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Evaluation of micro-earthquake de-noising using wavelet decomposition

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Summary

A wavelet de-noising method is evaluated for its applicability and effectiveness on earthquake events recorded by a local seismic network. The performance of the method is evaluated both on synthetic events with various signal to noise ratios (SNR) and on a real dataset collected by a local network in a passive seismic tomography (PST) setup.

Introduction

Micro-earthquakes recorded by local seismic networks during passive seismic tomography surveys and while monitoring hydrofracturing are presenting some specific challenges. These micro-earthquakes have small magnitudes where ambient noise results in a very low signal to noise ratio (SNR) making their use in subsequent steps such as detection or picking rather difficult. De-noising of signals reduces noise while minimizing loss of information and this can be an important initial step in utilizing these data. Wavelet de-noising can be a powerful tool for achieving that goal as the wavelet transform on which it is based is suitable for non-stationary signals where the frequency content varies with time (Misiti, et al., 2009).

Wavelet de-noising for local earthquakes

A noisy signal (*s*) recorded by a seismic station can be expressed as the sum of the useful part (*m*) plus the added noise (*n*).

$$s(t) = m(t) + l\, n(t)$$

where *s* is the time signal to be de-noised t is the time, *m(t)* is the useful part of earthquake and *n(t)* is the added noise with level *l*. The aim of the de-noising is to minimize the *ln(t)* parameter in order to get the useful signal *m*.
De-noising using wavelet transform is based on wavelet thresholding (sometimes also referred to as shrinkage) and consists of three steps.

- Initially, the signal is decomposed using the discrete wavelet transform (DWT) into a shifted and scaled version of an original wavelet
- Then thresholding of the detail coefficients is performed on the levels of the decomposed signal according to a chosen thresholding method aiming to preserve as much as possible the main characteristics of the signal while reducing the details.
- Finally, the de-noised signal is reconstructed by using an inverse discrete wavelet transform (IDWT).

<u>Wavelet transform</u>
Wavelet transforms are based on wavelets in contrast to the Fourier transform that is based on sinusoids. For the purposes of the wavelet transform, a wavelet is considered as a usually irregular and asymmetric waveform that has limited duration and zero average value. There are several families of wavelets that are used in wavelet transform such as the daubechies and symlet. After selecting a wavelet to use, the signal (*s*) is decomposed according to that wavelet and in this way both frequency and temporal information can be obtained.
The DWT is calculated by using the algorithm depicted in Figure 1. According to this the signal (*s*) passes first through a high pass filter and then through a lowpass one decomposing it into the following two sub-bands:

$$D_L(n) = \sum_{k=-\infty}^{\infty} h_d(k)\, x(2n-k)$$

$$A_L(n) = \sum_{k=-\infty}^{\infty} l_d(k)\, x(2n-k)$$

Where L is the level of decomposition (for L=1 , x is the signal s), h_d the high-pass decomposition filter, l_d the low-pass decomposition filter and n and k denote discrete time coefficients. For every decomposition level L, the high-pass filter, which forms the wavelet function, produces the high frequency or detail D_L part of the signal, while the complementary low-pass filter, which forms the scaling function, produces the low frequency or approximation part of the signal A_L. The filtering process alters the resolution, changing the scale either up-sampling or down-sampling by 2.

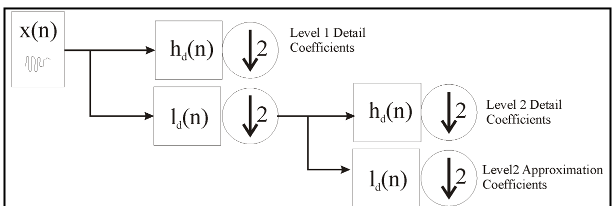

Figure 1: Calculation of DWT producing details and approximations.

The wavelet coefficients represent a measure of similarity in the frequency content between a signal and a chosen wavelet function (Misiti, et al., 2009)

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Thresholding

A technique that is used for regulating the de-noising process is thresholding (or "shrinkage"). Its application is based on the fact that if the smaller coefficients of the detail sub-bands are omitted the main features of the signal will not be significantly affected thus retaining its main features and discarding noisy ones. If zeroing of the coefficients is too aggressive (high threshold value) then the signal will be corrupted, while if too small, the noise reduction may not be sufficient. Estimation of the optimum threshold level has been studied and several methods have been proposed. Some of the more widely used methods are the universal threshold, the Stein's unbiased risk estimator (SURE) (Stein, 1981) threshold and minmax threshold. For our implementation, we have used the SURE threshold estimation.

Finally, thresholding can be either 'soft' or 'hard'. We have used a 'soft' threshold where except from setting all the details coefficients smaller than the selected threshold to zero (as in the 'hard' threshold) the threshold value is subtracted from the rest of the detail coefficients.

Inverse wavelet transform

The inverse discrete wavelet transform (IDWT) aims to reconstruct the initial signal. To achieve this the process up-samples by 2 and filters the wavelet coefficients of D_L and A_L using the reconstruction filters h_r (the high-pass reconstruction filter) and l_r the low-pass reconstruction filter following the equation.

$$x(n) = \sum_{k=-\infty}^{\infty} \left(D_L(k) h_r(2k-n) + A_L(k)\, l_r(2k-n) \right)$$

The reconstruction filters h_r and l_r are the same as the decomposition filters h_d and l_d but reversed in time. The IDWT will reconstruct the initial signal if the signal is of finite energy and satisfies the admissibility condition (Nguyen et al., 1996). These conditions apply to natural signals such as seismic ones.

Application on synthetic data

This method was first applied on synthetic data that were constructed using the following technique. Initially, a synthetic earthquake event was modeled using the ISOLA software (Sokos et al. 2013) while a segment of real seismic noise recorded by a single component 1Hz S-100 borehole seismometer and 24-bit SR-24 recorder was added to the signal creating the signal to be de-noised (Figure 2).

$$s(t) = m(t) + l\, n(t)$$

By modifying the level parameter l it is possible to control the Signal to Noise Ratio (SNR) of the signal that is used. SNR is defined as

$$SNR = 20\log_{10}\left(\frac{\sigma_{signal}}{\sigma_{noise}} \right)$$

The method was used on a number of different signals in which the SNR was gradually lowered until the result was no longer satisfactory. The method produced a satisfactory result up to an SNR of ????????

A decomposition level of 4 was selected after several tests.

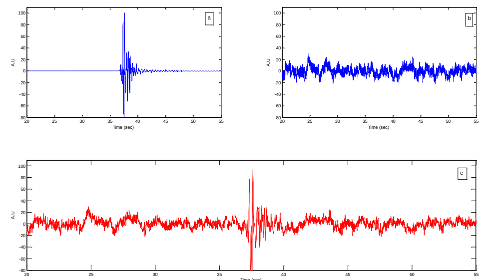

Figure 2: (a) synthetic signal (b) noise (c)Creation of synthetic event.

Next, the signal was decomposed to details and approximations with decomposition level L=4 (Figure 3) as the one used for the real dataset. After applying SURE thresholding the signal was reconstructed using IDWT (Figure 4). The original synthetic signal was recovered satisfactorily and the noise was suppressed as shown by the difference between the real noise free signal and the reconstructed/ de-noised one.

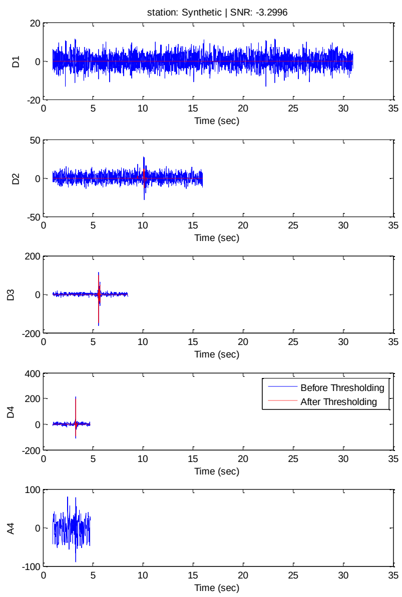

Figure 4: The wavelet coefficients of the synthetic signal before and after thresholding.

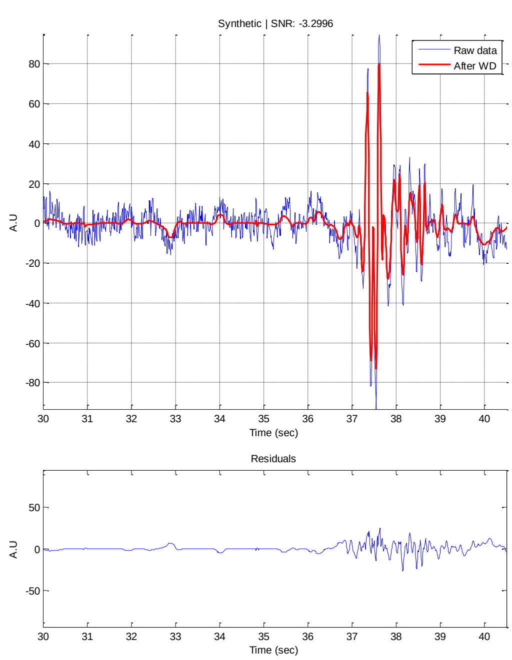

Figure 3: (a) De-noised synthetic signal. (b) the residuals of the denoised signal minus the real signal.

Application on real data

In order to evaluate the performance of wavelet de-noising on a real dataset, several events that were recorded during a PST survey by a local seismic network in Delvina S. Albania were used (Figure 5). Each station was instrumented with a 3-component 1Hz S-100 LandTech borehole seismometer and 24-bit SR-24 LandTech recorders were used to digitize and record the data. The instruments have a flat transfer function in the frequency range from 1Hz to 100Hz. The seismometers were placed in shallow boreholes at a depth of 6m in order to improve the SNR of the recorded data.

The network was setup bearing in mind acquisition parameters that are suitable for recording events in a PST experiment. That meant generally small magnitude earthquake events with maximum offsets of 60-70km and relatively high frequency content that can be in excess of 25 to 30Hz. The positioning of the stations meant that at some stations anthropogenic noise could be a factor deteriorating the quality of the records.

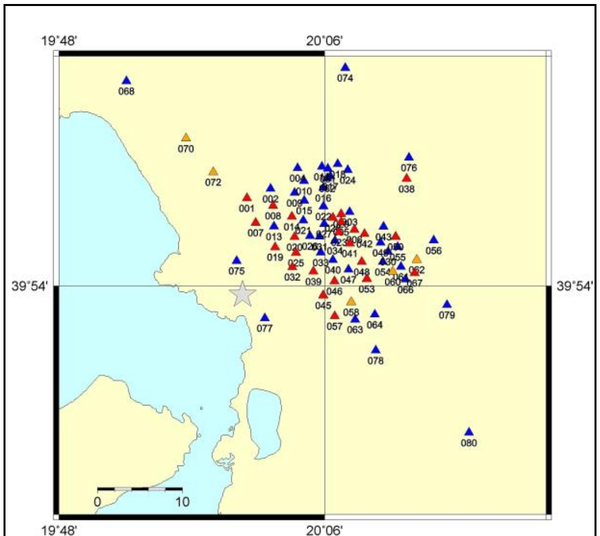

Figure 5: Map of the local seismic network used. The triangles indicate station positions while the star indicates a selected event that was used in the present work. Red stations indicate where both P and S arrivals were detected, orange stations indicate where only P could be detected and blue stations indicate where no pick was possible for various reasons.

The real signals were decomposed to details and approximations with decomposition level L=4 (Figure 6). Following tests, SURE thresholding was determined to produce the best results. After the signal was reconstructed using IDWT (Figure 7) the real signal was de-noised enabling easier picking of first arrivals.

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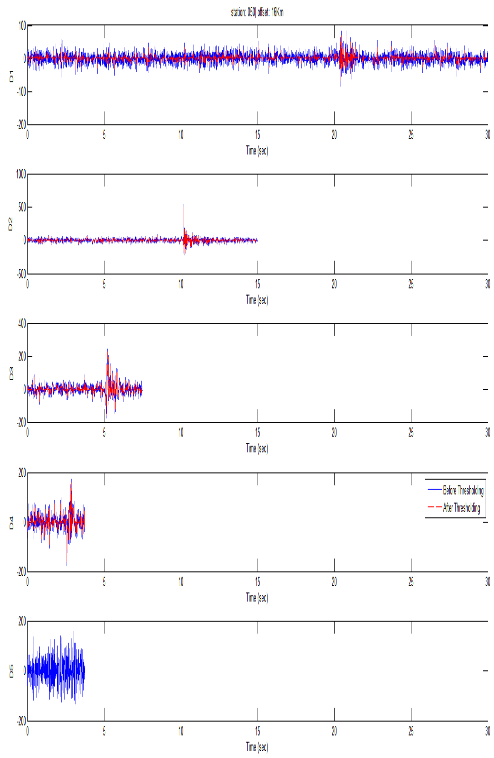

Figure 6: Wavelet coefficients of the real signal after wavelet transform (blue) and after thresholding..

Conclusions

A methodology based on wavelet transform has been tested in order to evaluate its effectiveness on removing noise from signals with varying frequency content with time and high levels of noise. Such signals are commonly encountered during reservoir or shale fracking monitoring.
The methodology was tested on real data obtained from a Passive Seismic Tomography survey and on synthetic data as well. It proved to be very effective in increasing the SNR and reduce the uncertainty in measuring the seismic phase arrivals

Acknowledgments

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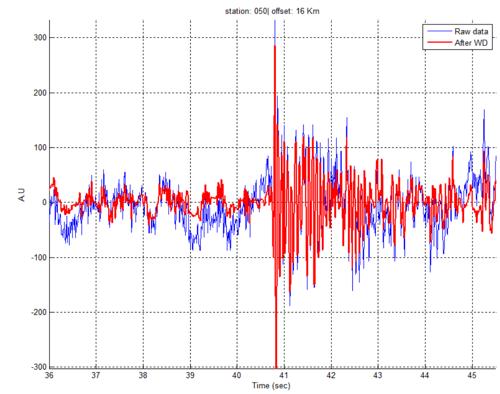

Figure 7: Wavelet denoising applied on a selected event and station.