Blind deconvolution of seismic data

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Abstract

A great number of blind deconvolution methods have been presented in the litterature. In seismic prospecting the observed signal results from the convolution of the ground response by the wavelet due to the emitter and to the wave propagation. The wavelet is generally not known. In order to recover the ground response it is necessary to apply a blind deconvolution.

Using higher order statistics (HOS) blind deconvolution methods, we develop two deconvolution schemes taking into account the specificity of the data collected in seismic prospecting. We introduce new tools in order to deal with the finite lenght of the data and to correct the time delay non-observable in blind deconvolution. The potentialities of these new algorithms are illustrated on experimental data.

1 Introduction

In reflection seismic prospecting the emitter and the receiver are located on the ground made of several rock layers. The down-going emitted wave is reflected at each layer, giving rise to up-going waves which are registered by the receiver (figure 1). In this simplified model, $w(n)$ being the emitted wave (wavelet), the received signal, called the trace, is

$$t(n) = \sum_i r_i w(n - k_i) + b(n),$$

where r_i is the reflection coefficient of the ith layer, k_i the time delay of propagation and $b(n)$ the noise. This relation can be written

$$t = r * w + b$$

where $r(n) = \sum_i r_i \delta(n - k_i)$ is the impulse response of the ground.

The first objective of seismic processing is to recover the ground impulse response in order to evaluate the

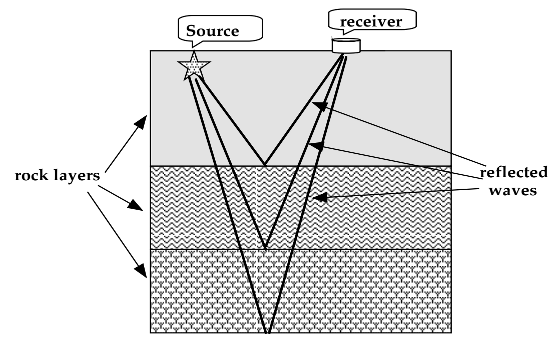

Figure 1: Seimic reflexion

deepness and the position of the different layers. This can be done by deconvolution. If the wavelet is known, the deconvolution is made using a Wiener filter. Usually the wavelet is not known, then a blind deconvolution must be applied.

After a presentation of the methods of blind deconvolution, we develop two approaches of seismic deconvolution. In these methods, two key points are to be solved. In seismic context the available data are of limited duration leading to important estimation errors. We introduce procedures allowing to minimise the estimation errors. Another limitation is due to the fact that, in deconvolution, the output is given with an arbitrary time delay. This is a major limitation in seismic prospecting where the time location of the echos is an essential parameter to localise the layers. We discuss this delay incertainty and propose solutions to correct time delays. Finally two global procedures developped are illustrated on experimental data.

2 Blind deconvolution

The basic hypothesis used in deconvolution is the whiteness of the ground impulse reponse $r(n)$. So, the samples of $r(n)$, are statistically independent variables.

With this whiteness hypothesis the blind deconvolution can be carried out if the $r(n)$ samples are not gaussian [2].

The whiteness of $r(n)$ is used in second order whitening methods. This whitening, using Wiener filters, cannot achieve the deconvolution if the phasis of the wavelet is not known. In order to deconvolve, we have to use higher order statistics. Three classes of blind deconvolution methods have be developped:

- in the $KARMA$ method proposed by [5] and used in seismic processing by [1] the $ARMA$ wavelet is identified, by zeros and poles, using the second-order Yule-Walker method. Then the zeros and poles locations, limited to the initial ones or to their inverse relative to the unit circle in the complex plane, are determined in maximising a higher order criteria. In the $KARMA$ method, the criteria used is the kurtosis of the output $r(n)$

$$\kappa_r = \frac{N \sum_n r^4(n)}{\left(\sum_n r^2(n)\right)^2} - 3.$$

  Trying to apply this method to seismic data, we have experienced that it is very difficult to determine the right number of poles and zeros. So, we do not recommand to use this strategy.

- methods using the multispectra have been proposed and used in seismic deconvolution [6]. In these methods we point out the two steps ones

  - in the first step a second order whitening is applied using a null phase Wiener filter. This filter is estimated with the spectrum of the trace.
  - in the second step the wavelet phase, $\phi(m)$, is recovered using the phase of the bispectrum of the whitened trace, $\Psi(m_1, m_2)$, by [4]

  $$\phi(_1) = \frac{1}{N} \sum_{m_2} \Psi(m_1, m_2),$$

    N beeing the length of the DFT used in bispectral estimation.

- the $MAMV$ method has been proposed by [7]. In this method it is supposed that the inverse filter has an $MA(2p+1)$ model which can be non-causal. The criterium used to estimate the MA, $2p+1$ coefficients, is the maximum likelihhood. The maximisation of the likelihood leads to

$$\underline{\underline{C}}_\Phi . \underline{w} = \underline{w}$$

  where $\underline{w}$ is the column vector of the inverse filter coefficients. The matrix $\underline{\underline{C}}_\Phi$ is made with the values of a "higher order" correlation of the output $r(n)$

$$\underline{\underline{C}}_\Phi(k) = E[\Phi(r(n))r(n-k)]$$

  where $\Phi(u) = \frac{p_r'(u)}{p_r(u)}$, given by the probability distribution of the output samples p_r, is the score.

3 The data

The data set recorded is a collection of 101 traces got on an array of sensors regularly disposed on a straigh line on the ground. The traces are given on figure 2 in function of the horizontal position of the sensors (offset) and of the time of arrival. The time coordinate is proportionnal, through the wave velocity, to the deepness. Using an usual method of presentation in seismic the positive greater hoops of the time plot are blacken in order to draw black lines that visualise the layer boundaries. On the data set shown on figure 2, we see a black pattern near the sample 20 and an oscillating black patterns near the sample 100. The upper pattern, made of a well identified wavelet, has been used to ajust the time delays between the traces. The two patterns show multiple blacken values of the signal which are due to the oscillating character of the wavelet. In order to be more precise in time (deepness) localisation we must null, or attenued strongly, these oscillations by deconvolution.

4 Bispectral deconvolution

The bispectral deconvolution is done in two steps: second order whitening with the estimated spectrum and phase correction by the estimated bispectrum.

4.1 Spectrum and bispectrum estimation

One trace does not contains enough "independents" events in order to estimate correctly the spectrum and the bispectrum : an estimation strategy must be adopted to get valuable estimators. One can postulate that the wavelet is stationary on the whole data set and then use all the traces. We suppose that the stationarity of the wavelet is local : neighbour traces have quite identical wavelet but, from the variations of the propagation conditions, the wavelet can change slowly with the location. In order to use this "local stationarity"

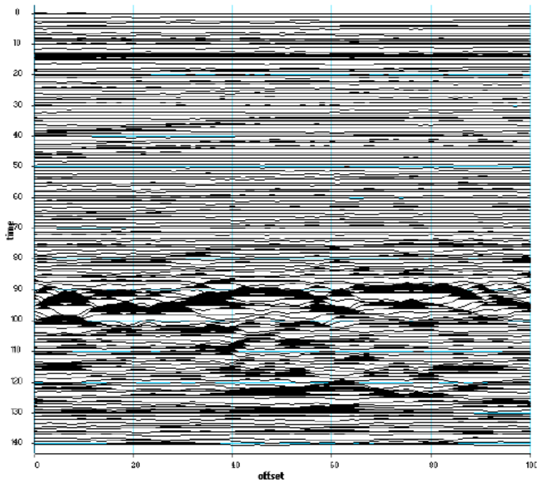

Figure 2: The initial data

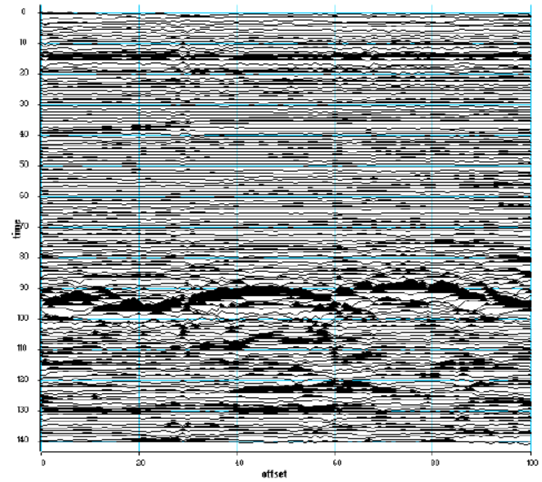

Figure 3: The data after bispectral deconvolution

we estimate the spectrum and the bispectrum on sub-arrays made of $2l+1$ traces surrounding the processed trace.

We estimate the spectrum by the DFT of an estimator of the correlation function given by the sub-array. With the estimated spectra, $S_1(m)$, we whiten the traces in the frequency domain by the Wiener filter of null phase whose complex gain is $1/(S_1(m)+\epsilon)^{(1/2)}$. ϵ is a regularisation factor taking into account the effect of noise (supposed white).

From the whitened data set, we estimate the bispectrum. The bispectrum estimation is done by the averaged biperiodogram method [3]. In this method we have to cut the sub-array data in short segments before averaging on these segments. Using short data lenght the cutting out of the data is very sensitive to the position of the segments. So the results are not so stable : some time good, other time bad. In order to get stable results, it is necessary to state a strategy for the determination of the segments positions. We use the kurtosis in order to select the best cutting way. We try all the possible cutting positions and retain the position that maximises the kurtosis of the output.

In order to illustrate the importance of this "synchronisation" we show on figure 4 the variations of the kurtosis versus the segment position. In this example the maximal value of the kurtosis is 30 and the minimal one 6 showing the large domain of variation of the quality of the estimation.

Another important parameter is the arbitrary time delay introduced by deconvolution. In the frequency domain this delay is the linear part of the phase variation with frequency. A linear phase variation is not controled by the bispectrum phase. In order to avoid the parasistic delays after the phase identification, we make a linear regression, versus frequency, on the phase and subtract the linear term.

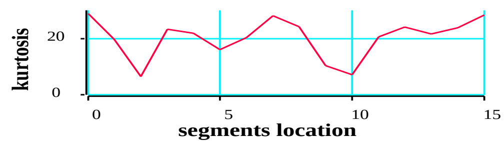

Figure 4: Variation of the kurtosis of the output with segments location

4.2 Results

The whole data set after bispectral deconvolution is shown on figure 3. The spectrum and bispectrum are estimated using sub-arrays of 9 traces. It is apparent that the first pattern (near sample 20) is been compressed, by attenuation of the multiple maxima due to the oscillations of the wavelet. The same comment can be done on the second pattern near sample 100. The mutiple positive mounts and negative valleys have been concentrated into a dominant watershed that represents the structure of the limit between two rock layers.

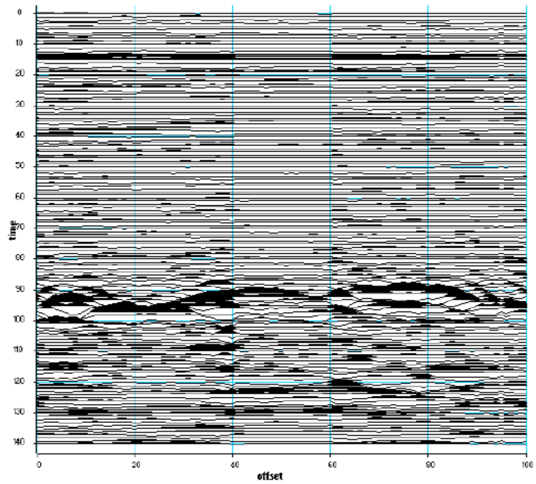

Figure 5: The data after $MAMV$ deconvolution

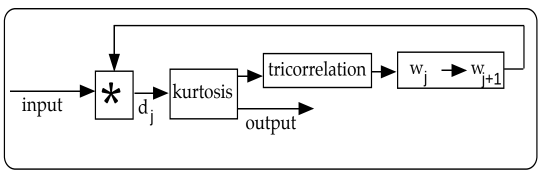

Figure 6: Organigram of $MAMV$ deconvolution

5 $MAMV$ deconvolution

In $MAMV$ deconvolution the impulse response of the inverse filter is obtained iteratively. $\underline{w}_j$ being the filter vector at the iteration j

$$\underline{w}_{j+1} = \underline{w}_j + \mu(\underline{w}_j - \underline{\underline{C}}_{\Phi,j} \cdot \underline{w}_j),$$

where μ is a constant determining the convergence speed and $\underline{\underline{C}}_{\Phi,j}$ the higher order correlation matrix of the output obtained at the iteration j.

We use, as higher order correlation, a line of the tricorrelation. At the delay k

$$C_{\Phi,j}(k) = E[r_j^3(n) r_j(n-k)] - 3E^2[r_j(n) r_j(n-k)].$$

As in the bispectral method, the tricorrelation is estimated on a sub-array of $2l+1$ traces surrounging the trace processed. In order to control the convergence of the iterations, we use the kurtosis of the output as criterium. We stop the iteration when the kurtosis reaches a maximum value.

The organigram of the $MAMV$ method is given on figure 6

5.1 Results

The data set deconvolved by the $MAMV$ method using a non-causal MA filter of lenght 33 is given on figure 5. As in the bispectral algorithm the boundaries between the rock layers are more well definite as in the initial data set.

6 Conclusion and perspectives

We have presented an application of deconvolution on experimental data. We have shown that, in order to get usefull algorithms, a processing strategy has to be stated in order to get good estimators of the spectral or correlation characteristics of the observed signal. A particular care must be taken to the time localisation of the outputs.

The presented results use a linear array of data. We have to extend this procedure to surfasic arrays, extended on a rectangle, that are now used giving cubes of data ($3D$ data set). We have also to combine these technics with the wave separation schemes using cubes of vectorial data.

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References

[1] M. Boumahdi, *Blind identification using the kurtosis with applications to field data*, Signal processing, Vol: 48, no 3, pp: 205-21, Feb. 1996.

[2] Donoho D, *On minimum entropy deconvolution* Applied time series analysis II, Academic Press Inc., pp.565-607, 1981.

[3] J.L. Lacoume, P.O. Amblard et P. Comon, Statistiques d'ordre suprieur pour le traitement du signal, *MASSON,* 1997.

[4] A.Lannes, *Remarkable algebraic structure of phase closure imaging and their algorithmic implications in apertures synthesis,* J. Opt. Soc. Amer. A, vol 7, pp 500-512, 1990.

[5] K.S. Lii and M.Rosenblatt, *Deconvolution and estimation of transfert function phase and coefficients for nongaussian linear processes,* The annals of statistics Vol 10, n.4 pp1195-1208, May 1982.

[6] T. Matsuoka and T.J.Ulrych, *Phase estimation using the bispectrum,* Proc. IEEE, vol 72, pp 1403-1411, 1984

[7] A. Taleb, J.Sole-Casals and C. Jutten, *Blind inversion of Wiener systems,* Lecture notes computer science, 1607, Vol. II, pp. 655-664, Springer-Verlag, 1999.