GEOSCIENCES

journal homepage: www.gsjournal.ir

Pervasive white and colored noise removing from magnetotelluric time series

Hanieh Mardomi[1], Mir Sattar Meshinchi Asl[*2], Hamid Reza Siahkoohi[3] & Max Moorkamp[4]

[1]*Ph.D. Student, Science and Research Branch, Islamic Azad University, Tehran, Iran*

[2]*Assistant Professor, Science and Research Branch, Islamic Azad University, Tehran, Iran*

[3]*Professor, Tehran University, Iran*

[4]*Leicester University, U. K.*

ARTICLE INFO

Received: 2017 May 28

Accepted: 2017 December 09

Available online: 2018 March 17

Keywords:
Wavelets
Magnetotelluric
Time series
Denoising

**Corresponding author:*
M. S. Meshinchi Asl
E-mail: m_meshin@yahoo.com

ABSTRACT

Magnetotellurics is an exploration method which is based on measurement of natural electric and magnetic fields of the Earth and is increasingly used in geological applications, petroleum industry, geothermal sources detection and crust and lithosphere studies. In this work, discrete wavelet transform of magnetotelluric signals was performed. Discrete wavelet transform decomposes signals into coefficients in multi-scales. Noise and signal portions are separable in multi-scale mode. Therefore, noise can be discarded in each scale; a threshold value is constructed dependent to coefficients of the scale then, the noise coefficients are discarded by thresholding the coefficients with the proper values. Proportional threshold values can be used to remove white and ۱/f noise from time series. After that, a new signal is constructed using clean coefficients. This method is widely used in various fields of sciences from image processing to seismic studies. This work tried to show the effectiveness of this technique in decreasing pervasive noise from magnetotelluric signals. The results emphasized the advantageous effect of wavelet techniques in magnetotelluric data noise removing process.

1- Introduction

Magnetotelluric field is a specific electromagnetic field which satisfies the impedance relation, E = ZB, under some general conditions of MT studies such as nearly vertical external electromagnetic sources, Ohmic earth assumption, quasi-static electric displacement currents and negligible electric permittivity and magnetic permiability (Simpsone and Bahr, 2005; Chave and Jones, 2012) and also noise free data. In the impedance relation, E and B are orthogonal electric and magnetic fields measured on surface of the Earth and Z is a 2×2 response tensor. This is a traditional linear relation and least squares had been a standard solution of it however, linear relation seems inadequate for MT model definition because of the finite size of the data sample and the presence of noise. Moreover, least squares is shown to be corrupted at the presence of noise as if bias, erratic variability and unreliable error estimates are commonly shown (Chave, 2016; Goubau et al., 1978; Gamble et al., 1979). The more precise the data, the more reliable the impedance estimation. There are some tactics that provide better selection of the data samples within the processing sequence which modify the data by identifying the problematic data and providing better manual selection of data including remote reference and robust estimators. Robust estimators are being introduced (Egbert and Booker, 1986; Chave et al., 1987) to provide these improvements and became the standard approach. Consequently, bounded influence estimator (Chave and Thomson, 2004), robust remote reference (Chave and Thomson, 1989) and the multi-site principle approach introduced by Egbert (1997, 2002) are introduced which are extensions to standard robust estimators.

In addition to the above standard tools, wavelet processing techniques seem helpful means for MT data processing as they have been used widely in other disciplines of signal processing. They also have been used in MT data processing;

Zhang and Paulson (1997) proposed a new method for the estimation of impedance tensor in noisy environments using wavelet transforms. Trad and Travassos (2000) proposed a weighted thresholding method to remove outliers and leverage points from MT data and Garcia and Jones (2008) used a robust wavelet processing method for coherence thresholding of high power segments of AMT dead band data. The studies investigated positional noise while this work focuses on pervasive noise in MT time series. They are based on rejection or down weighting the contaminated segments of data while this approach tries to alleviate noise samples.

2- Magnetotellurics

The magnetotelluric method as a passive electromagnetic exploration method is a technique for imaging the Earth. It is based on measuring fluctuations of the natural electric and magnetic fields on surface of the Earth and relating them using an impedance function by which, conductivity structure of the Earth can be determined. Apparent resistivity and impedance phase are possible to be extracted from the principal relation (E=ZB). Impedance phase is given by $\varphi = \tan^{-1}(\frac{\mathrm{Im}(Z)}{Real(Z)})$ and apparent resistivity of a homogeneous half space by $\rho = \frac{1}{\mu_0 \omega}|z(\omega)|^2$.

Electromagnetic fields that are naturally induced in the Earth and are used for magnetotelluric studies can penetrate to possible depths in the range of ~160 m to >500 km. Therefore, broad span of depths can be imaged using the MT method compared to other methods.

3- MT data

Synthetic MT data used in this work was generated by fundamental assumptions of MT and Cauchy distribution assumption of the data (Chave, 2014) for a uniform half space. Input time series were generated as random time series with the identified distribution, and then output channels were generated using the impedance relation (Egbert, 1992).

4- Noise types

Common problems with MT data are;

- instrumental noise; temporary sensor problem or saturation on AD converter
- terrain noise or geological noise.
- disturbance field EM noise; non-plane wave assumption in high latitudes and solar activity.
- cultural noise; various electromagnetic sources such as pipelines, power lines etc.,
- disturbances by human or animals moving in the vicinity of the instrument.

All noise types can affect the signal with local or pervasive effect. Local noise is easier to deal with as most of the algorithms reject or discard contaminated sections but in pervasive noise case, more progressive algorithms are required. Noise of any type must be recognized and eliminated with proper solutions.

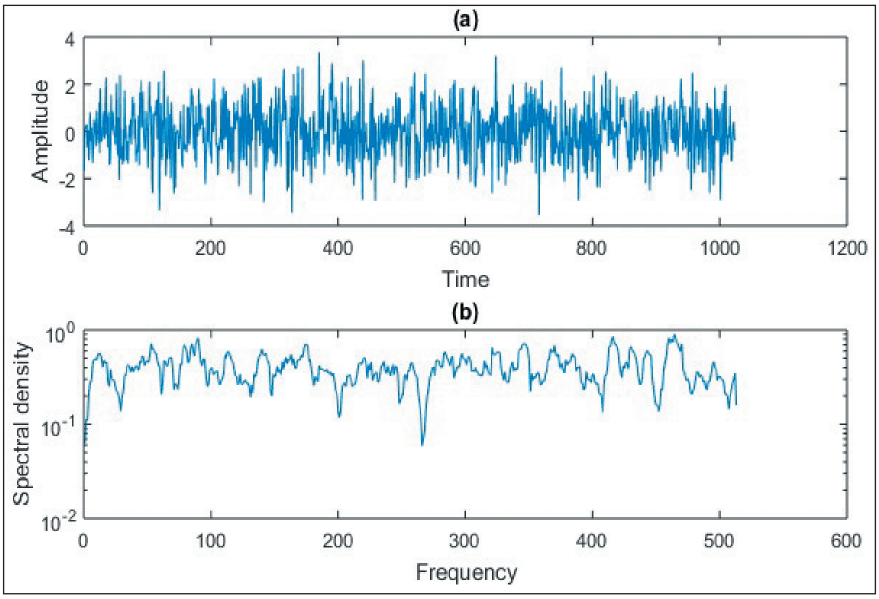

Fig. 1- a) White noise time series; b) flat power spectrum of it, which was predicted to be flat.

5- Noise from statistical concept

5- 1. White noise

White or back ground noise is a random signal with flat power spectrum and equally distributed power in each center frequency. Figure 1 shows a white noise time series and the power spectrum of it. As can be seen from the figure, the time series has a flat power spectrum. Gaussian white noise includes multiple frequencies and would be a good approximation of many real world processes providing arranged mathematical models. Gaussian distribution is defines as

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}} \quad (1)$$

where μ is mean and σ is standard deviation.

5- 2. 1/f noise

1/f noise (Chave and Jones, 2012) is a signal generated in electronic devices due to DC current. Ohm's law (V=IR) causes resistivity fluctuations transform to current or voltage fluctuations shown up as a frequency phenomena. 1/f noise is dominant at low frequencies. Corner 1/f frequency is where 1/f and background noise coincide. Figure 2 shows a 1/f noise time series and it's power spectrum. As shown in the figure, power of the signal is dominant in lower frequencies.

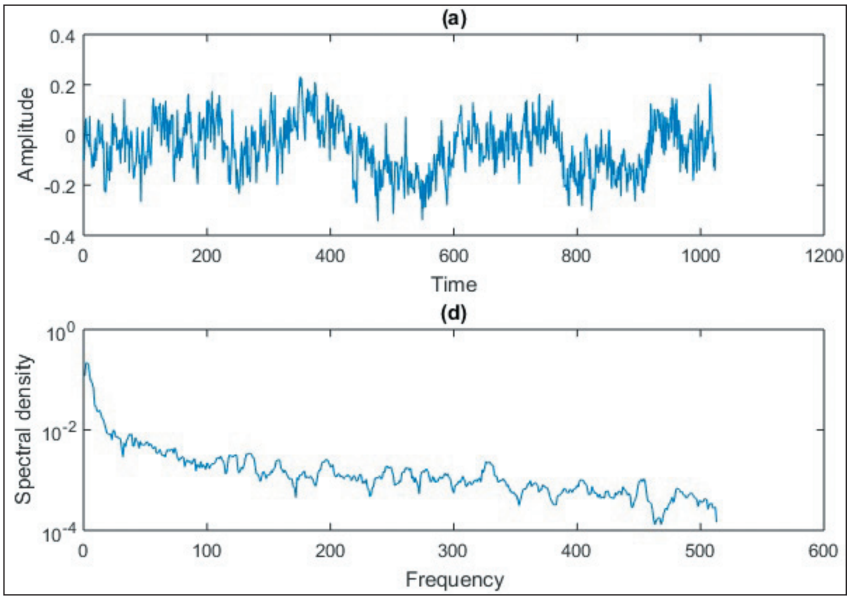

Fig. 2- a) Colored noise time series; b) its power spectrum.

6- Discrete wavelet transform

Wavelet transforms facilitate locating places of concern by translation, and analyze the signal at different levels by scaling. Consequently, the signal is decomposed to wavelet coefficients at multiple levels categorized from higher to lower frequencies from finest to coarsest levels, respectively. Wavelet transform of a signal decomposes the signal into two parts; Approximate and detail. The approximate part is used as a new signal for decomposition to the next level and the detail parts are being processed, for instance the denoising procedure is performed on this parts of data.

For this purpose filter functions are required that comprise high and low pass filters.

Each wavelet comprise a specific wavelet function and a scaling function for calculation of high pass and low pass filter coefficients. For instance, Daubechies4 wavelet contains four coefficients of high and low pass filters as:

$h_0 = \frac{1+\sqrt{3}}{4\sqrt{2}}, h_1 = \frac{3+\sqrt{3}}{4\sqrt{2}}, h_2 = \frac{3-\sqrt{3}}{4\sqrt{2}}, h_3 = \frac{1-\sqrt{3}}{4\sqrt{2}}$ and $g_0 = h_3, g_1 = -h_2,$ $g_2 = h_1, g_3 = -h_0$

The decomposition algorithm is as the below equations,

$$y(high)[n] = (x*h)[n] = \sum_{k=-\infty}^{k=+\infty} x[k]h[2n-k] \quad (2)$$

$$y(low)[n] = (x*g)[n] = \sum_{k=-\infty}^{k=+\infty} x[k]g[2n-k] \quad (3)$$

where x is signal, and h and g are high and low pass filters. The resulted data are detail (from high-pass filter) and approximation coefficients (from the low-pass filter) (Soman et al., 2010, Mallat, 2008). Figure 3 shows the flowchart of the process.

Figure 4 represents a schematic signal and discrete wavelet transform of it. As can be seen from the figure,

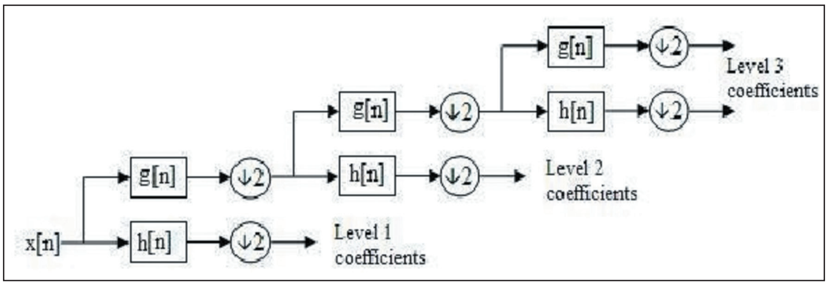

Fig. 3- Flowchart of DWT process

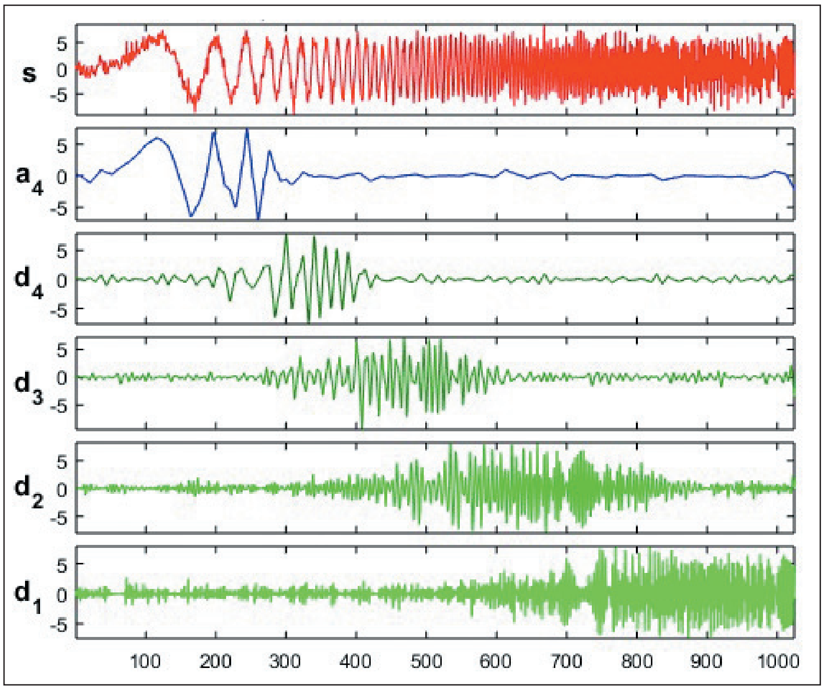

Fig. 4- Discrete wavelet transform of a schematic signal

signal is decomposed into various scales; approximate and detail parts.

7- Processing

While the data transformed to wavelet coefficients in various scales, denoising step is performed. At fist a threshold value must be adopted; there are several available options which some of them are briefly reviewed.

There are some rules proposed for constructing a threshold value (Donoho and Johnstone, 1995), some of the available options are briefly reviewed.

Universal threshold (λ) is calculated as:

$$\lambda = \sigma\sqrt{2\log n} \quad (4)$$

where σ^2 defines noise variance which could be estimated by the data.

8- Stein's Unbiased Risk Estimation (Sure)

The threshold value was obtained by minimizing risk estimation of each possible thresholding choice performed by soft thresholding with respect to λ over a range of $\left[0, \sigma\sqrt{2\log n}\right]$ (Donoho and Johnstone, 1995; Stein, 1981).

$$\lambda_j^s = \arg\min_{\lambda>0}\left[SURE^S(\lambda, d_j)\right] \quad (5)$$

d_j represents detail coefficients at level j and $SURE^S(\lambda, d_j)$ is Stein's unbiased estimator of threshold function risk. Using soft threshold function (T_λ^{soft}) with SURE criteria would result in:

$$SURE^S(\lambda, d_j) = N_j - 2\sum_{k=1}^{N_j}(|d_k| \le \lambda) + \sum_{k=1}^{N_j} \min(|d_k|.\lambda)^2 \quad (6)$$

N_j is the number of coefficients at level j.

While the threshold value is chosen, wavelet coefficients are adjusted according to hard or soft thresholding rules. The rules suppress the wavelet coefficients as follows (Donoho and Johnstone, 1994),

Hard thresholding: if the absolute value of a wavelet coefficient is greater than a threshold value, the coefficient is not changed and the other ones are set to be zero.

$$\delta_\lambda^{Hard} = \begin{cases} x & |x| \geq \lambda \\ 0 & otherwise \end{cases} \quad (7)$$

Soft thresholding: if the absolute value of a wavelet coefficient is less than a threshold value, the coefficient is set to be zero. For the coefficients that are greater than the threshold value, the threshold value is subtracted from the coefficient value and the threshold value is added to the coefficients for the rest.

$$\delta_\lambda^{Soft} = \begin{cases} x - \lambda & x \geq \lambda \\ x + \lambda & x \leq -\lambda \\ 0 & |x| \prec \lambda \end{cases} \quad (8)$$

In both Equations (4) and (5), λ defines threshold value, x is wavelet coefficient and δ is coefficient.

9- Impedances

Synthetic MT data are processed by this method; white and 1/f noise time series are added then noise removing procedure is implemented using the explained techniques. At first, signal is decomposed into several levels; a six level decomposition is for colored noise removing in this work since l^2 norm of the changes in reconstructed signal remained almost constant after this level. Then, threshold values are adopted by mentioned proper algorithms and the coefficients are modified. After that, a new signal is reconstructed from modified coefficients.

Figures 5 and 6 are real and imaginary parts of the reconstructed signal in the presence of white noise compared to the original signal.

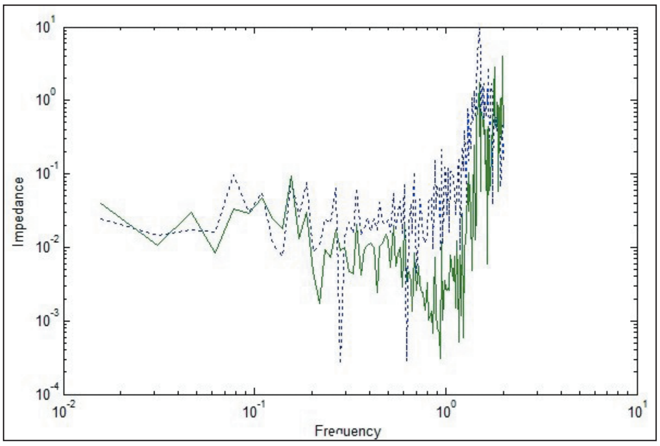

Fig. 5- Real part of impedance parameter in pure (dashed line) and reconstructed data after being contaminated with white noise (solid line).

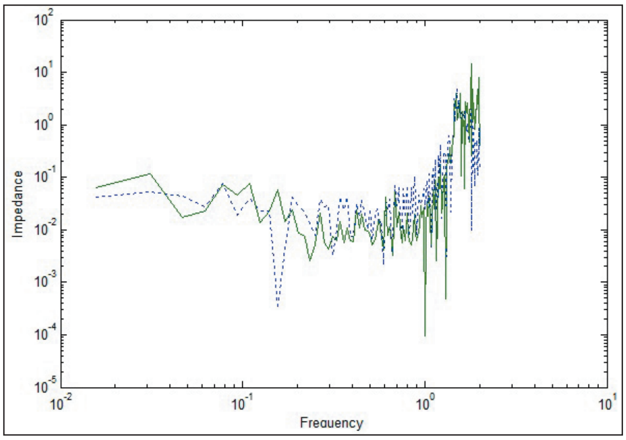

Fig. 6- Imaginary part of impedance parameter in pure (dashed line) and reconstructed data after being contaminated with white noise (solid line).

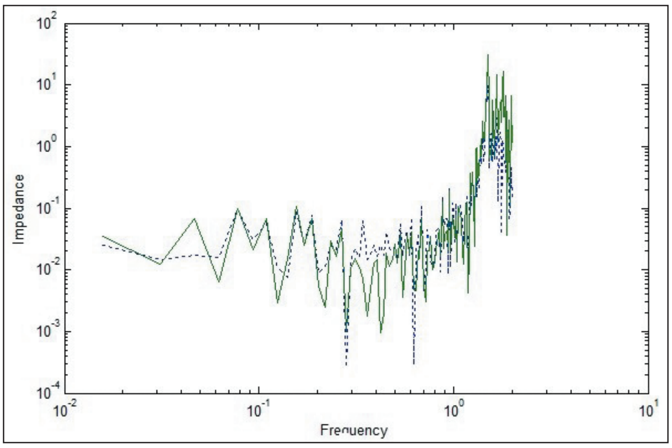

Fig. 7- Real part of impedance parameter; dashed line is the value of pure data and solid line is the data after reconstruction in the presence of 1/f noise.

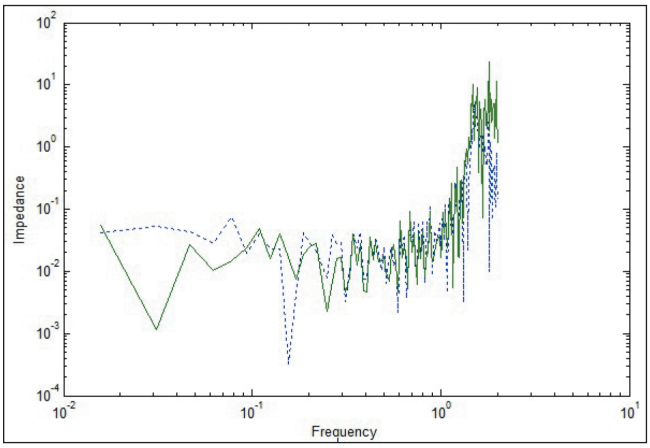

Fig. 8- The imaginary part of impedance parameter; dashed line is the value of pure data and solid line is the data after reconstruction in the presence of 1/f noise.

In both figures the dashed line is the original data and the solid line is reconstructed data. The figures imply good adjustment especially in imaginary parts.

In the following, the noise removing process algorithm is implemented on the same data set contaminated by 1/f noise. Then, level dependent noise removing process was implemented. The resulted impedances are illustrated in figures 7 and 8.

In these figures, the original data is shown by the dashed line and reconstructed data is shown by solid line. Both figures imply good adjustment in both real and imaginary parts. The results are even better compared to the white noise case (figures 5 and 6). According to these remarkable performances, pervasive white and 1/f noise can be eliminated from MT data successfully using discrete wavelet transform.

10- Conclusion

Pervasive white and 1/f noise were eliminated from MT data successfully. While the current methods of MT data processing, down weight or reject the contaminated segments of data, wavelet processing techniques try to deal with noise parts straightforward. The processed MT time series contaminated by white and 1/f pervasive noise were prosperously reconstructed. Wavelets have been widely used by various branches of sciences however, they have not been used noticeably in MT data processing. The results motivated to implement the methods in this field as an applicable solution of noise along with other routines.

References

Chave, A. D. and Jones, A. G., 2012- The Magnetotelluric Method Theory and Practice: Cambridge University Press.

Chave, A. D. and Thomson, D. J., 1989- Some Comments on Magnetotelluric Response Function Estimation, Journal Of Geophysical Research, 94, 14215-14226.

Chave, A. D. and Thomson, D. J., 2004- Bounded influence estimation of magnetotelluric response functions, Geophys. J. Int., 157, 988-1006.

Chave, A. D., 2014- Magnetotelluric Data, Stable Distributions and Impropriety: An Existential Combination, Geophysical Journal International, 198(1), 622-636.

Chave, A. D., 2016- Estimation of the Magnetotelluric Response Function: The Path from Robust Estimation to a Stable MLE, Review paper, 23rd EMI workshop, Thailand.

Chave, A. D., Thomson, D. J. and Ander, M. E., 1987- On the Robust Estimation of Power Spectra, Coherences, and Transfer Functions, Journal Of Geophysical Research, VOL. 92, NO. B1, 633-648.

Donoho, D. L. and Johnstone, I. M., 1994- Ideal spatial adaptation by wavelet shrinkage, Biometrika, 81, 425-455.

Donoho, D. L., and Johnstone, I. M., 1995- Adapting to Unknown Smoothness via Wavelet Shrinkage, Jouunal of the American Statistical Association, Vol.90, No. 432, Theory and Methods

Egbert, G. D. and Booker, J. R., 1986- Robust estimation of geomagnetic transfer functions, Geophysical Journal International, 87, 173–194.

Egbert, G. D., 1992- Short Note: Noncausality of the discrete-time magnetotelluric impulse response, Geophysics, VOL. 57, NO.10, 1354-1358.

Egbert, G. D., 1997- Robust multiple-station magnetotelluric data processing. Geophys. J. Int., 130, 475-496.

Egbert, G. D., 2002- Processing and interpretation of electromagnetic induction array data. Surv. Geophys., 23, 207-249.

Gamble, T. D., Goubau, W. M. and Clarke, J., 1979- Magnetotellurics with a remote reference. Geophysics, 44, 53-68.

Garcia, X. and Jones, A. G., 2008- Robust processing of magnetotelluric data in the AMT dead-band using the Continuous Wavelet Transform, Geophysics, 73, F223-F234.

Goubau, W. M., Gamble, T. D. and Clarke, J., 1978- Magnetotelluric data analysis: Removal of bias. Geophysics, 43, 1157-1162

Mallat, S., 2008- A wavelet tour of signal processing, Academic press is an imprint of Elsevier.

Simpson, F. and Bahr, K., 2005- Practical Magnetotellurics: Cambridge University Press.

Soman, K. P., Ramachandran, K. I. and Resmi, N. G., 2010- Insightd into wavelets from theory to practice, Phi learning private limited, New Delhi-110001.

Stein, C., 1981- Estimation of the mean of multivariate normal distribution. Annals of statistics 9, 6, 1135-1151.

Trad, D. O. and Travassos, J. M., 2000- Wavelet filtering of magnetotelluric data, Geophysics, 65, 482-491.

Zhang, Y. and Paulson, K. V., 1997- Enhancement of signal to noise ratio in natural source transient magnetotelluric data with wavelet transform, Pure and applied Geophysics, 149, 405-419.