A generic procedure for noise suppression in microseismic data

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Summary

Here we describe a generic data processing flow that attenuates ringing as well as stationary and transient correlated noise. The procedure consists of two steps; firstly, large errant frequencies are suppressed using a winsorising procedure in the frequency domain, whereby anomalously large frequencies are reset to a median value. Secondly, the data is passed through an adaptive subtraction procedure, where the noise is modeled using a multi-channel Weiner filter (MCWF). The method makes no assumptions regarding the origin of desired signals or their manifestation in the data, for example, it can be applied where the signal moveout is non-linear and or polarities are inconsistent, preserving the original moveout and polarization. This means our procedure can be applied prior to any modeling or subsequent processing operations such as sensor orientation.

Using real and semi-synthetic data (synthetic signal plus real noise) we examine the efficacy of the processing flow. Input data for these tests comes from a 40 level downhole array with 3 components stations at each level. We find that whilst the procedure produces fairly modest gains in signal to noise ratio (typically 4-12 dB) both geophone ringing and correlated noise from tube waves is effectively removed with minimal distortion to the microseismic waveforms. This suggests the procedure could provide a useful precursor to subsequent processing and analysis. Our experiments also show relatively little sensitivity to the input parameters provided sensible values are chosen.

Introduction

Despite the best efforts in acquisition microseismic data is often contaminated by noise. This noise can come from a number of sources, for example electrical noise in the geophone may manifest as a ringing frequency. Alternatively (in downhole surveys) tube waves which are manifested as signals with linear moveout along the array may also contaminate microseismic data. Clearly it is desirable to limit the amount of noise contamination during microseismic monitoring as this will lower the detection threshold for microseismic events, leading to a better understanding of the fracturing process.

In this study we present and test one such processing flow. In order to examine the efficacy of the processing method we utilize data from a 40x3C downhole array deployed during hydraulic fracturing. We demonstrate aspects of the method using semi-synthetics (a synthetic arrival superimposed upon real noise). Using semi-synthetics with a variety of different settings we gauge the sensitivity of the method to the various input parameters and measure the gains in signal to noise ratio produced by the procedure. Finally we show the results of the processing method applied to a real microseismic arrival.

Procedure and Semi-Synthetic Example

Figure 1 A shows the semi-synthetic data prior to application of any noise suppression. In the plot, ringing frequencies are clearly visible as vertical stripes, whilst tube wave noise is visible as bands with linear moveout. The superimposed synthetic arrival dips from right to left at approximately 0s.

The first part of our procedure is designed to attack frequency spikes such as the geophone ringing. These could be suppressed using notch filter; however, this would create un-wanted artifacts particularly in the traces that do not show the ringing. Instead we opt for a procedure that only suppresses anomalous frequencies where they are present.

We use a procedure similar to that of (Elboth et al., 2010) to remove high amplitude monochromatic frequency components visible on some of the data. The procedure is as follows:

1. The 2s traces are divided into windows of length 0.2s with the start of successive windows delayed by 0.025s.
2. The data within each time window is transformed to the frequency domain (so called time frequency transform)
3. For each time window and frequency amplitude the median value across the array is computed
4. Frequency amplitudes greater than 3 times the median are, reset to the median value (winsorisation).
5. Traces are transformed back to the time domain for sub sequent processing

The procedure has the advantage that it can remove both time and frequency spikes. Additionally traces, frequencies and times that do not have any spurious features are left largely un-altered. Figure 1 B and C display the result and the residual noise removed by the time-frequency winsorisation.

The ringing frequencies are completely removed as well as some of the high amplitude tube wave noise on component Z. The signal is now visible in the panels of Figure 1B as the dipping event around 0.s. There is some leakage of the signal into the removed noise; however, this effect is minor.

Following time-frequency winsorisation, the panels still contain a large amount of tube wave noise. The most dominant tube wave signal being the wave travelling down the well (left to right in the panels), however, there is also an up going reverberation which has a similar moveout to our desired arrival. The second step in our processing flow is designed to attack this correlated noise.

This tube wave noise could be suppressed using a number of different techniques such as tau-p filtering (Claerbout, 1985), SVD or Eigen trace decomposition ((Freire and Ulrych, 1988), (Bekara and Baan, 2007)). However, we adopt an adaptive subtraction technique as it makes no assumptions regarding the nature of the signal we wish to extract. Thus the procedure is applicable in a wide range of settings where source position is unknown. The technique is similar to that used by (Wang et al., 2009), where the noise is simulated in the frequency domain using a multi-channel Weiner filter (MCWF). Mathematically the procedure is summarized as:

$$D_i{}'(\omega) = D_i(\omega) - N_i(\omega) = D_i(\omega) - F_{ij}(\omega)R_j(\omega) \quad (1)$$

Where, $D_i{}'(\omega)$, is the filtered data in channel, i and angular frequency, ω. $N_i(\omega)$, is the estimate of the noise on that channel which is formed by applying the linear filter, $F_{ij}(\omega)$ to a selection of the reference data channel $R_j(\omega)$.

The filter coefficients are formed from a sample of the noise, recorded without event arrivals taking place solving the normal equations

$$R_k^*(\omega)R_i(\omega) = R_k^*(\omega)R_j(\omega)F_{ij}(\omega) \quad (2)$$

Where $R_i(\omega)$ is the noise channel we are trying to predict, and $R_j(\omega)$ are the reference channels being used are using to perform the prediction ($R_i(\omega) \neq R_j(\omega)$). $R_k^*(\omega)$ denotes elements of the conjugate transpose of the elements of, $R_j(\omega)$.
The filter coefficients were computed using a 68 second sample of noise (taken prior to the 2s used to make the semi-synthetic) transformed in to the time-frequency domain using overlapping windows of Length, L, with the start of successive windows delayed by 0.025s. For each data channel reference channels were chosen to be the closest G (group) channels to that particular sensor (but not including channels from the sensor itself). An SVD algorithm was used to solve for filter coefficients, which leads to the third free parameter in the procedure the condition number for the inversion (the ratio of the smallest to the largest eigenvalue used, C)

Figure 1D shows the semisynthetic result after adaptive subtraction for L=0.3s G=18 C=0.3. The tube wave noise has now been largely removed. It can also be seen from the residual panel, Figure 1, that there is minimal distortion to the portion of the traces containing the arrival.

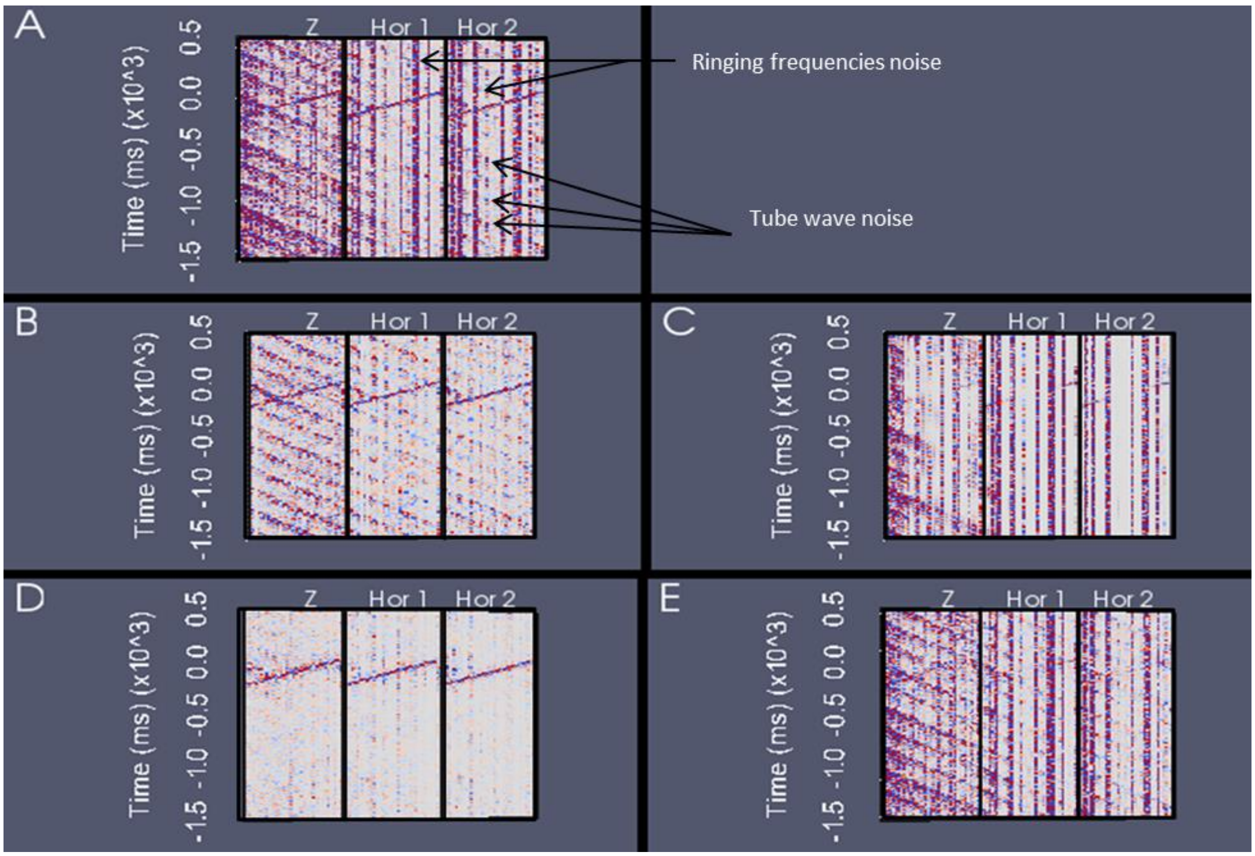

Figure 1 –Panels showing the results of the noise suppression method applied to the semi synthetic data. A – Input semi-synthetic input data (ringing frequencies and tube wave noise is clearly visible). B – result after time frequency winsorising with window length of 0.3s, C- the noise removed by time-frequency winsorising (i.e. A-B) the ringing frequencies are attenuated but the correlated tube wave noise remains, D – the result after adaptive subtraction the tube wave noise has now been removed leaving the arrival we wish to separate, E- the noise removed by the entire procedure (i.e. A-D)

SNR Analysis

We examine the efficacy of the filter for a variety of input settings. In each case we compute the signal to noise ratio on each channel in decibels (SNR_{DB}) using

$$SNR_{DB} = 20\log_{10}(RMS_{signal}/RMS_{noise}) \tag{3}$$

Where the signal RMS, RMS_{signal}, is measured over a short window around the arrival and the RMS_{noise} is measured over the time window prior to addition of the synthetic arrival. Figure 2 shows the SNR of each channel for the input data, after time-frequency winsorization, as well as for 3 settings of the adaptive subtraction filter. As expected the time-frequency winsorization only produces SNR changes on certain traces. Application of the adaptive subtraction produces further SNR gains across the array. There appears to be little variation in the amount of SNR gain from the different settings for the adaptive subtraction, suggesting the MCWF procedure is relatively insensitivity to input parameters provided sensible values are chosen. In general the SNR gains from the procedure are fairly modest and less than the amount of variation across the array.

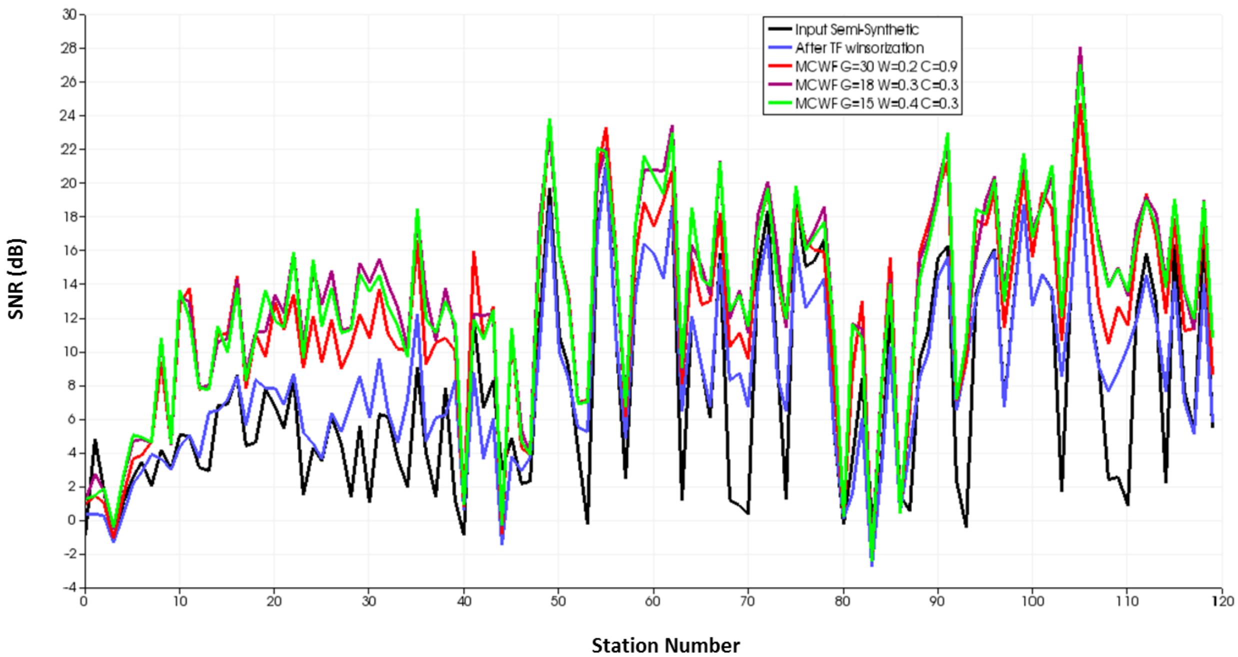

Figure 2 - Signal to Noise Ratio (SNR) for each Channel (same Channel order as Figure 1). The black curve represents the input before noise supression. Blue corresponds to SNR after time-frequency winsorization. The Red, Purple, and Green curves show the results of Multichannel Wiener Filter application with different parameters. The purple line corresponds to the recommended parameters with the highest average SNR: Group Size (G) = 18, Window Length (W) = 200ms, and Condition Number (C) = 0.3.

Real data application

Figure 3 shows the application of the processing steps to a real microseismic arrival, recorded using the same deployment as used of the semi-synthetic noise. As with the semi-synthetic example the time-frequency winsorisation removes the ringing frequencies, whilst leaving the majority of the data unaltered. The subsequent application of the adaptive subtraction also removes the correlated tube-wave noise. The result Figure 3 D shows several clearly delineated arrivals, corresponding to signals from one or more sources. In particular note that complicated waveform features are preserved by the procedure including changes in the arrival slope across the array.

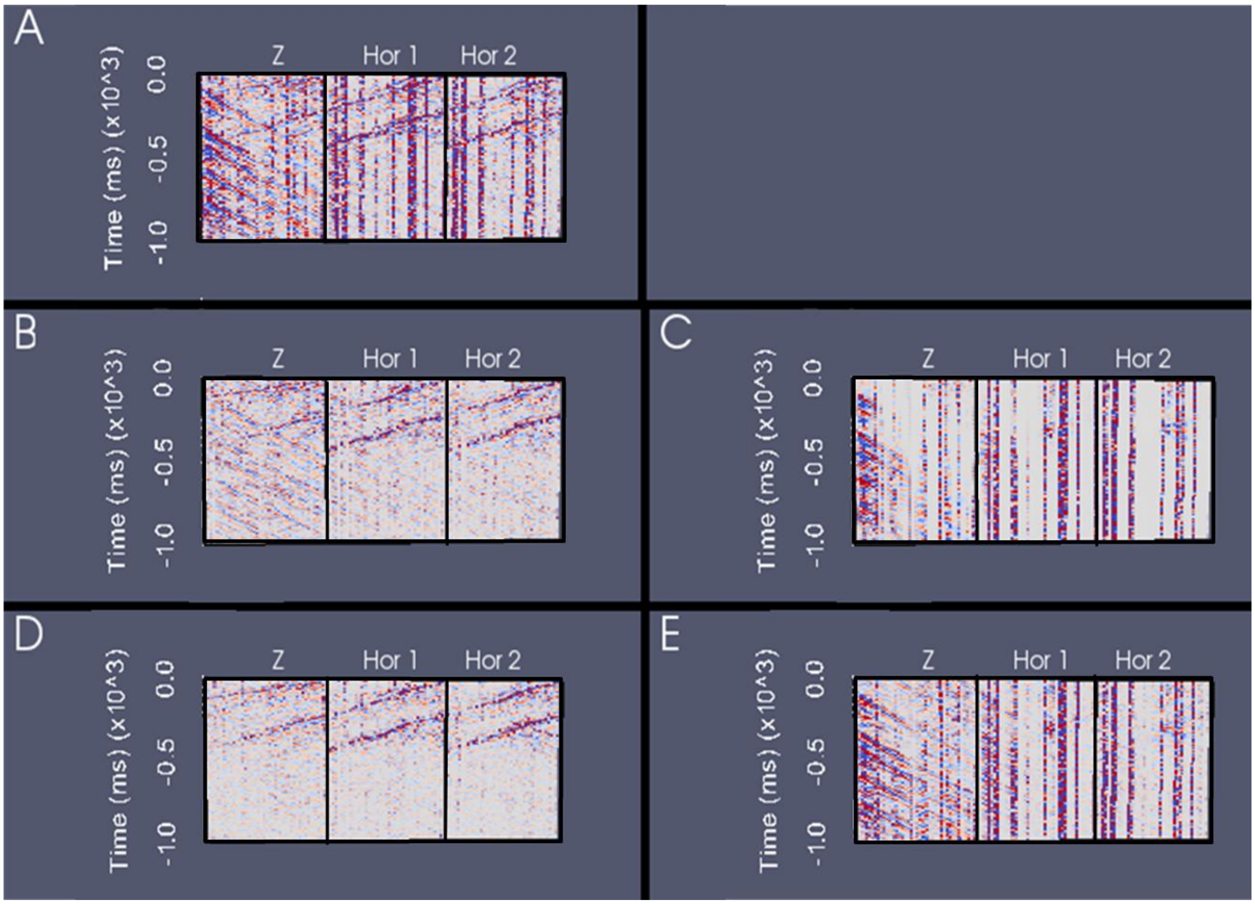

Figure 3 - Panels showing the results of the noise suppression method applied to a real microseismic arrival. A – Input data, B – result after time frequency winsorising with window length of 0.3s and a factor of 12 overlap, C- the noise removed by time-frequency winsorsing (i.e. A-B), D – the result after adaptive subtraction, note that the complex nature of the arrival is now much clearer. E- the noise removed by the entire procedure (i.e. A-D)

Conclusions

Noise Attenuation is a key step in microseismic data processing which enhances signal to noise ratio, enabling accurate interpretation or picking of microseismic wave's arrivals. Here we have described and applied a noise suppression workflow designed to remove ringing frequencies and tube wave noise. The ringing frequencies were attenuated using a time-frequency winsorisation procedure, whereas correlated noise from tube wave was suppressed using an adaptive subtraction method.

The method makes no assumptions regarding the origin of signals or its form in the data. For example, it does not require consistent polarities across the array or certain features for the desired signal (such as linear moveout) meaning it can be applied prior to any modeling or subsequent processing operations (such as sensor orientation).

Our tests using semi-synthetic and real data indicate that the procedure produces only modest gains in the signal to noise ratio (up to 12dB). Nonetheless the examples show the method is effective at removing the noise and leaving signal preserved. Furthermore there is relatively little sensitivity to variations in the input parameters.

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