Refinement of arrival-time picks using an iterative, cross-correlation based workflow

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Summary

Cross-correlation based techniques are widely used for time-delay estimation in electrical engineering and in the processing of passive and active seismic data. We present an iterative cross-correlation based workflow to refine arrival time picks on microseismic data that were initially picked either manually or using a single-trace based algorithm such as short and long-term average ratio (STA/LTA). We then evaluate the performance of this workflow on both synthetic and real microseismic data using a Monte Carlo approach. The proposed workflow provides an arrival-time accuracy of • ±0.5 − 1ms for both synthetic and real microseismic data examples considered in this study.

Introduction

Arrival-time picking is an important step in the processing of downhole microseismic data, since it determines the accuracy of hypocentre locations. Numerous algorithms that are applied to single or multi-channels are commonly used and widely discussed in the literature. Among the single-trace based algorithms, short and long-term average ratio (STA/LTA; Allen, 1978; Withers et al., 1998), modified Coppens' method (MCM; Sabbione and Velis, 2010), modified energy ratio (MCM; Han et al., 2009), phase arrival identification-kurtosis (PAI-K; Saragiotis et al. 2002; 2004) and Akaike information criterion (AIC; Takanami and Kitagawa, 1991; Sleeman and Van Eck, 1999) are well-known. These algorithms have been evaluated on both synthetic and real microseismic data in Akram et al. (2013). The performance evaluation of these algorithms shows that the accuracy and stability of these algorithms depend greatly on signal-to-noise ratio (S/N) of microseismic data. The single trace algorithm take no advantage of other traces in the array in arrival-picking. On the other hand, a multi-channel algorithm takes advantage of the similarity of detected P- and S-wave microseismic signals for different sensors, and thus can improve the quality of time-picks. Cross-correlation is an example of a multi-channel algorithm that is widely used for time-delay estimation in electrical engineering (Tamim and Ghani, 2009), in the estimation of static corrections for surface seismic data (Bagaini, 2005) and in microseismic and earthquake data processing for event identification and phase arrival picking (Raymer et al., 2008; De Meersman et al., 2009; Eisner et al., 2008).

In this paper, we present a workflow based on iterative cross-correlation for refinement of arrival-time picks. The proposed workflow is modified from an arrival-pick refinement procedure presented in De Meersman et al. (2009). Several real and synthetic data examples are used to evaluate the performance of the proposed workflow. The initial arrival-time picks, polarity and amplitudes are perturbed randomly and an error analysis on the picked arrivals is performed using a Monte Carlo approach.

Iterative cross-correlation based workflow

The following form can be assumed for the microseismic data recorded at two different receivers (Bagaini, 2005)

$$x_1(t) = s(t) + n_1(t)\,, \tag{1}$$

$$x_2(t) = as(t-\tau) + n_2(t), \tag{2}$$

where $s(t)$ is the signal, τ denotes time delay, $n_1(t)$ and $n_2(t)$ are the noise in the recorded data and a denotes the amplitude ratio of trace 2 to trace 1. The time delay is estimated from the lag at the peak value of the cross correlation between $x_1(t)$ and $x_2(t)$. Bagaini (2005) evaluated the performance of different time-delay estimators where reference traces obtained from various selection schemes are used. It is shown that the iteratively updating the reference signal provides better time-delay estimation than non-iterative schemes where reference trace is selected from sensors within the array or by simple stacking.

De Meersman et al. (2009) described an iterative cross-correlation workflow for refined arrival picking (Figure 1). In this workflow, initial manually picked arrival-times are used to align the microseismic traces. Before the computation of stacked trace, all the traces are rescaled to equalize to the pre-event noise level. A stacked reference trace is then computed and correlated with all the traces to update the time-shift. This process repeats until the time delay converges to a user-defined threshold value (ε), which represents the optimal re-alignment of the data.

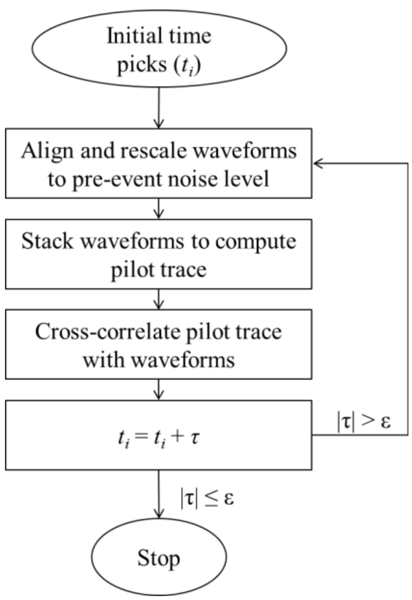

Figure 1: Iterative cross-correlation based workflow for refined arrival time picking by De Meersman et al. (2009).

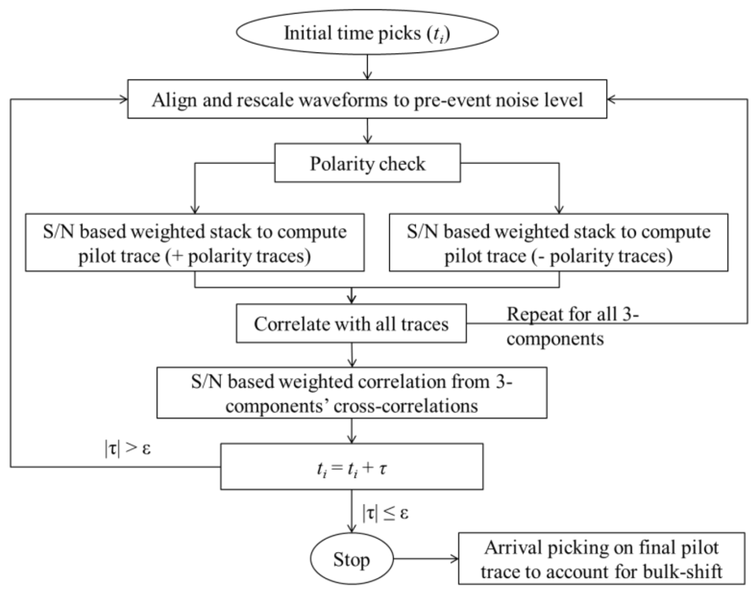

Figure 2: The proposed workflow, modified from De Meersman et al. (2009).

Microseismic waveforms are typically accompanied with both amplitude and polarity variations considering the source radiation pattern. Additional waveform complexity comes from the amount of noise typically observed in the microseismic data. In many cases, one of the three components is noisier than the others in the recorded data. This workflow does not explain the case where both amplitude and polarity variations are present. Assuming that the complex analytical signal is used to address the polarity variations or phase shifts, the performance of this workflow might not be optimal in noisy datasets as shown in Bagaini (2005).

We propose the following modifications to the above workflow.

1. Initial time-picks are estimated using one of the single-trace based methods, such as AIC.
2. Microseismic traces are aligned and re-scaled to equalize the pre-event noise level which is the root-mean square (RMS) value in a user-defined noise window for each trace.
3. A polarity check is then established on the dataset using the initial time-picks. In this step, all traces in each of data components are classified into positive and negative polarity groups of traces.
4. To minimize the effect of noisy traces on the stacked pilot trace, a S/N weighting scheme is applied in trace stacking. The optimal pilot traces that honour data amplitude and polarity, are computed for both polarity groups of traces.
5. These pilot traces are correlated with all traces in the corresponding data component. The main reason for this step is to ensure that no errors from polarity check are propagated into pilot traces.
6. Following Arrowsmith and Eisner (2006), S/N weighted cross-correlation is computed to reduce the effect of noise on individual components on the time-delay estimation. Previously, trace based S/N weighting was used. In this step, whole receiver gather's S/N (computed from the median S/N values of all traces in that data component) is used as weighting factor. The weighted cross-correlation from all three components is

$$C_i(\tau_i) = \frac{\left(\frac{S}{N}\right)_{xi} C_{xi}(\tau_i) + \left(\frac{S}{N}\right)_{yi} C_{yi}(\tau_i) + \left(\frac{S}{N}\right)_{zi} C_{zi}(\tau_i)}{\left(\frac{S}{N}\right)_{xi} + \left(\frac{S}{N}\right)_{yi} + \left(\frac{S}{N}\right)_{zi}}. \tag{3}$$

7. Time lag value is estimated from the absolute maximum of the S/N weighted cross correlation. All traces are then shifted using the time lag value.
8. Steps 2 - 7 are repeated until the absolute lag value becomes lower than a pre-defined threshold or another stopping criterion such as maximum number of iterations.

Since the cross-correlation method provides relative arrival-time information, a bulk time shift is applied if necessary to correct the onset times. The bulk time-shift is computed as follows

$$S_{1+} = \frac{median\left(\frac{S}{N}\right)S_{x+} + median\left(\frac{S}{N}\right)S_{y+} + median\left(\frac{S}{N}\right)S_{z+}}{median\left(\frac{S}{N}\right) + median\left(\frac{S}{N}\right) + median\left(\frac{S}{N}\right)}, \tag{4}$$

$$S_{1-} = \frac{median\left(\frac{S}{N}\right)S_{x-} + median\left(\frac{S}{N}\right)S_{y-} + median\left(\frac{S}{N}\right)S_{z-}}{median\left(\frac{S}{N}\right) + median\left(\frac{S}{N}\right) + median\left(\frac{S}{N}\right)}, \tag{5}$$

$$S = \begin{cases} |S_{1+}| + |S_{1-}| & if\ both\ polarities\ exist \\ |S_{1+}| & if\ only + polarities\ exist \\ |S_{1-}| & if\ only - polarities\ exist \end{cases}, \tag{6}$$

where S is the final weighted stack of positive and negative weighted stacks (S_{1+} and S_{1-} respectively). We then use AIC to find the required bulk shift (if any) and apply this to all picked times.

Examples

Figure 2 shows synthetic data examples that were created using an 80 Hz minimum-phase wavelet and P-arrival-time information from one of the real microseismic picked events. The signal amplitude were perturbed by adding white Gaussian noise which was generated using MATLAB subroutine *wgn*. Figure 2a and 2b show the waveform data with amplitude perturbations. The picked arrival-times using the proposed workflow are also shown. A Monte Carlo approach was used to evaluate the performance of our proposed workflow. The absolute errors between the picked and the actual arrival time were computed for 100 realizations. In each realization, a different noise level was added in the input data and arrival times were perturbed using a normal distribution denoted as *N(0,10)* where 10 represents the standard deviation in number of samples. Figure 2c shows the absolute error histograms for the picked arrival times, the majority of which are picked with ±2-4 samples accuracy. Figure 2d shows the absolute error in the picked arrival times with respect to the S/N of the input data. It suggests that our workflow performs within the above-mentioned accuracy majority of the time for very poor S/N data and as can be seen in Figure 2, it provides high quality time-picks for medium to high S/N data.

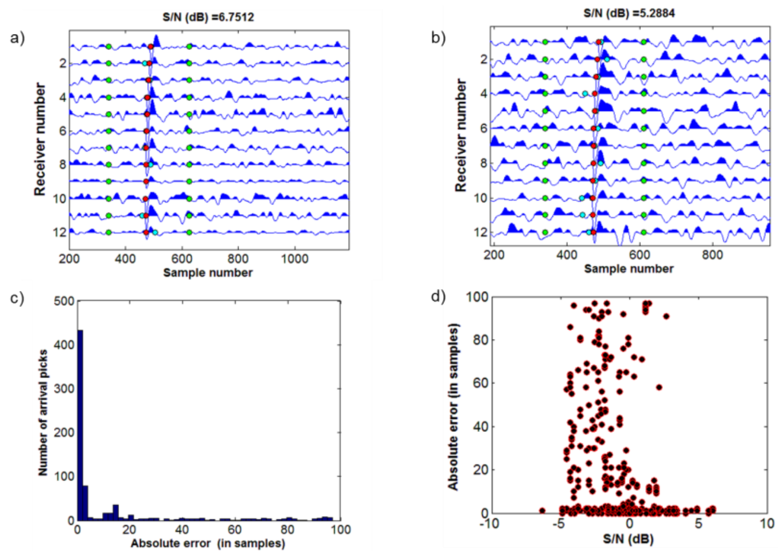

Figure 1: Performance and error analysis of our proposed time-picking workflow for synthetic data. a) and b) shows the quality of picked arrival times on the waveform data. The initial times are shown by cyan colored dots. The analysis window is shown by the green colored dots representing the lower and upper bounds. The red colored dots represent the picked arrival times using our proposed workflow. c) and d) suggest that the arrival times using our workflow can be picked in majority of times within an accuracy of ±2-4 samples.

Figure 3 shows absolute errors (in samples) for picked arrival times where the input data also has polarity variations. The polarity of the data is flipped for the first five traces in the record. Similar to the previous case, both the initial data and the arrival times are perturbed with random noise. Although majority of arrivals are picked within the same time accuracy as is seen in the previous case, the performance of the workflow slightly deteriorates. One of the factors that may affect the picked-time accuracy is the amount of added random noise and the complex changes in the waveforms. As in majority of the cases, the initial input data studied here for time picks has S/N below 0 dB which suggests that the noise level is higher than the signal level.

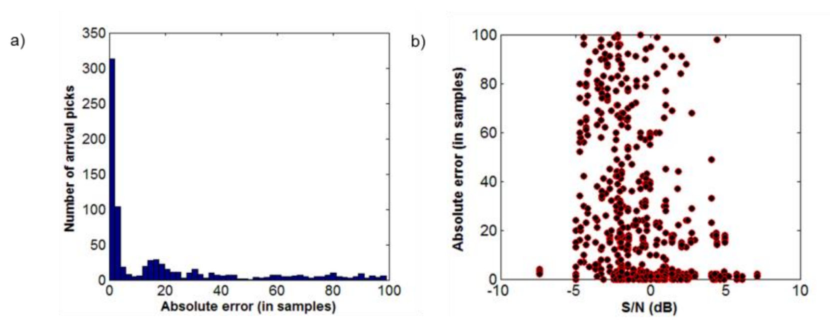

Figure 2: Performance and error analysis of our proposed time-picking workflow for synthetic data with polarity and amplitude variations. Majority of the picked errors remain within ±2-4 samples as was the case in Figure 2. However, the accuracy is slightly deteriorated from what is observed in Figure 2.

We now apply this approach to P-wave arrival time picks for real data from a two-stage fracture treatment. The monitoring well is approximately 150m south and 350m east of the treatment location. The data were acquired with a sampling interval of 0.25ms using 12 three-component receivers, with 10m inter-receiver spacing. We have chosen this dataset because all three components have a different S/N (Figure 4).

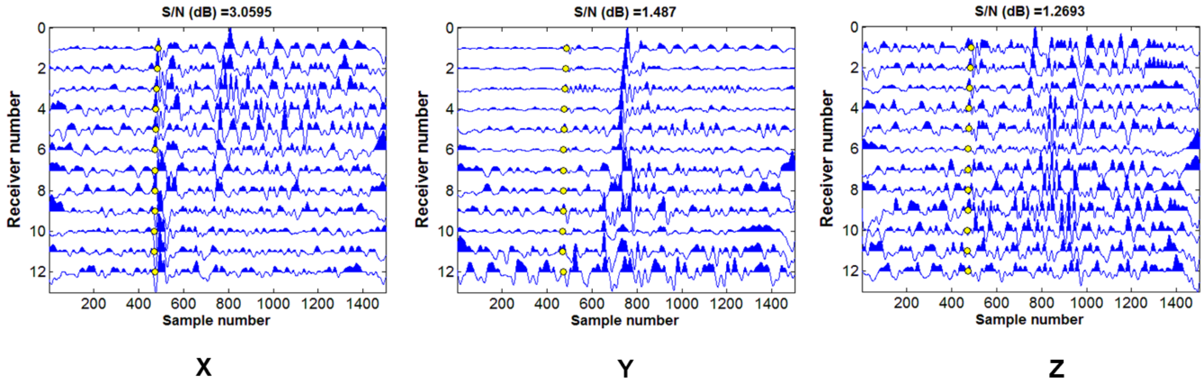

Figure 3: Real microseismic data (un-rotated) examples showing different S/N for each component.

Figure 5 shows the P-wave arrival time-picks using our proposed iterative cross-correlation based workflow. Here, we have also flipped the polarities of the first six traces and added the random perturbations in arrival time in a similar way described for synthetic data examples. The correct arrival times are identified in all the cases. However, the precision of picked arrival-times becomes less when the data S/N is very low.

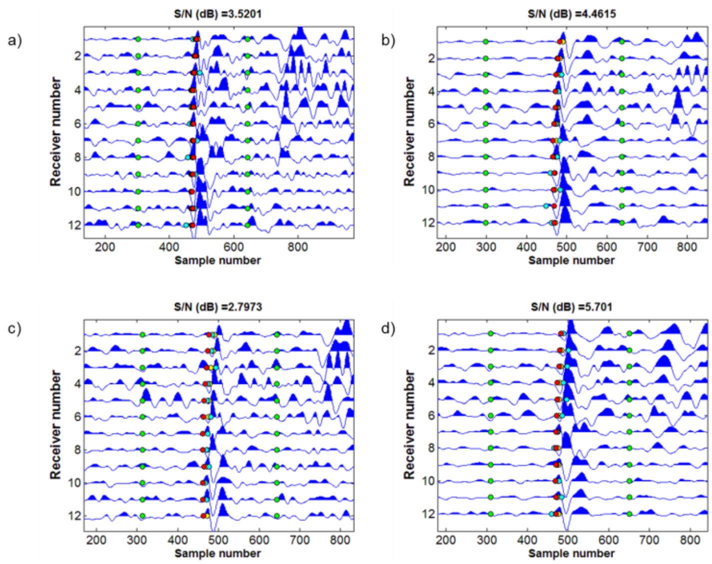

Figure 4: Example of arrival time-picks using our proposed workflow on real microseismic data with various levels of noise add-back. The description of colored dots is same as shown in previous figures. Here, manually picked times are shown with yellow colored dots.

Conclusions and future work

We have presented an iterative, cross-correlation based workflow for enhanced arrival time-picks. We have tested the performance and error analysis of this workflow using both synthetic and real microseismic data examples. In the evaluation of algorithm performance, we perturbed the amplitudes, polarity and the initially picked arrival times to present a realistic scenario in which the quality of picks is affected by the poor S/N of data and the inaccurate initial arrival times. For the cases considered, synthetic data yield arrival time picks within ±2-4 samples accuracy. However, the introduction of polarity flips in the synthetic data deteriorates the quality of picks for poor S/N data. Similar accuracy scale is observed for real microseismic data which was kept un-rotated to evaluate the performance of our algorithm in poor S/N and complex waveforms.

Future applications of this approach will make use of ray-centered coordinate rotation to enhance both the S/N and the quality of waveforms that it is expected from the cross-correlation. This will help to ensure similar performance for both P- and S-waves.

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References

Akram, J., Eaton, D.W., and St. Onge, A., 2013. Automatic event-detection and time-picking algorithms for downhole microseismic data processing: 4th EAGE passive seismic workshop, Amsterdam, Netherlands.

Allen, R., 1978. Automatic earthquake recognition and timing from single traces: Bulletin of the Seismological Society of America, 68, 1521-1532.

Arrowsmith, S.J., and Eisner, L., 2006. A technique for identifying microseismic multiples and application to the Valhall field, North Sea: Geophysics, 71, 31-40.

Bagaini, C., 2005. Performance of time-delay estimators: Geophysics, 70, 109-120.

De Meersman, K., Kendall, M., Van der Baan, M., The 1998 Valhall microseismic data set: An integrated study of relocated sources, seismic multiplets, and S-wave splitting: Geophysics, 74, 183-195.

Eisner, L., Abbott, D., Barker, W.B., Lakings, J., and Thornton, M.P., 2008. Noise suppression for detection and location of microseismic events using a matched filter: SEG 2008 Las Vegas annual meeting.

Han, L., Wong, J., and Bancroft, J., 2009. Time picking and random noise reduction on microseismic data: CREWES Research Report, 21, 1-13.

Raymer, D., Rutledge, J., and Jaques, P., 2008. Semi-automated relative picking of microseismic events: SEG Annual Meeting, 1411-1414.

Sabbione, J.I., and Velis, D., 2010. Automatic first-breaks picking: New strategies and algorithms: Geophysics, 75, 67-76.

Saragiotis, C.D., Hadjileontiadis, L.J. and Panas, S.M., 2002. PAI-S/K: A robust automatic seismic P phase arrival identification scheme: *IEEE Trans.* Geosci. Remote Sens, 40**,** 1395–1404.

Saragiotis, C.D., Hadjileontiadis, L.J., Rekanos, I.T. and Panas, S.M., 2004. Automatic P phase picking using maximum kurtosis and *κ*-statistics criteria: IEEE Trans. Geosci. Remote Sens, 1**,** 147–151.

Sleeman, R., and van Eck, T., 1999. Robust automatic P-phase picking: an online implementation in the analysis of broadband seismogram recordings: Physics of Earth and Planet Interiors, 113, 265-275.

Takanami, T., and Kitagawa, G., 1991. Estimation of the arrival times of the seismic waves by multivariate time series models: Ann. Inst. Stat. Math. 43, no. 3, 407-433.

Tamim, N.S.M., and Ghani, F., 2009. Hilbert transform of FFT pruned cross correlation function for optimization in time delay estimation: Proceedings of the 2009 IEEE 9th Malaysia International Conference on Communications, Kuala Lumpur Malaysia.

Withers, M., Aster, R., Young, C., Beiriger, J., Harris, M., Moore, S., and Trujillo, J., 1998. A comparison of select trigger algorithms for automated global seismic phase and event detection: Bulletin of the Seismological Society of America, 88, 95-106.