Akaike Information Criterion Applied to Detecting First Arrival Times on Microseismic Data

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Abstract

The onset of a microseismic signal on a geophone trace is determined by modeling the noise and seismic signal in windows using the Akaike Information Criterion (AIC). Initially developed to predict an optimal order for an autorecursive filter, the criterion can be used to demark the point of two adjacent time series with different underlying statistics. The AIC first-break pick algorithm is robust in the presence of high-amplitude random noise, computationally fast and could be implemented automatically.

Introduction

Techniques have been presented in the literature and at conventions to detect and pick the arrival times of different seismic waves. A class of first-break detection algorithms has utilized the work of Akaike (1973). He proposed "an Information Criterion" (later changed by others to "Akaike Information Criterion" or AIC). In seismic data, the AIC is a measure of the order of the variance of the component not explained by an autorecursive (AR) process modelled to fit the data. An algorithm is proposed here based upon the work of Sleeman and van Eck (1999). A window of microseismic data is analyzed to look for first-break events. The algorithm is compared to an STA - LTA difference method and an energy trace windowing approach on microseismic data. Finally, short length AIC windows will be automated for a first-break picking scheme.

Autoregressive Model Order and the AIC Picking Algorithm

Akaike's information criterion was developed in 1971 (Akaike, 1973). He was studying the goodness of fit of an estimated statistical model for a given order of an AR process to try to find the lowest order that would best fit observed data. The AIC is a test for selecting lengths of feedback loops. A side benefit is that the criterion can efficiently separate events in the same time series. Assume a time series of length "nsamp" can be broken down into two pseudo-stationary time series. As defined here, a pseudo-stationary process has unchanging mean, variance and autocorrelation over the time of the investigation. The first series is random noise and the second series records an energy motion over an adjacent interval (Figure 1). For an autorecursive filter of length M, the AIC at sample k for a time series of length nsamp is expressed as:

$$AIC(k) = (k - M)\log(\sigma^2_{1,max}) + (nsamp - M - k)(\log(\sigma^2_{2,max}) + const \qquad \textbf{(Eqn. 1)}$$

Again, M is the order of an AR process fitting the data, and $\sigma^2_{1,max}$ and $\sigma^2_{2,max}$ are the variances in the time series intervals (from $t_{1 \text{ to } k}$ and $t_{k+1 \text{ to } nsamp}$) not explained by the auto regressive analysis. In Eqn. 1, the value for M must be estimated before the AIC can be calculated. However, if M is small compared to nsamp, Eqn. 1 can be simplified:

AIC(k)=k*log(var(y(1:k))) + (nsamp–k -1)*(log(var(y(k+1:nsamp))) **(Eqn. 2)**

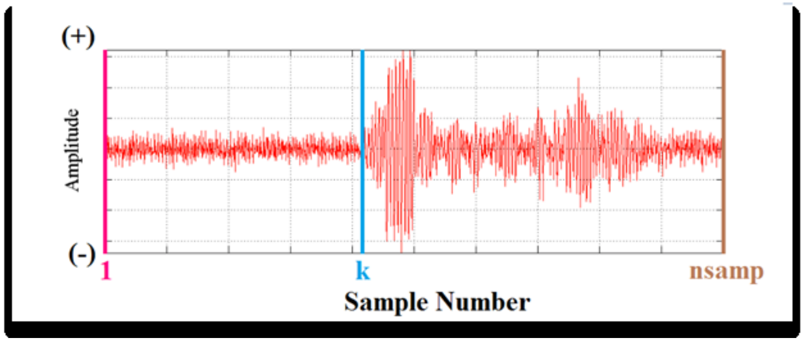


Figure 1 – A sample of the microseismic data from a single vertical component geophone. The separation point k delimits two adjacent time series with different statistical properties. Random noise is from sample 1 to k, and energy motion is recorded from sample k+1 to nsamp.

AIC Algorithm Applied To Microseismic Data

Data from a microseismic survey recorded during the hydraulic fracturing of a well in NE British Columbia in November 2009 was used to test the algorithm. Equation 2 was used to calculate the AIC array values shown on Figure 2. The time series initiates with low-amplitude random noise followed by a high-amplitude impulse. Initially, a low k sample value is multiplied by the log of the variance from sample 1 to k. The variance of a low-amplitude time series is a small number. This number will become smaller as k increases. At the energy onset, the samples from 1 to k have a larger variance than before, so the first term begins to increase in amplitude. The resulting AIC array plot has the appearance of a slanted "v". This AIC minimum is chosen as the first-break.

AIC Algorithm Compared To Two Other Algorithms

Two other methods were used to detect the arrival time of an event embedded in increasingly higher amplitudes of random noise. The first method was presented by Chen and Stewart in 2005. The "before time average-after time average" (BTA to ATA) windowed trace energy before and after a time sample. Once a threshold was met, a first-break time was assigned. The second algorithm is the "short-term average minus the long-term average" (STA – LTA). Here, the energy of a short window is compared to that of a longer window. Once a threshold is reached, a first-break time is assigned.

All three algorithms were applied to the data in the presence of increasing amounts of random noise. The added noise ranged from zero up to the approximate amplitudes of the largest impulse amplitudes. Consider Figure 3. These data were used as an input 17 times into a program that added random noise to produce Figure 4. All algorithms behaved predictably. The STA-LTA usually picked times later than the other algorithms on the high S:N data. The BTA-ATA windowed trace picker had similar time picks as the AIC algorithm, except when the S:N ratio became close to 2.5.

Figure 2 – The calculated 0.2115 sec onset of energy for trace 49.

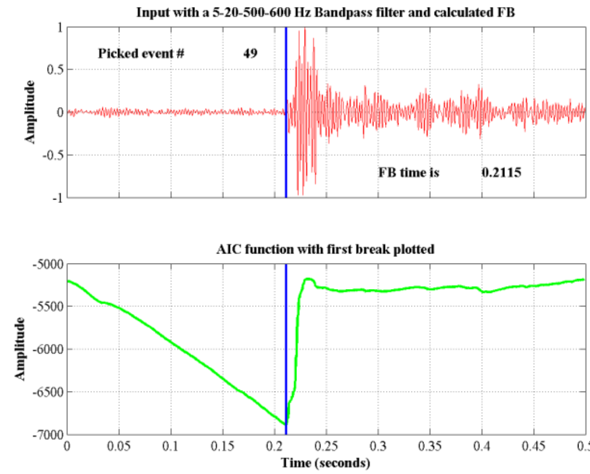


Figure 3 – Event 69 with added noise. The AIC pick is close to its original ; the others have shifted in the presence of the relatively high amplitude noise.

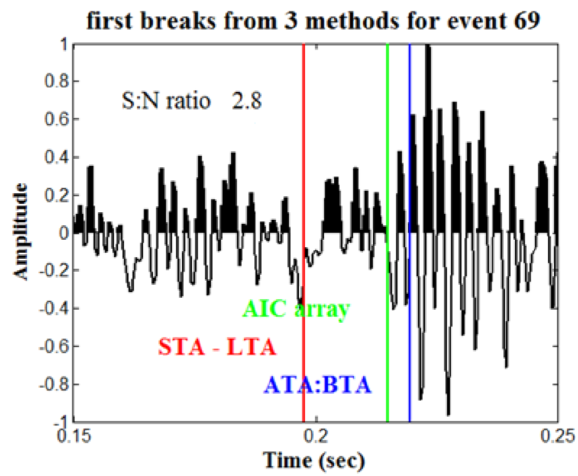
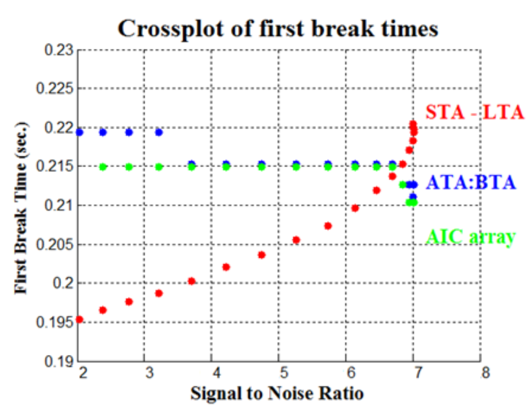


Figure 4 – a crossplot of calculated first-break times for event 69 using the three algorithms in the presence of increasing random noise. The AIC and BTA - ATA algorithms were close except at high noise levels.



AIC Algorithm Automated Using Short Time Windows

Shorter over lapping windows be used to construct a number of AIC windows. The smaller windows may detect individual events without being influenced from other arrivals. Consider Figure 5, which was constructed by running short AIC arrays only where the variance of the trace exceeded a preset minimum.

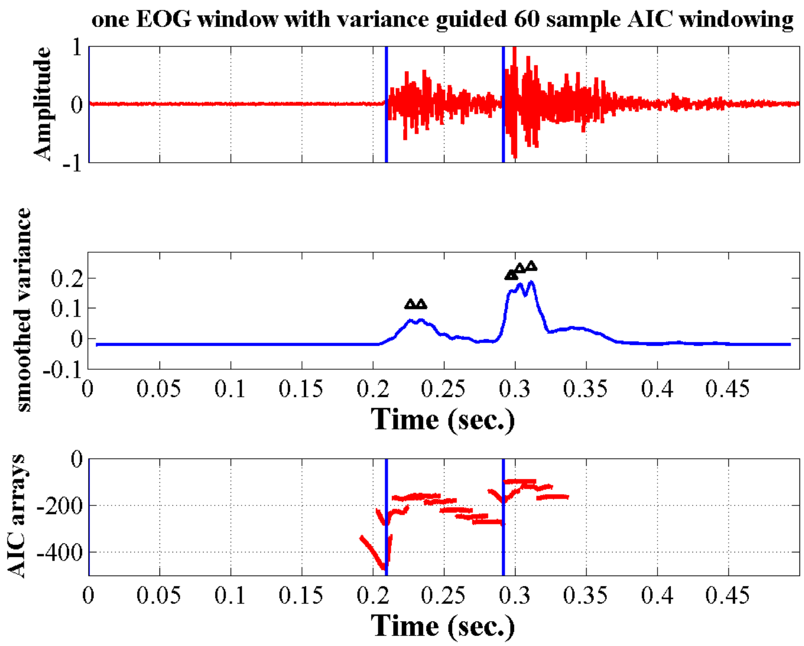


Figure 5 – The onset of energy of one apparent P-wave event is shown by the vertical blue line. The smoothed variance of the trace was used to "bracket" the time series. Within this bracket, 60 sample AIC arrays (shown in red on the bottom) were calculated. Two of the AIC windows detected the onset of energy at the same time for the first arrival.

Conclusions

A first-break picking algorithm based upon the Akaike Information Criterion (AIC) should be considered for interpreting microseismic data. The method was able to detect first-breaks more consistently than two other algorithms. The picker is robust in the presence of random noise with amplitudes as large as the impulsive arrivals. The quick algorithm and could be implemented for large volumes of microseismic data.

Acknowledgments

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