$

If post SNR is higher than the pre SNR the denoising is considered to be successful [17].

Crest Factor (CF): It is defined as [18]:

$$CF = \frac{|x|_{peak}}{x_{rms}} \qquad (32)$$

Where $|x|_{peak}$ = amplitude of waveform

x_{rms} = RMS value of waveform

Table 1: Performance for VLF Whistlers

Signal	SNR (in db)	Creast Factor
Observed	12.89	9.21
Denoised	13.73	9.23

Table 2: Performance for VLF Hiss

Signal	SNR (in db)	Creast Factor
Observed	23.56	4.35
Denoised	26.00	4.21

Visual analysis: For visual inspection of observed and denoised VLF whistlers and hiss signal spectrogram were used which is illustrated in Figure 9 and Figure 10.

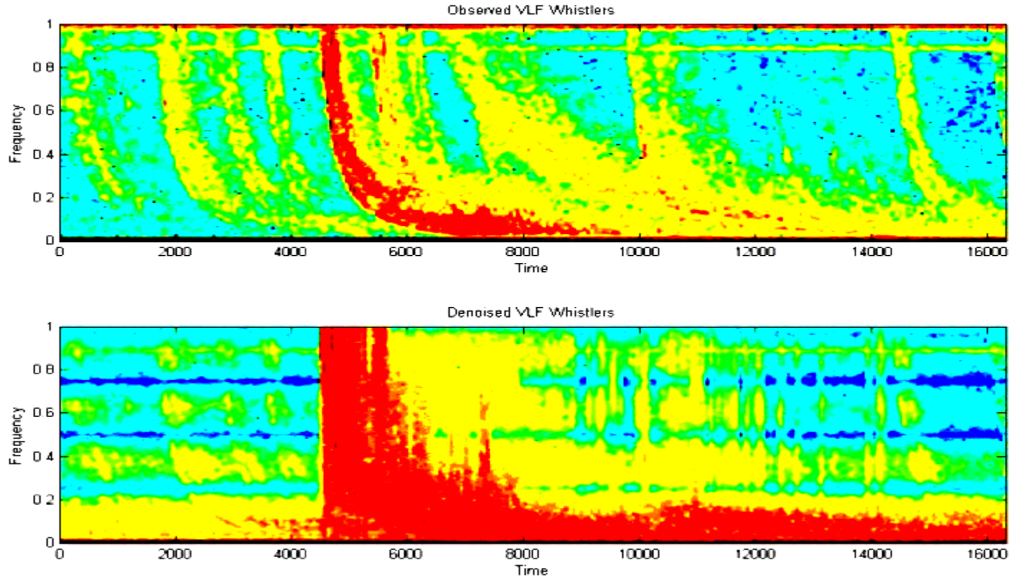


Figure 9: Spectogram of VLF Whistler

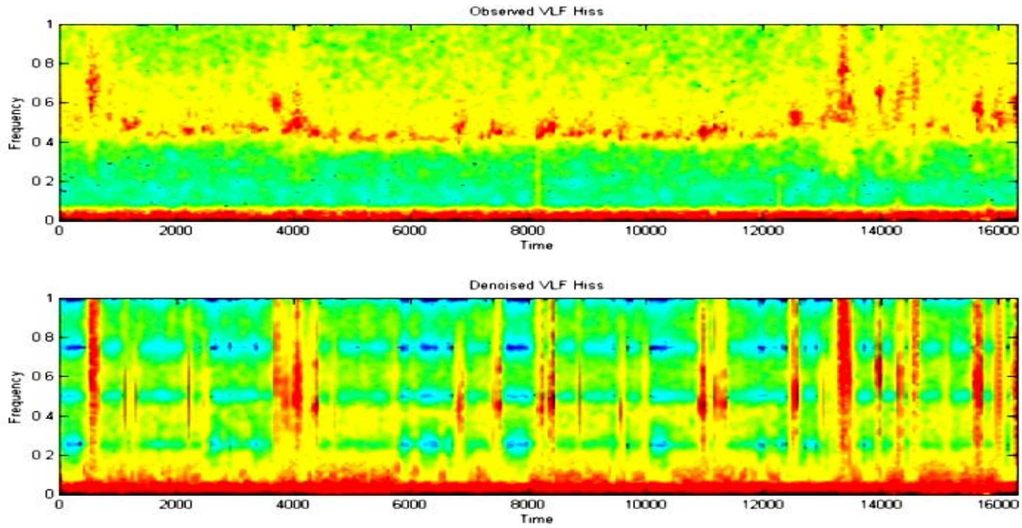


Figure 10: Spectogram of VLF Hiss

IX. NOISE REDUCTION WITH WAVELET BASED COMPRESSION TECHNIQUE

Natarajan [19] proposed a method for additive noise removal from the signal. The advantage of this method is that it does not required any information of observed signal and its frequency content. Further Natarajan [20] used piecewise linear compression technique for reduction of noise in the signal. Many researcher used compression technique in denoising processing e.g. seismic data compression [21], Kiely and Stromberg et al., use sub band coding [22] and Low bit-rate compression method for seismic data [23] and atmospheric data compression [24]. Various data compression techniques based on wavelet transform have been used for scientific data, compression and noise reduction [26]-[33].

Level Dependent Thresholding

It is characterized by the three parameters (Birge-Massart strategy);
J = level of decomposition,
M = length of coefficients coarsest approximation
α = always real and greater than 1 [34].

The strategy is such that:

1. At level $J_0 + 1$ all is kept.
2. The absolute value of larger coefficient n_J for level J from 1 to J_0 is given by:

$$n_J = \frac{m}{(J_0 + 1 - J)^\alpha} \tag{33}$$

The suggested value for α is 1

Let us consider L represents the length of coarsest approximation coefficients for the VLF transients. On the basis of value of L three different choices scarce high, medium and low are proposed for M for which M=L, M = 1.5*L and M = 2*L respectively.

X. NOISE REDUCTION AND COMPRESSION USING BY-LEVEL WAVELET THRESHOLDING

The process used for signal compression is depicted in Figure 11. It involves three steps:

1. Wavelet Decomposition
2. Thresholding the detail coefficient
3. Reconstruction

The waveform of VLF whistler and were shown in Figure 12 and Figure 13.

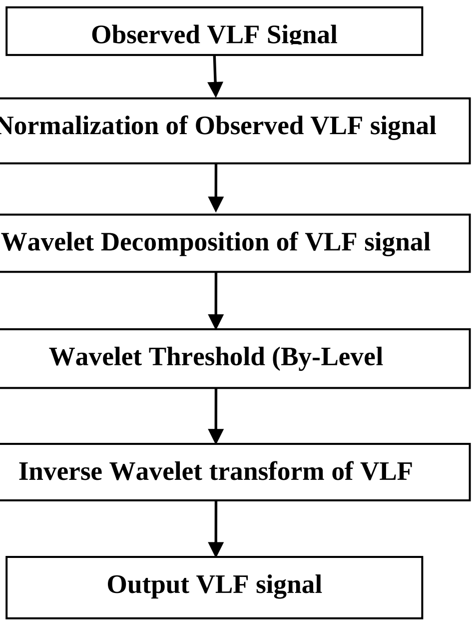


Figure 11: VLF Signal Noise Reduction and Compression

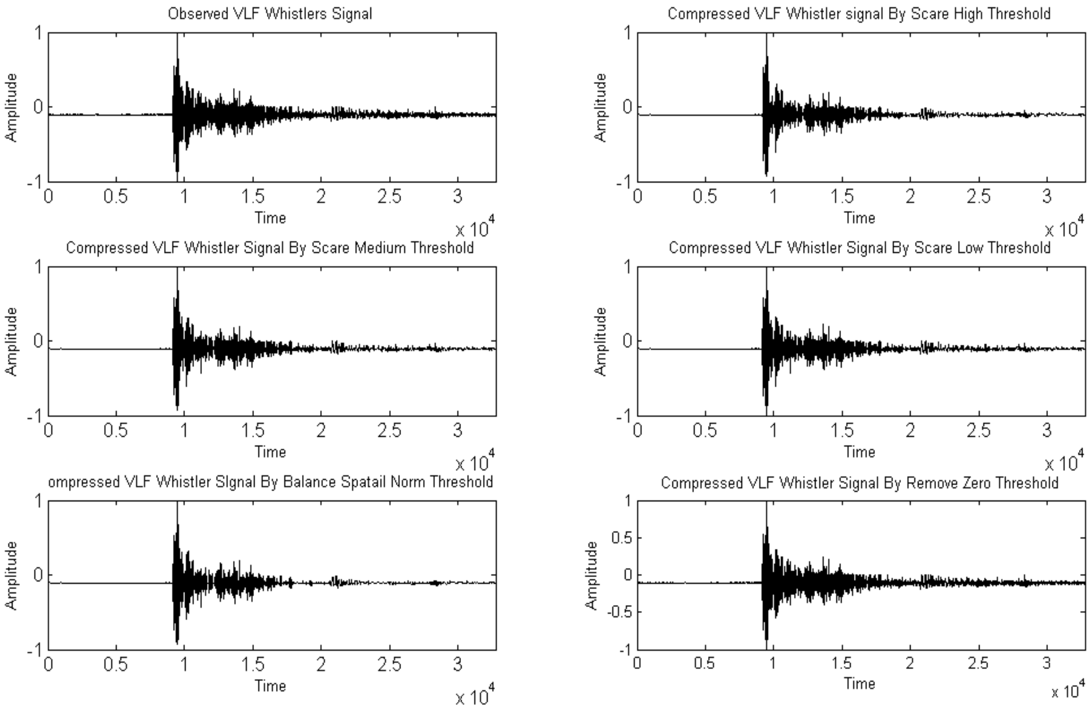


Figure 12: Observed and Compressed VLF Whistlers signal

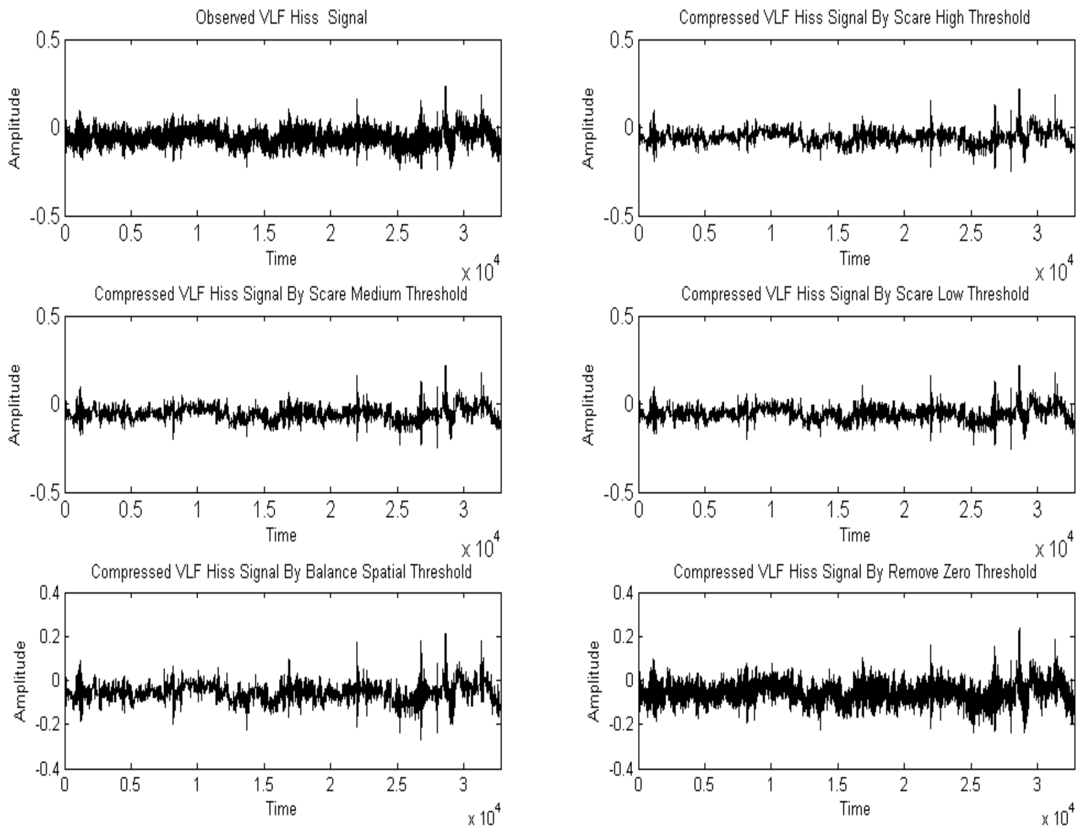


Figure 13: Observed and Compressed VLF Hiss Signal

During analysis, we have tested various denoising methods such as Scare Low (SL), Scare Medium (SM), Scare high (SH), Near Zero (NZ) and Balance Spatial Norm (BSN) method. Each method produced different results for some size of signals.

XI. PERFORMANCE ANALYSIS OF PROPOSED NOISE REDUCTION ALGORITHM BASED ON LEVEL THRESHOLDING

To test the performance of proposed algorithm SNR and CF were calculated and results were summarized in Table 3 and Table 4.

Table 3: Performance of Level dependent Thresholding for VLF Whistlers signal

Signal	Thresholding Method	SNR	CF
Observed	-	13.42	13.14
Reconstructed	SL	16.03	15.14
Reconstructed	SM	15.55	14.16
Reconstructed	SH	15.35	14.25
Reconstructed	NZ	14.79	13.56
Reconstructed	BSN	13.43	13.01

Table 4: Performance of Level dependent Thresholding for VLF Hiss signal

Signal	Thresholding Method	SNR	CF
Observed	-	25.39	5.27
Compressed	SL	25.99	5.24
Compressed	SM	25.90	5.22
Compressed	SH	25.80	5.27
Compressed	NZ	2.04	5.12
Compressed	BSN	25.13	5.11

An enhanced SNR value indicate the enhancement quality of signal. The value of C.F. is approximately same in most of the cases.

XII. CONCLUSION

In this chapter two different methods were proposed for denoising of VLF signal, which is based on wavelet thresholding. For this purpose soft thresholding is used. To maintain the stability of a representation translation invariant denoising is used in this work. Proposed denoising algorithm is depends on resolution, hence to increase the resolution level chosen threshold function must be changed. The algorithm is particularly more important, when signal contains the same variation pattern like VLF Hiss. It also provides more detail picture of Whistlers transients. It was concluded that wavelet based methods were efficient for denoising of VLF transients.

REFERENCES

[1] S. Umbaugh, "Computer Vision and Image Processing," Prentice Hall, PTR, New Jersey, 1998.
[2] K. Toyamu, K. Krumm, B. Brumitt and B. Meyers, "Wallflower: Principles and practice of background maintenance", Computer vision, The proceeding of seventh IEEE international conference, 1999.
[3] D.L. Donoho, " Denoising by Soft Thresholding", Technical Report no. 409, University, December 1992.
[4] J. Karam and R. Saad, "The Effect of Different Compression Schemes on Speech Signals", International Journal of Biological and Life Sciences 1:4, 2005.
[5] S.G. Mallat and W.L. Hwang, "Singularity Detection and Processing with Wavelets", IEEE Transactions on Information Theory, vol. 38, 1992, pp. 617–643.
[6] M.G.E. Schneiders, "Wavelets in control engineering", Master's thesis, Eindhoven University of Technology, 2001.
[7] G. Strang and T. Hguyen. "Wavelets and Filter Banks", Wellesley-Cambridge Press, second edition, 1997.
[8] I. Daubechies, "Ten lectures on wavelets", Society for industrial and Applied Mathematics , PA, 1992.
[9] P.S. Addison, "The Illustrated Wavelet Transform Handbook", IOP Publishing Ltd, 2002.
[10] D. Donoho and I. Jonhstone, "Ideal Spatial Adaptation by Wavelet Shrinkage", Biometrika, Journal of the American Statistical Association, Vol. 81, issue 3, 1994, pp.425-455.
[11] M. Leadbetter, G. Lindgren and H. Rootzen, "Extremes and Related properties of random sequences and Process", Speinger-verlag, New York, 1983.
[12] D. Donoho and I. Johnstonne, "Adapting to Unknown Smoothness via Wavelet Shrinkage", Vol. 90, 1200-1244, 1995.
[13] C. Stein, "Estimation of the Mean of a Multivariate Normal Distribution", Annals of Statistics, vol. 9, 1981, pp. 1135-1151.
[14] A. Bruce, H. Gao and Waveshrink, "Shrinkage Functions and thresholds", Technical Report, Statsci Division of Mathsoft, Inc, 1995.
[15] R. Coifman and D. Donoho, "Translational-Invariant Denoising", Internal Report, Department of Statistics, Stanford University, 1995.
[16] C.S. Buckheit, D. Donoho and J. Scargle, "Wavelab.700", http://www.wavelab/playfair.stanford.edu, 1996.
[17] S. Mallat, "A Wavelet Tour of Signal Processing: The Sparse Way", Academic Press, 2008.
[18] P.D. Hill, B.W.V Lee, J.S. Osborne, E.L. Osman, "Palatal snoring identified by acoustic crest factor analysis", PHYSL MEAS, vol. 20, issue 2, 1999, pp. 167-174.
[19] B.K. Natarajan, "Filtering random noise via data compression", Proceeding IEEE Data Compression Conf., Snowbird, Utah, 1993, pp. 60-69.
[20] B.K. Natarajan, "A General Technique for Filtering Random Noise", Computer Systems Laboratory, 1994.
[21] B.P. Jefryes, "Data compression for Seismic Signal data" United States patent, patent number 593370. 3,1999.
[22] A. Kiely and F. Pollara, "Subband Coding Methods for Seismic Data Compression", DCC, 1995.
[23] J.O. Stromberg, R. Coifman, A. Vassiliou, A.Z. Averbuch and F. Meyer, "Low bit-rate efficient compression for seismic data", IEEE transactions on image processing, vol. 10, issue 12, 2001, pp. 1801-1814.
[24] Z. Huang, "3D Laser holographic interferometry measurements", Phd thesis, The University of Michigan, 2006

[25] P. Hedström and J. Arbring, and J.M. Johansson, "Data Compression using Time-Frequency masking for TDOA localization of Radio Transmitters" RF Measurement Technology Conference, Gävle, Sweden, 2011.

[26] J. Chen, S. Itoh and T. Hashimoto, "ECG data compression by using wavelet transform" IEICE Trans. Inform. Syst. Vol. E76-D, issue 12, 1993, pp.1454–1461.

[27] Y. Xu, J.B. Weaver, M. Denni, J. Healy and L.U. Jian, "Wavelet Transform Domain Filters: A Spatially Selective Noise Filtration Technique", IEEE Transactions on Image processing, vol. 3, 1994.

[28] Y.K. Sun, "Wavelet Transform and its Applications", China Machine Press, Beijing, 1998, pp. 219-244. (in Chinese).

[29] B.A. Rajoub, An efficient coding algorithm for the compression of ECG signals using the wavelet transform. IEEE Transactions on Biomedical Engineering, vol. 49, issue 4, 2002, pp. 355–362.

[30] I.B. Ciocoiu, "ECG Signal Compression Using 2D Wavelet Foveation", International Journal of Advanced Science and Technology, Vol. 13, 2009.

[31] S. Sunjay "High Performance Computation by Graphics Processor Unit Technology for Geophysical Seismic Signal Processing", Search and Discovery Article, 4072, 2011.

[32] J. Jing, M. Lidong, J. Shijin, J. Lin, "A Signal Denoise Algorithm based on Wavelet transform" American Journal of Engineering and Technology Research, vol. 11, issue 9, 2011.

[33] J. Karam, "A Global Threshold Wavelet-Based Scheme for Speech Recognition", Third International conference on Computer Science, Software Engineering Information Technology, E-Business and Applications, Cairo, Egypt, Dec. 27-29, 2004.

[34] J. Karam and R. Saad, "The Effect of Different Compression Schemes on Speech Signals", Inter-national Journal of Biomedical Sciences, vol. 1, issue 4, 2006, pp. 230-234.