A method for microseismic event detection and P-phase picking

G-Akis Tselentis ,University of Patras, Nikolaos Martakis,LandTech Enterprises,Paraskevas Paraskevopoulos, University of Patras, Athanasios Lois, LandTech Enterprises and Efthimios Sokos, University of Patras.*

Summary

A combined method is proposed for seismic events detection, signal enhancement and automatic P-phase picking. This method is comprised by a Chi-squared based test statistical test for the event detection, filtering in the S-transform domain, for denoising and an automatic picker based on the Kurtosis criterion. The performance of the method is tested and evaluated on both synthetic and real data.

Introduction

During a passive seismic investigation, either high resolution tomography survey or hydrofracturing we use small magintude earthquakes. Most of them have small magnitudes and often are hard to detect since they can be corrupted by noise.

For microfracture monitoring in addition to the noisy borehole environment most hydrofracturing events typically radiate smaller P –waves than S- waves therefor, identification of the weak p-wave arrivals is important for locating the microearthquakes and the accuracy of event azimuth relies mainly on the P-wave vector.

For high resolution passive seismic tomography (PST) applications, we need as many as possible small magnitude events which can be characterised as point sources. These small events, especially if acquired in urban areas are often strongly affected by noise, so we also require procedures that allow a reliable first arrival picking, without losing important information.

Theory and method

Chi-squared based test statistic for event detection

Chi-squared goodness-of-fit test (referred also as Karl Pearson's test) is a special type of hypothesis test that is often used to test the equivalence of a probability density function of sampled data with a theoretical one. For the seismic event detection we propose a new parameter free Chi-Square based statistic under a sequential hypothesis testing framework. Let us consider a set of N independent observations from a random variable x with a probability density function $p(x)$. Let the N observations are grouped into K intervals, called class intervals or bins, which together form a frequency histogram. The number of observations falling within each class interval is called the observed frequency (O_i), and the number of the observations that are expected to fall within each bin is called the expected frequency (E_i). To measure the total discrepancy for all class intervals we introduce the following sum (Bendat and Piersol, 1986):

$$q = \sum_{i=1}^{K} \frac{(O_i - E_i)^2}{E_i}$$

The fact, that: a) the distribution of the seismic noise is unknown b) specific bins' selection could falsely result in zero estimations, a fact that would drive the classical Pearson's statistic to infinity and c) the noise process consists of segments of the record, that are not independent and identically distributed sets of observations, prompted us to apply a modified Pearson's test (Lois et al. 2010). We estimate the expected frequencies from a properly selected noise segment of the record. Instead of equal length bins we can use equal number of observations per bin and instead of the frequencies O_i and E_i we use the corresponding lengths of the bins L_i^O, $\hat{L}_i^E$.These are obtained from the equiprobable partitioning of the support of the observed and the estimated theoretical *pdfs* respectively. Thus we introduce the finally proposed statistical test for the event detection:

$$q_m = \ln\left(\sum_{i=1}^{K} \frac{L_i^O - \hat{L}_i^E}{\hat{L}_i^E} \right)$$

The proposed modification of the Pearson's statistical test does not follow a X_{K-1}^2 distribution and in order to solve the event detection problem we follow a thresholding type hypothesis testing framework using the Otsu's method (Otsu, 1978) that provides an optimal separation between the noise distribution and the distribution of the samples belonging to seismic events.

The S transform based denoising

The S-transform (Stockwell et al, 1996) is a method that localizes the spectrum in the time-frequency domain. It is a generalization of the short-time Fourier transform, but with a Gaussian window whose width scales inversely, and whose height scales linearly, with the frequency.

The S-transform of the signal x(t) is defined as:

$$S(\tau, f) = \int_{-\infty}^{\infty} x(t) \frac{|f|}{\sqrt{2\pi}} e^{-\frac{(\tau - t)^2 f^2}{2}} e^{-i2\pi ft} dt \,.$$

Where t is the time, f the frequency and τ controls the position of the Gaussian window along the time axis.
One important property of the S transform is that the signal x(t) is exactly recoverable from its transform S(τ,f). Simon et al. (2007) showed that the inverse S transform of the filtered data should be calculated using the following equation in order to avoid the creation of artifacts:

$$x(t)=\sqrt{2\pi}\int_{-\infty}^{\infty}\frac{S(t,f)}{|f|}e^{i2\pi ft}df\ .$$

Another important property of the S transform is its linearity, that for the case of additive noise to the signal the data can be modeled as data(t) = signal(t) + noise(t) thus the S transform can be written as:

S{data(t)} = S{signal(t)}+ S{noise{t)}.

The calculation of the S transform of the signal is the first step in denoising. In order to minimize the effect of the noise in the signal, the Otsu's method is used to separate the areas of the S transform dominated by the high energy of the signal and the noisy areas. Then, based on this clustering, a filter is designed and smoothed, which is then applied on the S transform. Next, the filtered data in the time-frequency domain are back transformed to the time domain and we continue with the next step of the processing.

P-phase picking using the Kurtosis - criterion

Since we have already detected and denoised the segments of the record that include seismic information, we can estimate the P-phase arrival time using higher order statistics (HOS) (Nikias and Petropulu, 1993) and specifically the kurtosis criterion (Saragiotis et al, 2002). Kurtosis, the zero-lag, fourth order cumulant of a N-sample, real and zero–mean process $\{X(k)\}$, is a measure of the heaviness of the tails of its distribution. The estimator of the kurtosis used in this research is:

$$kur(X)=\frac{\sum_{i=1}^{N}\{(X(i)-\hat{m}_x)^4\}}{(N-1)\hat{\sigma}_x^{\ 4}}$$

where $\hat{m}_x$ and $\hat{\sigma}_x$ are the estimates of the mean and standard deviation of $\{X(k)\}$ respectively. Since kurtosis provides a measure of heaviness of the tails, we take advantage of the fact that outliers, such as seismic events, have high values and appear in the tails of the distribution. As these tails become heavier, kurtosis assumes high values and therefore presents maxima in the neighborhood of the P-arrival. To avoid large delays on the estimation of P onset time we evaluate the maximum slope and not the maximum value of the HOS parameter curve. This is due to the fact that the maximum value of this parameter is reached only when a sufficient fraction of the time window used contains the seismic signal, which is beyond the P-arrival. The stages of the proposed are presented in Figure 1.

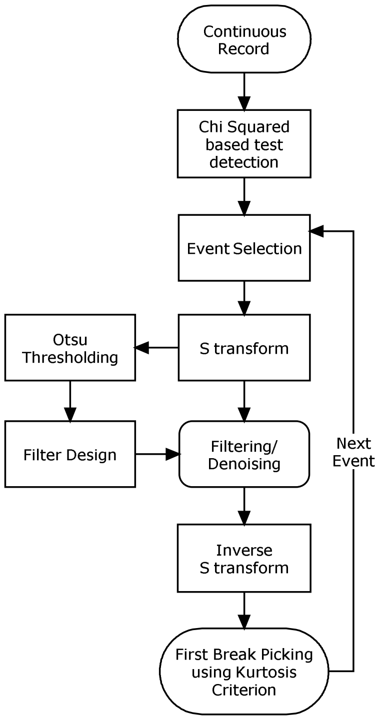

Figure 1: Flow chart of the stages of the proposed method.

Application on synthetic data

First, we test the proposed method to synthetic data. The synthetic seismograms are constructed by the following procedure: Initially Gaussian noise is filtered with a Park's – Mc Clellan optimal equiripple FIR filter. Next the signal is multiplied by a negative exponential function in order to simulate the effect of the attenuation of P- and S- coda (Figure 2).

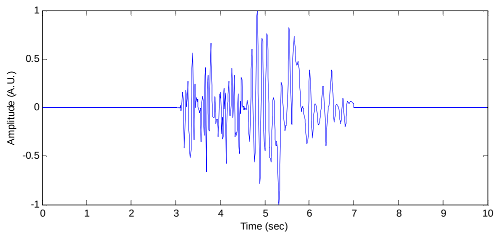

Figure 2: The noise free synthetic signal.

To control the signal to noise ratio (SNR) of the signal, a window with real noise from a seismic record is added. The synthetic event is scaled according to the amplitudes of the noise in order to achive the desired SNRs. The chi-squared based test statistic is applied to verify the existence of the event (Figure 3). The test has shown that it can detect the event sufficiently well.

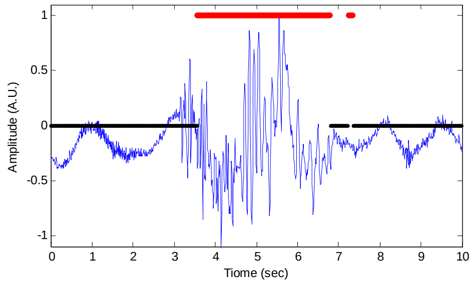

Figure 3: The synthetic signal with addition of noise and the results from the Chi squared based test's event detection. The red dots indicate the existence of seismic event, while the black indicate seismic noise.

The next step is to calculate the S transform. Using the Otsu's thresholding method both to the real and the imaginary part of the transform, the filter is designed and applied. Finally, the first arrival is automatically picked using the kurtosis criterion.
In Figure 4 the effect of the S-transform filtering can be seen on the synthetic seismogram at Figure 3. Figure 4a,b shows the automatic picking results using the kurtosis criterion to the unfiltered and the filtered seismogram respectivelly.

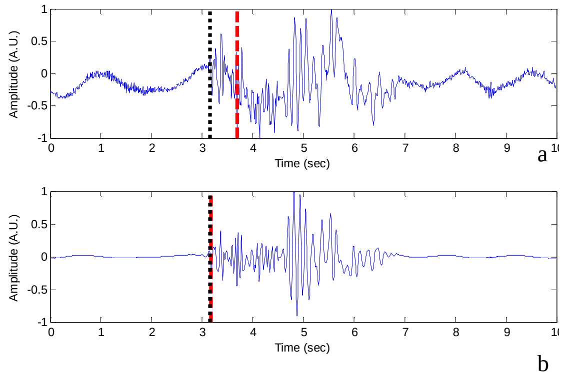

Figure 4: (a) Synthetic seismogram with addition of real seismic noise, (b) Filtered in the Time – Frequency domain signal. The red dashed line is the automatic pick as claculated using the kurtosis criterion and the black dotted line is the actual position of the first break arrival.

The signal is sufficiently cleared around the area of the first break. The end of the event is more attenuated but since the interest in this case is the first arrivals this is not a significant problem.
In comparison to the actuall pick we can see that the picking accuracy for the filtered signal is improved compared to the noisy one. An additional advantage of the proposed method is that the applied processes do not alter the P-pulse arrival.

Application on real data

In this section we test the proposed methodology on real data. A continuous record of 10 minutes is selected and the chi-squared based test apllied (Figure 5). All the events in this record were succesfully detected. From the detected events we select one with low SNR. Similarly as in the case of the synthetic data, the S transform is calculated and the event is filtered by the designed filter based on the Otsu's method thresholding (Figure 6). Finaly the first arrival is automaticaly picked using the kurtosis criterion.

Figure 7 shows the effect of the S-transform filtering on the selected low SNR event. The area around the P-phase arrival is improved while the end of the event is attenuated. Figure 7a shows the automatic picking results using the kurtosis criterion on the unfiltered event, in contrast to Figure 7b where the filtering is applied and improves the SNR

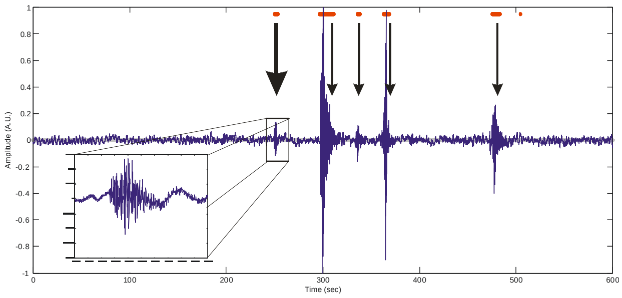

Figure 5: A section of data recording. The zoomed area shows the event selected to apply the propose methodology. Vectors indicate the detected events. and The red dots indicates the presence of the seismic events while the gray ones indicate seismic noise.

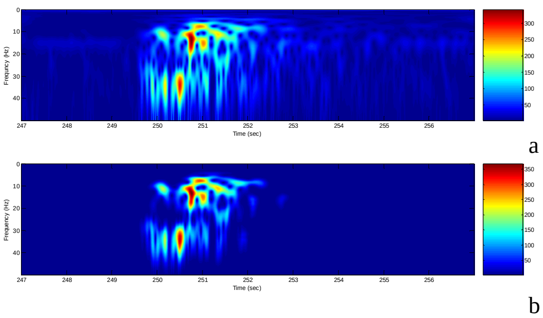

Figure 6: (a) The S transform of the selected event and (b) the coresponding S transform after the application of the filter.

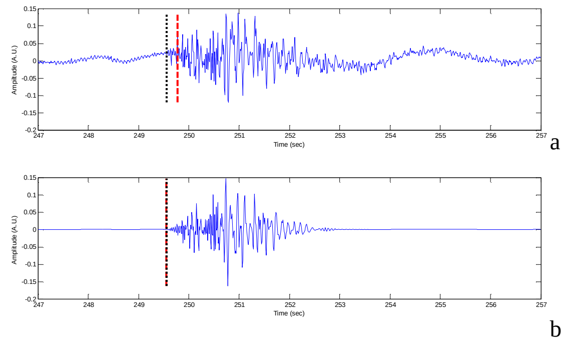

Figure 7: The event selected from (a) the real data and (b) the filtered in the Time – Frequency domain. The red dashed line is the automatic pick as calculated using the kurtosis criterion and the black dotted line is the actual position of the first break arrival.

Conclusions

We propose and apply an integrated method for seismic event detection, denoising and accurate P-phase picking. The modified Chi-squared test provides an almost free-parameter algorithm, for the events identification. It is easy to implement and its performance does not depend on any assumptions for the seismic noise distribution. The denoising of the events detected by the aforementioned algorithm, takes place in the S-transform domain using the Otsu's thresholding method. The SNR in the neighborhood of the P arrival can be significantly improved and this in term improves the automatic estimation of the accurateP-phase arrival time using the Kurtosis criterion. In general this hybrid method is straightforward to implement, demands low computational resources and requires minimum user intervention.

Acknowlwdgements

We want to thank the personnel of the computer center of LandTech enterprises for there help to implement the proposed methodology.

EDITED REFERENCES

Note: This reference list is a copy-edited version of the reference list submitted by the author. Reference lists for the 2011 SEG Technical Program Expanded Abstracts have been copy edited so that references provided with the online metadata for each paper will achieve a high degree of linking to cited sources that appear on the Web.

REFERENCES

Bendat, J. S., and A. G. Piersol, 1986, Random data, Analysis and measurement procedures, 2nd edition: Wiley-Interscience.

Lois, A., E. Z. Psarakis, V. Pikoulis, E. Sokos, and G. A. Gelentis, 2010, A new chi-squared based test statistic for the detection of seismic events and HOS based pickers' evaluation: 32nd European Seismological Commission Assembly.

Nikias, C. L., and A. P. Petropulu, 1993, Higher-order spectra analysis: A nonlinear signal processing framework: PTR Prentice-Hall.

Otsu, N., 1979, A threshold selection method from gray-level histograms: IEEE transactions on systems, man, and cybernetics, **9**, 62–66.

Saragiotis, C. D., L. J. Hadjileontiadis, and S. M. Panas, 2002, PAI-S/K: A robust automatic seismic P phase arrival identification scheme: IEEE transactions on geoscience and remote sensing, **40**, 1395–1404, doi: 10.1109/TGRS.2002.800438.

Simon, C., S. Ventosa, M. Schimmel, A. Heldring, J. J. Dañobeitia, J. Gallart, and A. Mànuel, 2007, The S-transform and its inverses: Side effects of discretizing and filtering: IEEE transactions on signal processing: **55**, 4928–4937, doi:10.1109/TSP.2007.897893.

Stockwell, R. G., L. Mansinha, and R. P. Lowe, 1996, Localization of the complex spectrum: the S transform: IEEE transactions on signal processing, **44**, 998–1001, doi:10.1109/78.492555.