DETECTING SMALL AMPLITUDE SIGNAL AND TRANSIT TIMES IN HIGH NOISE: APPLICATION TO HYDRAULIC FRACTURE MONITORING

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1. INTRODUCTION

In this paper, a two step integrated approach to extract small signals embedded in noise together with their first arrival times is presented. The first step resulting in a *event detection indicator* allows discriminating the signals of interest from background noise using a statistical hypothesis testing approach. The second one provides transit times of detected signals in noisy environment using a fast and robust beamforming method. This integrated methodology is applied to hydraulic fracture monitoring (HFM) data [1] corresponding to seismic events generated from oilfield production activities. These events can provide useful information in reservoir development and management decisions.

2. METHODOLOGY

The first part of this framework consists in scanning the recorded HFM data with a moving time window and making a determination whether each window contains a signal of interest or not [2]. Signals of interest include the recorded compressional and/or shear waves generated during oifiled production activities. Consider the windowed time series $x_{ml}(t), m = 1, ..., N_r; l = x, y, z; t = 1, ..., N$, where N_r, L, and N are respectively, the number of receivers in the array, the component type and the window length. This time series can be modeled as a sum of signal and noise: $x_{ml}(t) = s_{ml}(t) + \epsilon_{ml}(t)$ and we build vectors $X(t), S(t), \mathcal{E}(t)$ using some or all of the components above and let $X_N = [X(1), \ldots, X(N)]$. Assume that the noise process is stationary Gaussian with power spectral density matrix $F(\lambda)$, i.e. $\mathcal{E}(\lambda) \sim \mathcal{N}(0, F(\lambda))$ where λ is the frequency. The signal is given by $S(t) = \mu G(t) * s_0(t)$ where $\tilde{G}_{ml}(\lambda) = \exp(-i\delta_m\lambda)\exp(-j\phi_e); \phi_e = \{0, \pi\}$ is the transfer function of the media operating on a source signal $s_o(t)$ modeled as the convolution of a Ricker wavelet, $s_R(t)$ with a P-order FIR filter, $h(t)$. The power spectrum is separately estimated using data in signal free windows using Thomson's multitaper method [3] while h is estimated as part of the event detection as described below. As such we adopt a more general noise model than the autoregressive model used in [2] to address the hydraulic fracturing scenario and use a Ricker wavelet based model for the signal events that is an excellent fit for the observed microseismic signals.

The signal existence problem can be cast as the problem of testing between the hypotheses - $H_0 : \mu = 0\ vs. H_1 : \mu \neq 0$. The GLRT solution under the above assumptions of Gaussian noise and deterministic unknown signal and estimation of h leads after some calculation to a test statistic $\tau(X_N) = \Delta^\dagger\Gamma^{-1}\Delta$ where the vector $\Delta = \sum_{j=1}^{N_f} H_j^\dagger F_j^{-1}\tilde{X}_j$, the matrix $\Gamma = \sum_{j=1}^{N_f} H_j^\dagger F_j^{-1} H_j$ and $\tilde{X}_j$ and H_j are discrete Fourier transforms of X_N and h respectively evaluated at the frequency λ_j (and similarly for F_j). An event will be considered present in the window if $\tau(X_N) > \tau_o$. The threshold τ_o is chosen based on the statistical behavior of the τ under H_0; with Gaussian noise, it is possible to set this independently of the actual noise covariance and obtain a constant false alarm rate (CFAR) detector for testing at a given level of significance.

After the detection of the events has been performed, the delays between their arrivals across the array are estimated [4]. The delay e_{ij} between ith and jth waveforms is estimated by cross-correlating waveforms i and j and finding the time index for which the cross-correlation is maximized: $\hat{e_{ij}} = \arg\max_\tau r_{ij}(\tau)$. Having estimated the pairwise delays $\hat{e_{ij}}$, the next step is to estimate the desired parameters $\Delta\tau$ by solving the linear system $\mathbf{e} = \mathbf{A}\boldsymbol{\Delta}\tau$ with the pairwise delays as column vectors and the elements of matrix $\mathbf{A}$ at the (ij, k) position being defined as $A(ij; k) = \delta_{jk} - \delta_{ik}$. The convention adopted here for the ordering of the entries of $\mathbf{e}$ is that the index pairs i, j are ordered lexically: $i < j$ and j is varied more rapidly than i. The procedure described above has the advantage of being computationally faster than beamforming all the waveforms. However, any gross errors in the pairwise correlations will propagate into the estimates for the relative delays. To overcome this issue, we extend the previous method by beamforming larger size subsets (e.g. triples, quadruples, ...) and subsequently reconciling the resulting estimates by solving an overdetermined linear system. As the size of the subset being beamformed increases, more waveform averaging is performed, and the resulting estimates are less sensitive to gross errors.

3. RESULTS

Figure 1 (top left panel) presents HFM waveforms from a field acquisition while the bottom left shows the corresponding *event detection indicator* curve together with the threshold (dash line) used to detect the presence of events. Pink and green triangles indicate respectively the strong and weak events detected by the algorithm and show good correlation with visible events present in the waveforms. The right panel shows a zoom view wherein red marks indicate the first motion estimated by the hybrid beamforming algorithm presented here along with a first motion detection approach described in [5] applied to the first waveform. One can see the good performance of the time picking algorithm on the real field data.

4. CONCLUSION

In this paper, an integrated framework to detect signal embedded in noise and estimate their arrival times has been presented. This integrated framework was successfully applied to real HFM data demonstrating the effectiveness of the proposed methodology.

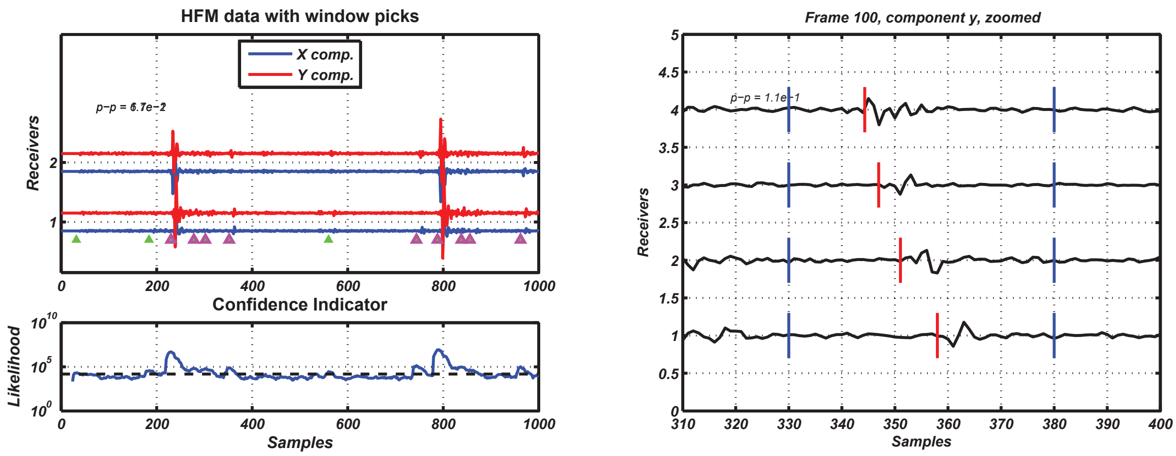

Fig. 1. Example of events detection (left) and time picking (right) obtained on HFM data.

5. REFERENCES

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