Z-99 Applications of adaptive beamformers on seismic data

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Introduction

Receiver arrays are used in seismic acquisition for data reduction. Synthetic modeling a receiver array shows the presence of some end-effects that introduce false "arrivals" on the seismic records. A beamforming technique has been proposed to attenuate their presence from seismic data. Two beamforming methods and their results are presented in this paper with applications on synthetic and field data. Both of them show good results on field data.

Seismic data recorded with receiver arrays can be heavily disturbed by interfering signals such as surface waves (Rayleigh wave, ground-roll and scattered waves). To be able to suppress the coherent noise from the recorded data, there is a tendency to use sets of single sensors and to combine these into a single output signal (beamforming) such that the undesired signals are attenuated. Adaptive beamforming techniques have been successfully used for this purpose in other fields such as sonar, radar, radio astronomy etc., and have been considered in exploration seismology, where Ozbek proposed a constrained adaptive beamformer that can be thought as a FK filter (2000). It is well known that the performance of adaptive beamforming degrades in the presence of mismatches between the presumed and actual array responses. In order to get an accurate beamformer response, different adaptive beamforming methods have been proposed in the last years, namely the Linearly Constrained Minimum Variance (LCMV) beamformer, the eigenspace-based beamformer, the Minimum Variance Distortionless Response (MVDR) beamformers and many others. The application of some of these beamformers to seismic data requires some additional steps, such as modeling the desired and noise response; in this case, we define a data independent LCMV beamformer, meaning that the computed weights are the same for each new analyzed set of array signals (e.g. 12 traces for 12 receivers into an array). An adaptive beamformer can be defined using the array signals to compute the optimal weights, as we will show later.

Designing adaptive beamformers

Many algorithms have been proposed to design an adaptive beamformer. In general, they are based on knowledge of the desired array response; in this case, the output of adaptive beamformer becomes very sensitive to any mismatch between the modeled and actual desired array responses used in the algorithm. Two types of beamformers will be discussed here; their algorithms have been modified to make them applicable to seismic data. The first one is the Linearly Constrained Minimum Variance beamformer (LCMV) (see Veen and Buckley for an introduction, 1988), which can be considered a *partially data-dependent beamformer* since the design of the constraint matrix is based on the recorded data analysis. The second one, the Minimum Variance Distortionless Response beamformer (MVDR) can be considered a *data dependent beamformer* in the version proposed by Shahbazpanahi et al (2003).

First, let us describe the LCMV beamformer. This type of beamformer constrains the response of the beamformer so that signals from a direction of interest are passed with a given gain and phase. The beamformer weights are computed based on a constraint matrix, C, and presumed array response, f; the constraint matrix, C, is calculated using modeled synthetics with a hyperbolic event (signal) and a linear one (noise) made redundant with the arrivals shifted with a known time interval.

The second type of beamformer is the MVDR beamformer. As written above, we used a MVDR beamforming algorithm proposed by Shahbazpanahi et al (2003). This beamformer computes the weights, w, based on the array signals, x, by using a sample covariance matrix, R, and a direction vector of the desired signal, a_s; since the desired signal is the reflected wave, the direction vector a_s is equal with the unity vector with size M×1, where M is the number of array elements. The beamformer weights are computed in the frequency domain; the inverse Fourier transform is used to get the signal in time domain.

(1) $$R = \frac{1}{N}\sum_{n=1}^{N} x(n)x^{H}(n)$$

(2) $$w = P\{R^{-1}(a_s a_s^{\,H} - \varepsilon I)\}$$

where x represents the recorded data, I is M×M identity matrix, ε is a known parameter, n is the time sample, $(.)^H$ is Hermitian and P{..} is an operator that yields the principal eigenvector of a matrix (the eigenvector for the largest eigenvalue).

Application of LCMV and MVDR on synthetic data

Let us consider a receiver array with 12 elements and 5 m spacing, without timing (phase/positioning) and amplitude errors. In Figure 1 we display the signals recorded with this array (left). Then, we compare the LCMV beamformer (center) and the MVDR beamformer (right) responses with a standard array-forming response, i.e. adding the 12 traces. It is clear that the MVDR response attenuates better the undesired noise compared to the LCMV response; in addition, the LCMV beamformer introduces some high frequency signals that can be a source for spatial aliasing. An error in amplitude, e_a, has been computed for the beamformer responses based on:

(3) $$e_a = \frac{1}{N}\sum_{n=1}^{N} \left| y_d - y_b \right|$$

where n is the time sample, y_d is the desired array response and y_b is the beamforming response.

The MVDR response is a function of ε (see eq. (2)); it becomes more similar to the standard array-forming response for larger ε; in this case, the calculated error in amplitude between the array-forming response and the MVDR response becomes very small.

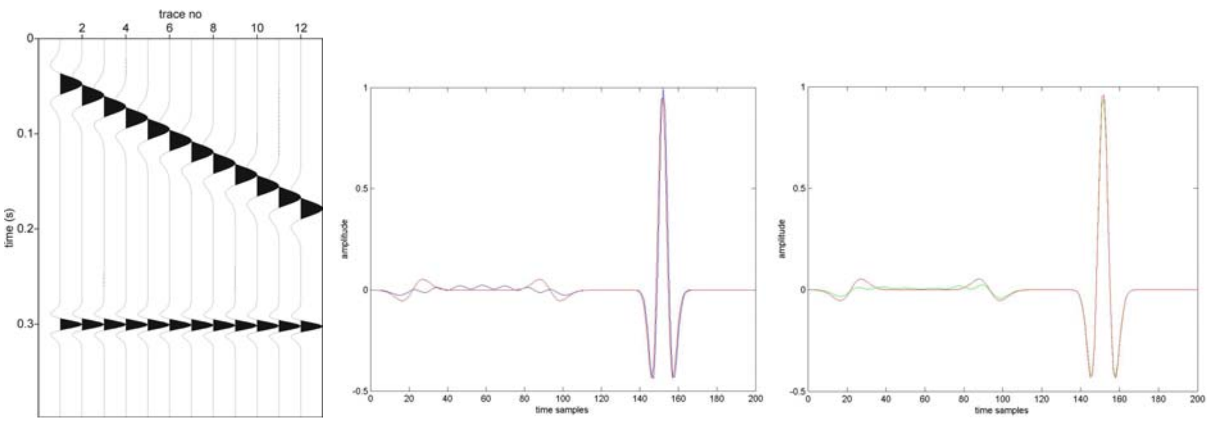

Fig 1. (left) Synthetic seismogram with 12 traces, 12 traces added (red), the LCMV response (blue), the MVDR response (green); calculated error in amplitude: e_a = 0.0417 (center) and e_a = 0.0154 (right)

It is important to study the beamforming response in the presence of timing/amplitude errors since, due to the field conditions, these errors will affect the recorded data.

First, we introduced random errors in the timing via mis-positionings of all receivers using a maximum error equal to 20 % of the receiver spacing (see Figure 2). Next, random weights have been applied to all receivers, via amplitude errors, using a maximum error of 20 % (see Figure 3). By comparing of these beamforming responses we notice that the LCMV beamformer protects the desired signal in the presence of these types of errors while the MVDR beamformer could not preserve the desired signal in the presence of amplitude errors.

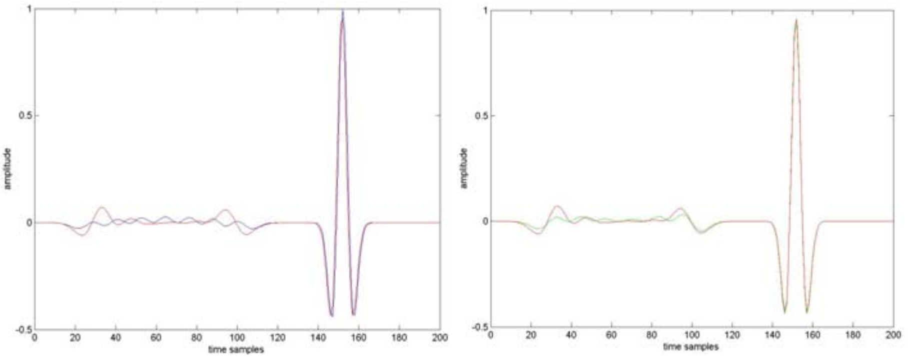

Fig 2. 12 traces added (red), LCMV (blue) and MVDR (green) response; calculated error in amplitude: $e_a = 0.0421$ (left) and $e_a = 0.0162$ (right)

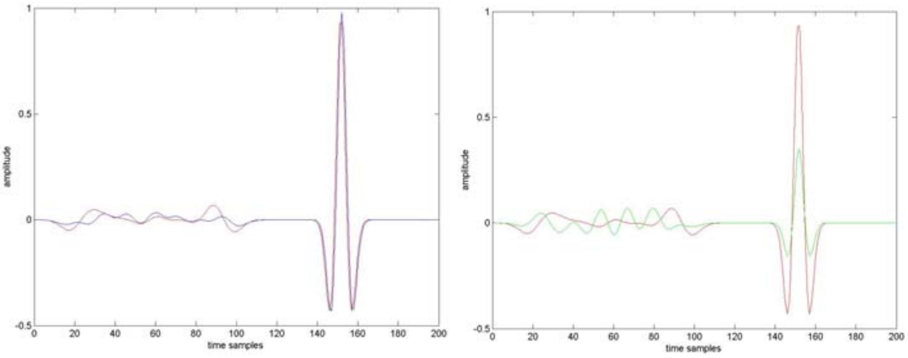

Fig 3. 12 traces added (red), LCMV (blue) and MVDR (green) response; calculated error in amplitude: $e_a = 0.0426$ (left) and $e_a = 0.0362$ (right)

The next step was to apply the designed beamformers to synthetic seismograms. Synthetic seismograms containing two types of arrivals have been modeled (60 traces with 5 m trace spacing); the linear event is characterized by low frequency and low apparent velocity (representing, e.g. surface wave) and the hyperbolic event is characterized by higher frequency and high apparent velocity. Both the LCMV and the MVDR beamformer have been applied to these data and we notice that the MVDR beamformer shows a bad response when the signal and noise are overlapping while the LCMV beamformer response is not affected (see Figure 4). Although not shown here in this abstract, the effectiveness of the beamforming methods can be further illustrated via the (f, k)-domain.

Application of LCMV and MVDR beamformers on field data

The same procedure as above is applied, this time using field data as input data (see Figure 5). The seismic data analyzed here were recorded using single sensors with the purpose to be used later for synthetic array-forming. The receiver spacing was 5 m and dynamite was used as the seismic source; the recording of this dataset was a part of a shallow seismic project performed in Romania in 2002. Timing/phase and amplitude variations affect this dataset due to the hilly field conditions. Phase variations are an effect of irregular receiver spacing and different statics between elements; amplitude variations were present due to local soil variations/ground coupling. Comparing the responses of the LCMV and MVDR beamforming applied to the field data we notice that the results are similar, even if the results based on synthetic data are different. In both cases, the surface waves have been well attenuated, better than on simple adding the data.

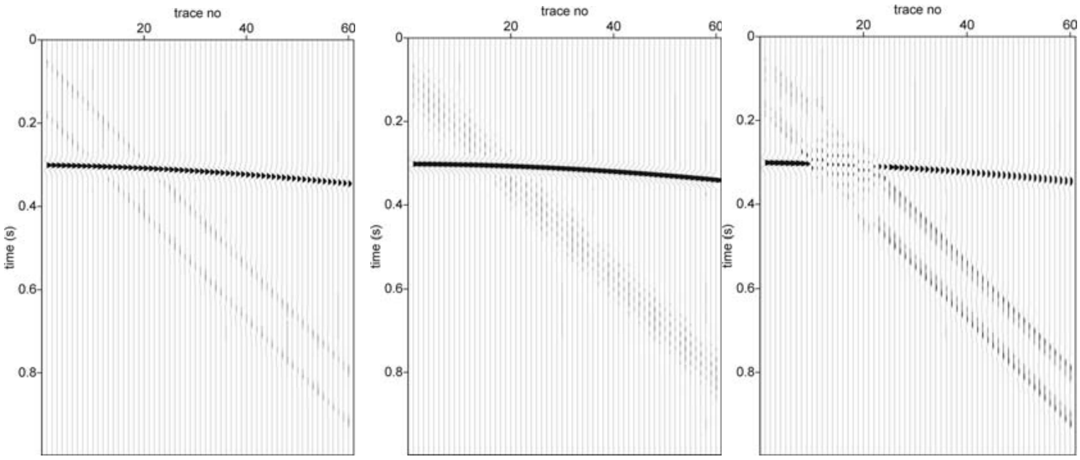

Fig 4. Array-forming, 12 traces added (left), LCMV (center) and MVDR (right) responses

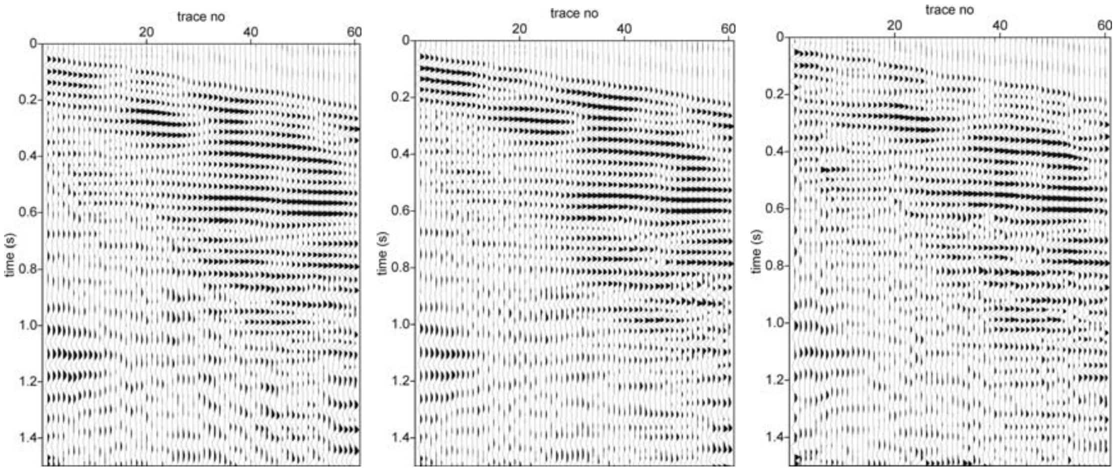

Fig 5. Array-forming, 12 traces added (left), LCMV (center) and MVDR (right) responses

Conclusions

Two types of beamforming methods have been presented in this paper and their effectiveness have been analyzed using synthetic and field seismic data; it has been shown that the LCMV beamformer preserves well the desired signal even in the presence of timing/phase and amplitude variations while the MVDR beamformer does not show a good response in the presence of amplitude variations. Their responses on field data show a better attenuation of the surface wave cone compared to the standard array-forming response. Even better results can be obtained when static corrections and amplitude equalization takes place before doing the beamforming.

References

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