Increasing the Robustness of Homomorphic Deconvolution for Non-stationary Seismic Wavelet

Muhammad Sajid and D.P. Ghosh

Department of Geoscience and Petroleum Engineering, Universiti Teknologi PETRONAS, Malaysia

Corresponding Author: Muhammad Sajid, Depatment of Geoscience and Petroleum Engineering, Universiti Teknologi PETRONAS, Malaysia

ABSTRACT

Study presents a novel algorithm to improve the frequency bandwidth of the seismic data through removal of non-stationary wavelet in cepstrum domain. Algorithm incorporates useful properties of both homomorphic deconvolution and spectral decomposition by this way it estimates and filters the wavelet at each translation of spectral decomposing Gaussian window which improve the resolution and tolerates the non-stationary properties of seismic wavelet. This study describes the comprehensive mathematical formulation of the algorithm and its testing on 1D, 2D synthetic and real seismic section to confirm its applicability. Comparative testing shows that the algorithm effectively removed the smearing effect of wavelet which led to broader frequency spectrum and improved seismic resolution.

Key words: Algorithm, seismic data, homomorphic deconvolution, non-stationary wavelet, frequency, cepstrum

INTRODUCTION

Seismic data is considered to be a convolution of the non-stationary wavelet with the sub-surface geology. Seismic wavelet changes its shape and frequency component continuously. Rather than the Fourier transform, Spectral decomposition contains both time and frequency information at the same instant and it is susceptible to local geology (Partyka *et al.*, 1999). Its spectral decomposing window can be of different shapes and size. Short-Time-Fourier-Transform (STFT) with Gaussian analysis window is known as Gabor transform (Gabor, 1946).

Cepstrum is defined as Inverse Fourier transform of the log of the magnitude of Fourier transform. It is mostly used in speech analysis and echo elimination (Oppenheim *et al.*, 1968; Oppenheim, 1965). In seismic, it is being used for homomorphic deconvolution (Ulrych, 1971; Stoffa *et al.*, 1974; Buhl *et al.*, 1974; Tribolet *et al.*, 1977) and for calculation of thin bed thickness with better accuracy (Hall, 2006; Liu *et al.*, 2008).

We developed a new algorithm which we named as Cepstrum-Wavelet-Filtering (CWF) which estimate and filter out the non-stationary wavelet at each translation of the spectral decomposing window in the cepstrum domain by this way it removes the stationary wavelet limitation of the homomorphic deconvolution algorithm by incorporation of spectral decomposition algorithm in it. It is simple, fast and perfectly reconstructs the seismic trace back from the cepstrum domain through preservation the phase information in its workflow.

MATERIALS AND METHODS

As Short-Time-Fourier-Transform (STFT) implement the Fourier transform on each windowed version of the signal (Eq. 1) (Allen and Rabiner, 1977; Auger and Flandrin, 1995), so application of natural logarithm on each translation Fourier coefficient provides the logarithm of the magnitude of Fourier coefficients as a real part whereas the imaginary part contains the phase spectrum of the given translation as described in Eq. 2. Inverse Fourier transform of the real part provides the real cepstrum (Eq. 3) which is being used to recover the reflectivity by filtering out the wavelet whereas the phase spectrum of each translation is preserved for later perfect reconstruction of signal from the cepstrum domain as described in Eq. 4.

$$F(\tau,f,h)= \int_{-\infty}^{\infty} \left(x(t)\times h(t-\tau)\right)e^{-i2\pi ft}dt \tag{1}$$

$$\ln(F(\tau,f,h))=\ln\left(\sqrt{(\Re(F(\tau,f,h)))^2 + (I(F(\tau,f,h)))^2}\right)+i\tan^{-1}\left(\frac{(I(F(\tau,f,h)))}{(\Re(F(\tau,f,h)))}\right) \tag{2}$$

$$C=R\left[\int_{-\infty}^{\infty}\left\{\ln\left(\sqrt{\left(R\big(F(\tau,f,h)\big)\right)^2 + \left(I\big(F(\tau,f,h)\big)\right)^2}\right)\right\}e^{i2\pi ft}dt\right] \tag{3}$$

$$CR(t)= \int\int_{-\infty}^{\infty}\left[\exp\left\{\Re\left(\int_{-\infty}^{\infty}C\times e^{-i2\pi ft}\right)+i\tan^{-1}\left(\frac{\left(I\big(F(\tau,f;h)\big)\right)}{\left(\Re\big(F(\tau,f;h)\big)\right)}\right)\right\}\right]\times\gamma(t-\tau)e^{i2\pi ft}\,dfdt \tag{4}$$

$$W_{gw}=\exp\left(\left(\frac{n-b}{w}\right)^2\right) \tag{5}$$

where, t is Time, f is frequency, x (t) is time domain signal, h (t) is decomposing window, τ is window translation along time axis, C is real cepstrongram, γ (t) is spectral reconstructiol window, n is total number of sample in trace, b is current location of window and w is half width of gaussian window.

Gaussian window (Eq. 5) flanks are used to smoothly filter out the initial quefrencies from each translation (τ) of real cepstrogram. Figure 1 shows a graphical illustration of Gaussian filtering operation on 1D synthetic thin bed model (Fig. 1b), created by convolution of Ricker wavelet (f_{dom} = 35Hz) with reflectivity series (Fig. 1a), in a simplified form without using STFT in the algorithm. Synthetic synthetic trace comprises a set of 6 thin beds models for the following conditions:

- Single event wavelet (f_{dom} = 35 Hz and Tuning thickness = 12 msec)
- Two events are in between 0 to flat spot thickness (i.e., 3 samples or 6 msec thickness)
- Two events are below flat spot thickness (i.e., 4 samples or 8 msec thickness)
- Two events are at Flat spot thickness (i.e., 5 samples or 10 msec thickness) (Ricker's Criterion) (Ricker, 1953)
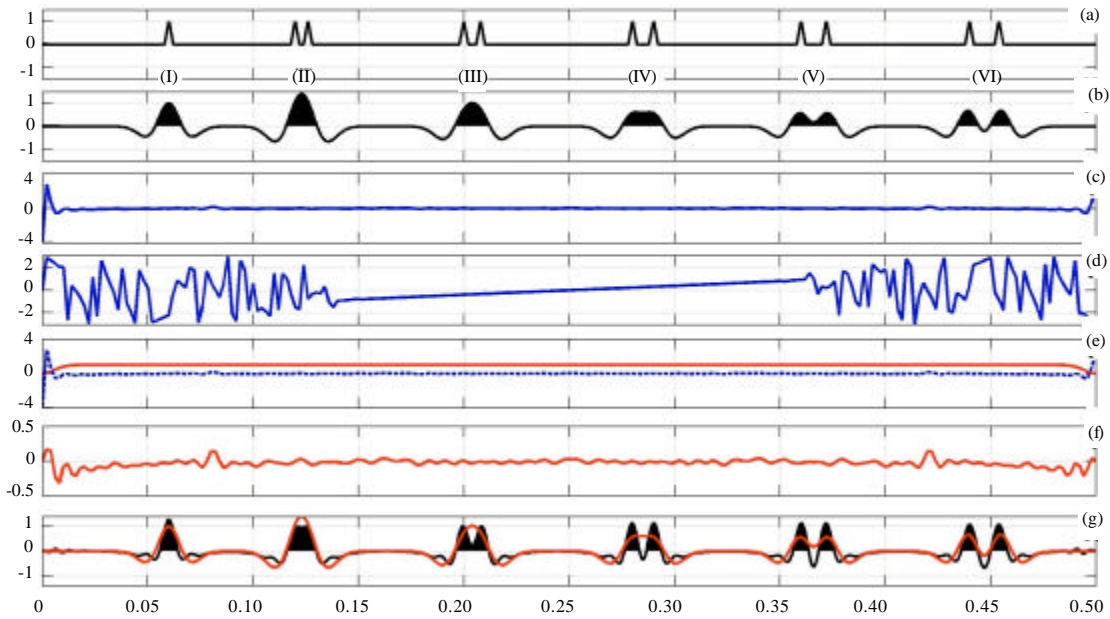
Fig. 1(a-g): (a) Thin bed reflectivity model, (b) Synthetic seismic trace created by convolution with Ricker wavelet f_{dom} = 35 Hz, (c) Real cepstrum of the synthetic trace, (d) Phase spectrum of the trace, (e) Initial quefrencies are zeroed out by point wise multiplication of the smooth negative of Gaussian window flank, (f) Real cepstrum after filtering and (g) Improved resolution after the application of the CWF algorithm (reconstructed black trace) as compared to original (red curve)

- Tuning thickness (i.e., 6 samples or 12 msec thickness) (Rayliegh's Criterion) (Kallweit and Wood, 1982)
- Greater than Tuning thickness (i.e., 7 samples or 14 msec thickness)

Figure 1c and d shows the real cepstrum and phase spectrum respectively whereas Fig. 1e shows the application of Gaussian filtering operation on real cepstrum by point wise multiplication of negative of the Gaussian window flanks with the initial quefrencies of the real cepstrum which smoothly reduces its values whereas Fig. 1f shows real cepstrum after filtering. Figure 1g shows the comparison of original synthetic trace (red curve) with CWF algorithm reconstructed trace which shows improved resolution.

APPLICATION

Application on thin bed model: Figure 2 shows the CWF algorithm implementation on synthetic thin bed model which is created by using the above mention parameters. Figure 2b shows its real cepstrogram whereas Fig. 2c shows the Gaussian filtering window for each translation of cepstrogram which is used to reduce initial quefrencies. Figure 2d and e shows the filtered real cepstrogram and its reconstructed seismic trace respectively. By comparison of the original synthetic trace (Fig. 2a) with CWF reconstructed trace, it can be observe that the resolution of events is effectively improved.
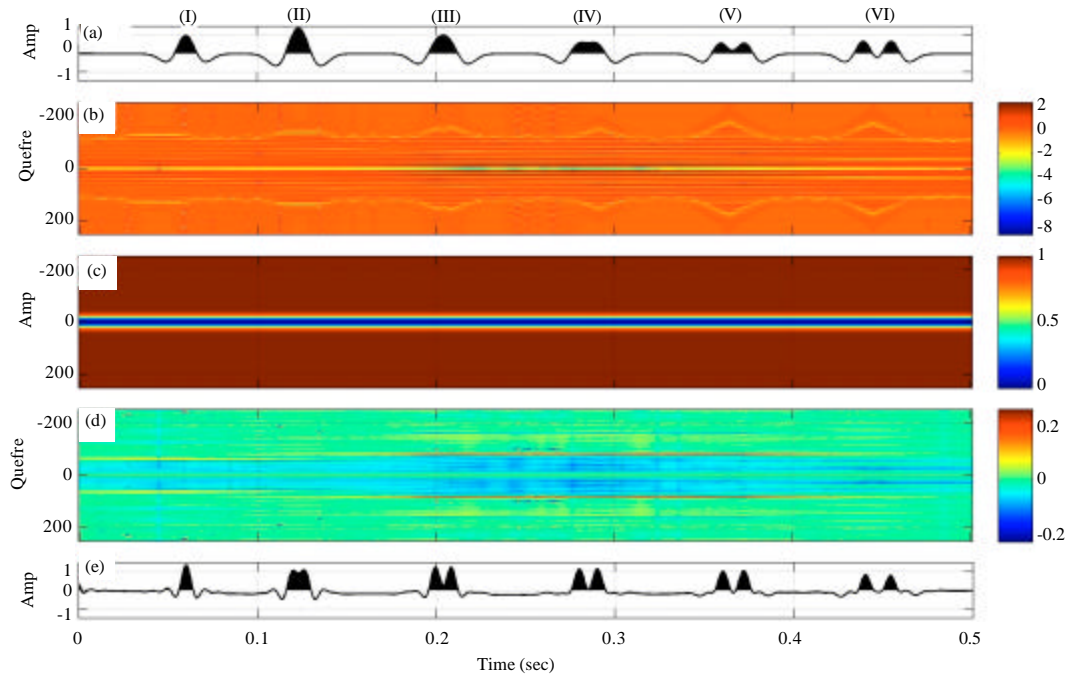
Fig. 2(a-e): (a) Original synthetic thin bed model, (b) Real cepstrogram, obtained by calculation of real cepstrum at each time step of spectrogram, (c) Gaussian filtering window for each time step of cepstrogram, (d) Filtered cepstrogram after implementation of the Gaussian window filtering and (e) Reconstructed synthetic trace from filtered cepstrogram which shows improved resolution

Application on synthetic wedge model: The 2D synthetic model is created from the geological model of the stratigraphic layer of known thickness and elastic properties. In the synthetic seismic (Fig. 3a), trace interval is 2 m, sample rate is 2 msec, the wedge layer velocity is 2700 m sec^{-1} and Ricker wavelet with the predominant frequency of 35 Hz:

$$(\text{tuning thickness } b_{time} = 12\,\text{m sec or } b_{space} = 2700\,\frac{m}{sec} \times \frac{0.012}{2}\,\text{sec}, b_{space} = 16.2\text{m})$$

is used.

As CWF algorithm filter out the wavelet at each translation (τ) without being the influence of user predefined spectral broadening window (Yilmaz, 2008) so the low frequencies of the synthetic seismic section remains whereas the higher frequencies become apparent because of the removal of the wavelet interference effect as can be observed in Fig. 3a. In comparison of improvement in seismic resolution, it can be observed that resolution of the wedge model is effectively improved after the application of CWF as can be observe through Fig. 3b and c. An event which started to merge at trace No. 22 is separable till trace No. 32 which shows a 10 m increase in resolution as highlighted by colour lines.

Application on real seismic data: Seismic data from Malay Basin are usually of high quality with good signal to noise ratio. Figure 4a shows the real seismic section which contains number of
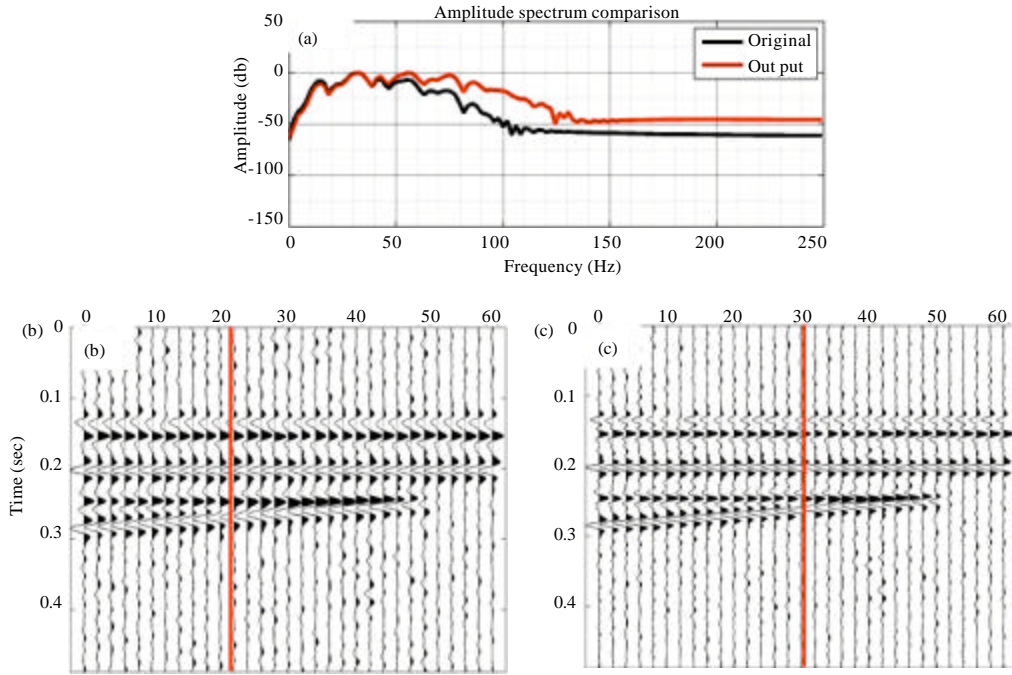
Fig. 3(a-c): (a) Amplitude spectrum of synthetic wedge model with almost same trend but with higher values, (b) Original synthetic wedge model with S/N ratio of 3 and trace interval of 2 m and (c) Improved resolution, events which started to merge at trace No. 22 still separable till trace No. 30 (8 m improve in resolution)
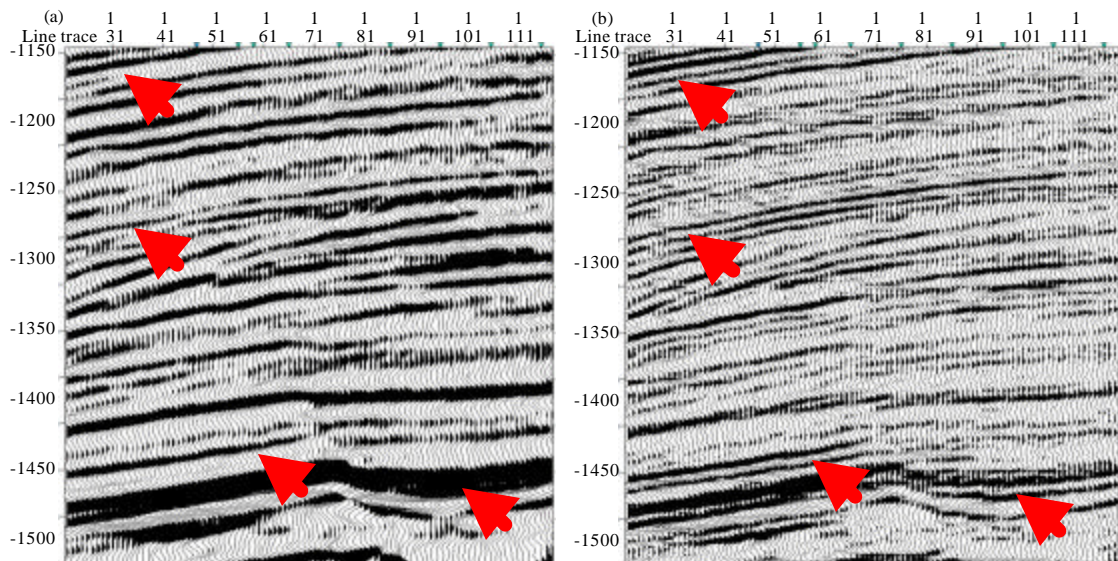

Fig. 4(a-b): (a) Real seismic section contains a number of hidden features and (b) Improved seismic resolution and number of hidden features are recovered after the application of CWF algorithm, some are marked with arrow signs
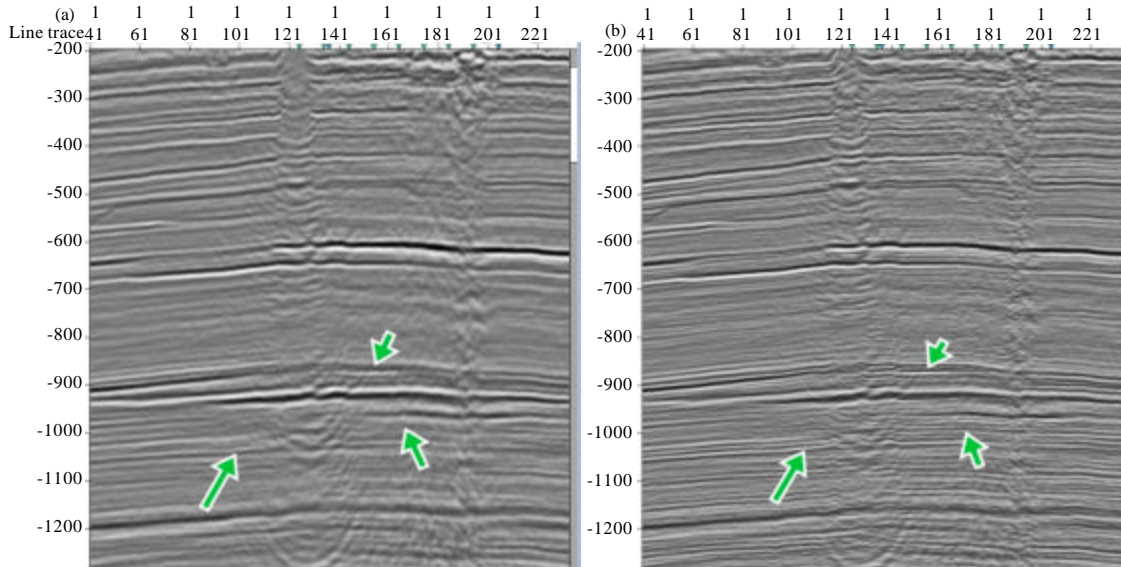
Fig. 5(a-b): (a) Real seismic from Malay Basin show gas seepage and (b) CWF algorithm improved resolution of seismic section without being much adversely affected by low frequency zones

hidden features due to the interference effect of the seismic wavelet. Figure 4b shows the same seismic section after the application of propose algorithm, it can be observe that the CWF algorithm extracted a number of hidden features as some of them are marked with arrow sign and effectively improved the seismic resolution. In another example shown in Fig. 5, shows the application of CWF algorithm on seismic section containing gas clouds. As gas clouds produce large high frequency attenuation which leads to shadowing effect to underlying layers. Figure 5a and b show the original seismic and seismic after the proposed CWF algorithm. It can be easily observed that the proposed algorithm has considerably improved the resolution of seismic without being much adversely affected by gas cloud in original data.

CONCLUSION

New proposed Cepstrum-Wavelet-Filtering (CWF) algorithm increase the robustness of homomorphic deconvolution by introduction of Short-Time-Fourier-Transform (STFT) in its algorithm. This incorporation leads to estimate and filter the seismic wavelet at each translation of spectral decomposing Gaussian window which improve the resolution of seismic data.

This improvement in seismic resolution which leads to better thickness estimation, correlation to well logs and thereby improves the stratigraphic interpretation. These results are achieved without being constrained by well log information and starting model, which leads to unbiased data driven better resolution. As evident from its testing on 1D, 2D synthetic and on real seismic section, the proposed algorithm has potential use in seismic interpretive data processing.

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REFERENCES

Allen, J.B. and L. Rabiner, 1977. A unified approach to Short-Time Fourier analysis and synthesis. Proc. IEEE, 65: 1558-1564.

Auger, F. and P. Flandrin, 1995. Improving the readability of time-frequency and time-scale representations by the reassignment method. IEEE Trans. Signal Process., 43: 1068-1089.

Buhl, P., P.L. Stoffa and G.M. Bryan, 1974. The application of homomorphic deconvolution to shallow-water marine seismology-Part II: Real data. Geophysics, 39: 417-426.

Gabor, D., 1946. Theory of communication. Part 1: The analysis of information. Electr. Eng. Part III: Radio Communi. Eng. J. Inst., 93: 429-441.

Hall, M., 2006. Predicting bed thickness with cepstral decomposition. Leading Edge, 25: 199-204.

Kallweit, R. and L. Wood, 1982. The limits of resolution of zero-phase wavelets. Geophysics, 47: 1035-1046.

Liu, C.Y., S.F. Xu, J.H. Yue and X.C. Wei, 2008. Application of cepstral analysis to thin beds. J. China Univ. Mining Technol., 18: 232-236.

Oppenheim, A.V., 1965. Superposition in a class of nonlinear systems. Ph.D. Thesis, Research Laboratory of Electronics, MIT, Cambridge.

Oppenheim, A.V., R.W. Schafer and T.G. Stockham Jr., 1968. Nonlinear filtering of multiplied and convolved signals. IEEE Trans. Audio Electroacoustics, 16: 437-466.

Partyka, G., J. Gridley and J. Lope, 1999. Interpretational applications of spectral decomposition in reservoir characterization. Leading Edge, 18: 353-360.

Ricker, N., 1953. Wavelet contraction, wavelet expansion and the control of seismic resolution. Geophysics, 18: 769-792.

Stoffa, P.L., P. Buhl and G.M. Bryan, 1974. The application of homomorphic deconvolution to shallow-water marine seismology-Part I: Models. Geophysics, 39: 401-416.

Tribolet, J., T.F. Quatieri and A.V. Oppenheim, 1977. Short-time homomorphic analysis. Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing, Volume 2, May 1977, IEEE, USA., pp: 716-722.

Ulrych, T.J., 1971. Application of homomorphic deconvolution to seismology. Geophysics, 36: 650-660.

Yilmaz, O., 2008. Seismic Data Analysis. SEG Publishing Co., Tuls, pp: 231-233.