An energy- and period-dependent P-wave onset picking algorithm

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Abstract

Initial P-wave's information of the first few second is vital for estimating an ongoing earthquake's source parameters in earthquake early warning systems. Most automatic picking algorithms were proposed depend on the energy change in a trace. Erroneous trigger is always occur in the case that P-wave onset is hidden in high-amplitude ambient noise or the energy difference between the seismic P-wave and ambient noise is indistinguishable. We have proposed a P-wave onset picking algorithm which depends on both amplitude and period change. The proposed algorithm is composed of two steps. The first step is determining a cursory onset through threshold value of both energy and period. The energy change is evaluated by kurtosis function and the period change is evaluated by apparent period which is approximated by zero-crossing. Once a cursory onset is confirmed, the second step is determining the precise onset by an AIC function, in which both amplitude information and period information are considered. The effectiveness of the proposed algorithm is verified by using three typical traces..

Keywords: Earthquake Early Warning; P-wave onset picking

1. Introduction

The automatic picking of the P-wave onset is a vital technique for real-time systems. various P-wave onset automatic picking algorithms such as STA-LTA[2,3,16], kurtosis and skewness function based algorithm[6,7], auto-regressive (AR) method[13,22,23], predominant period or instantaneous frequency based algorithms [8,18] and polarization involved algorithms [6,8], have been proposed to pick P- and S-wave onsets automatically or to enhance the picking precision. These algorithms were proposed mainly depend on the differences between seismic P-wave and background noise.

The first difference is that seismic wave's energy is generally larger than that of background noise, it is the most obvious difference exists between seismic wave and background noise. Meanwhile, calculating the energy change in the time domain is computationally efficient. So, most P-wave onset automatic picking algorithms are proposed based on this difference, e.g. STA-LTA [2,3,5,16], FilterPicker [4], PhasePApy [9], high-order-statistical function-based algorithms [7,12,6,21,14,24].

The second difference is that the period of seismic wave is generally larger than that of background noise. In order to evaluate the period change in real-time procedure, Bai, et al. have proposed an automatic phase detection algorithm [8] in which instantaneous frequency is obtained through applying Hilbert transform over time series to obtain instantaneous phase, and then applying time differentiation over the instantaneous phase time series to obtain the instantaneous frequency. Hildyard et al. proposed a time-domain predominant-period approximating function named T^{pd} and applied this function to the picking of the P-wave onset [17]. Costas et al. proposed an onset picking algorithm based on the energy and frequency combined, whereby the frequency is approximated from the peak number in a sliding time window [10].

The third difference is that background noise is not polarized vibration while seismic wave is polarized vibration. The change in the polarization feature is more notable at S-wave onset, and most polarization-dependent algorithms are thus applied to separate P- and S-phases instead of picking only the P-wave onset [20,19,21,11,25].

The proposed algorithm in this paper tries to combine the differences in both energy and period together to form a P-wave onset picking algorithm, and for the purpose of decreasing erroneous trigger.

2. Methodology

We have used two variables in the proposed algorithm to evaluate the energy and period change. The first variable is kurtosis function, which is first applied to P-wave onset picking by Saragiotis [7]. The second variable is apparent period, which is approximated by number of zero-crossing.

(1) Kurtosis function

The kurtosis function is defined as below:

$$kur_k = \frac{\sum_{k=1}^{M}\left(h_k - \hat{m}_x\right)^4}{\left(M-1\right)\hat{\sigma}_x^4} \tag{1}$$

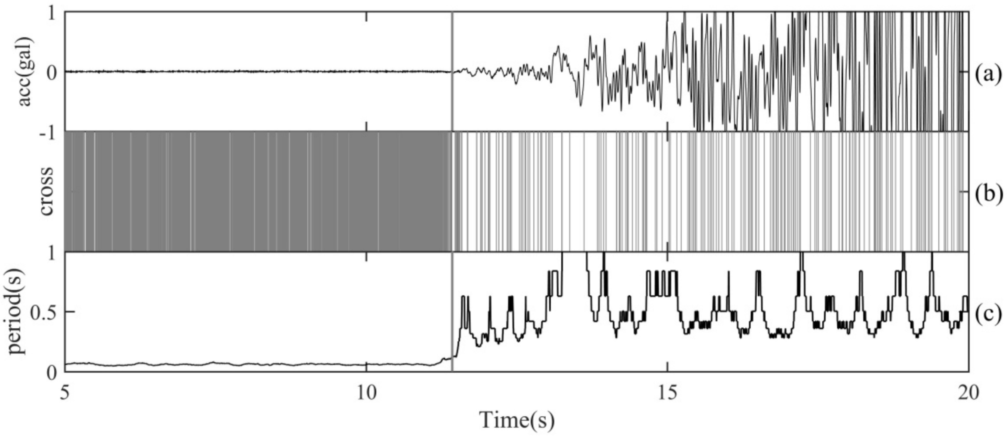
Where $\hat{m}_x$ and $\hat{\sigma}_x$ are the mean and standard deviation of the M-sample sliding window h. kur_k represents the calculated kurtosis and set to the end point of each sliding window.

(2) Apparent period

Owing to the inefficiency nature of determining instantaneous frequency from the short time Fourier transformation, we have used a simple approximation by counting the zero-crossing number to calculate apparent period:

$$p_j = \frac{2\pi \cdot T}{\left\{1 + \sum_{i=j-n_w+1}^{j} \left[\frac{1 - sign\left(x_i \cdot x_{i-1}\right)}{2}\right]\right\}} \tag{2}$$

Where x represents the time series of a trace as shown in Fig. 1(a); *T* represents the window length with unit of second for counting the number of zero-crossing as shown in Fig.1 (b), we have used a 0.2s time length in this paper; n_w represents the total samples involved in the window length *T*; p_j represents the apparent period as shown in Fig.1 (c).



(a) Seismic time series. (b) zero-crossing vary with time, if there is a zero-crossing, there we draw a straight line from zero to one over longitudinal coordinate. (c) Apparent period variation with time.

Fig. 1 Comparison diagram between apparent period of seismic wave and background noise

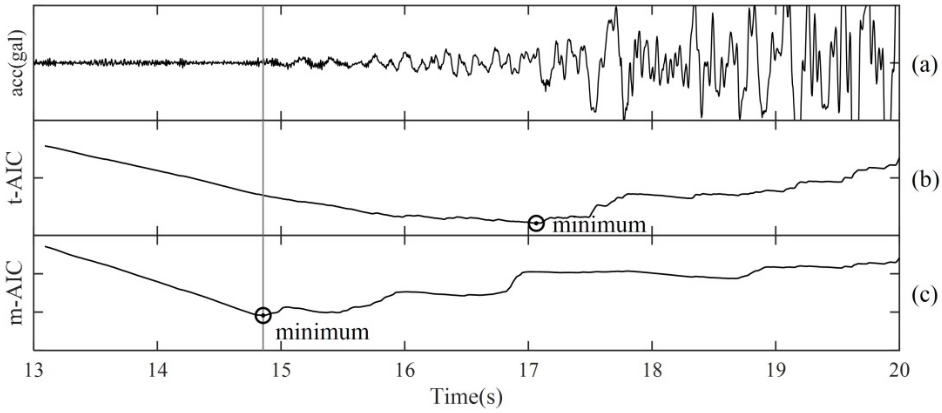
（3） Modified AIC

The AIC function [1] is a good tool for precise picking of the P-wave onset, and it has been applied in many P-wave onset picking algorithms; e.g., the AIC [15], AR-AIC [22], and STA/LTA-AIC [16]. However, the traditional definition of AIC for the purpose of precise picking P-wave onset is a merely energy dependent variable, it appeared inaccurate in picking those P-wave onsets with small energy and large period. In order to ensure the AIC function reflects both energy and period changes, we added the amplitude of the acceleration and predominant period together to a variable c, and then apply the AIC function to c:

$$\begin{cases} mAIC_k = k \cdot \lg\left[\mathrm{var}\left(c_1, \cdots, c_k\right)\right] + \left(N - k - 1\right) \cdot \lg\left[\mathrm{var}\left(c_{k+1}, \cdots, c_N\right)\right] \\ c_k = x_k + p_k \end{cases} \tag{3}$$

Where x_k and p_k represent the amplitude and apparent period corresponding to the sample index *k*; *k* vary from 1 to *N*, 1 represents the first sample of a pre-defined window and *N* represents the ending point of the window; $\mathrm{var}(*)$ is a variance calculating function.

For instance, if a cursory onset is confirmed at sample point *j*, the time window started from 3-second ahead the *j* and ended to a 0.2-second lag behind the *j*.



(a) Seismic time series; (b) curve of traditional AIC (t-AIC); (c) curve of modified AIC (m-AIC)

Fig. 2 Comparison diagram of traditional AIC and modified AIC

(4) Steps of picking

The automatic picking of the proposed algorithm is composed of two steps.

Step 1: The first step is monitoring the cursory P-wave onset by two pre-defined threshold values with respect to threshold of kurtosis function and threshold of apparent period. The two variables are calculated continuously sample by sample. If the value of both period and amplitude exceeded the pre-defined threshold value, then a cursory P-wave onset is confirmed.

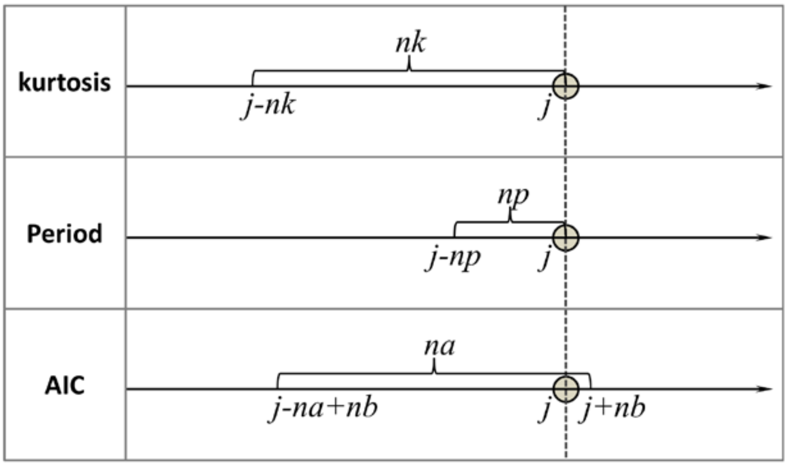


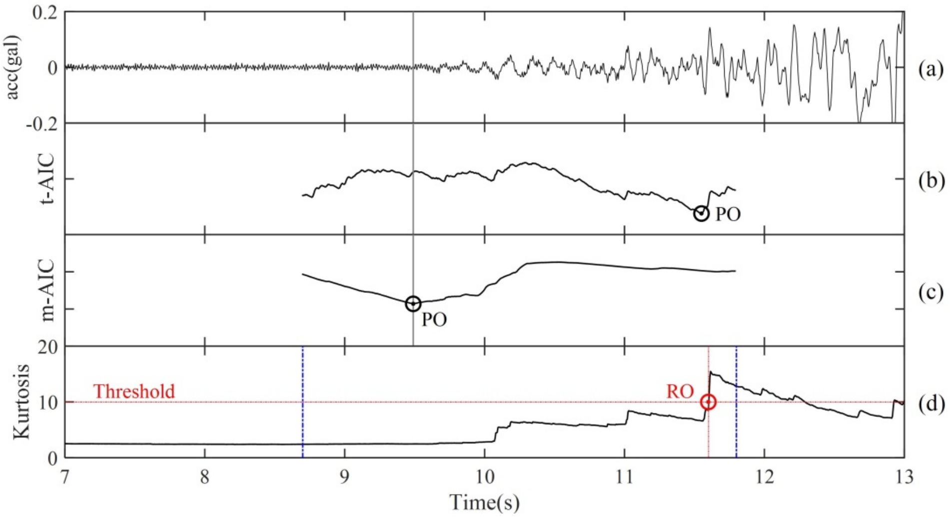
Fig. 3 Sliding windows relationship

Step 2: The second step is precise picking the exact onset of seismic P-wave. If a cursory onset is confirmed, the precise picking procedure is executed in a time window before the cursory onset with a certain time window length. Modified AIC is obtained in the time window. Through search for the minimum point of the AIC, the exact P-wave's onset is then determined. The relationship of sliding windows for calculating kurtosis, apparent period and modified AIC is shown in Fig. 3.

3. Examples

In order to show the effectiveness of introducing period into the picking procedure, three sorts of time series with respect to high-quality time series, noisy time series, small-amplitude and long-period time series, are chosen to show the effectiveness of the proposed algorithm.

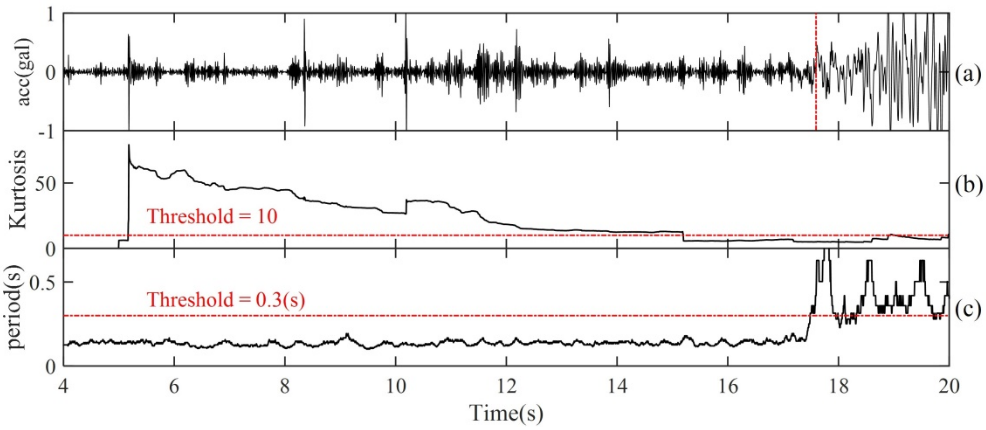
The first seismic trace is obtained from Wenchuan Ms 8.0 earthquake which is a typical small-amplitude and long-period P-wave's arrival. If we apply the traditional kurtosis function and AIC picking algorithm, the picked onset will be at 11.6 seconds on this trace. But if we apply the proposed algorithm, the exact time of P-wave's first arrival will be picked correctly. This is the first effects of frequency in the picking algorithm as shown in Fig. 4.



(a) Seismic time series; (b) curve of traditional AIC; (c) curve of modified AIC; (d) curve of kurtosis function.

Fig. 4 example diagram of picking the onset of small-amplitude and long-period time series

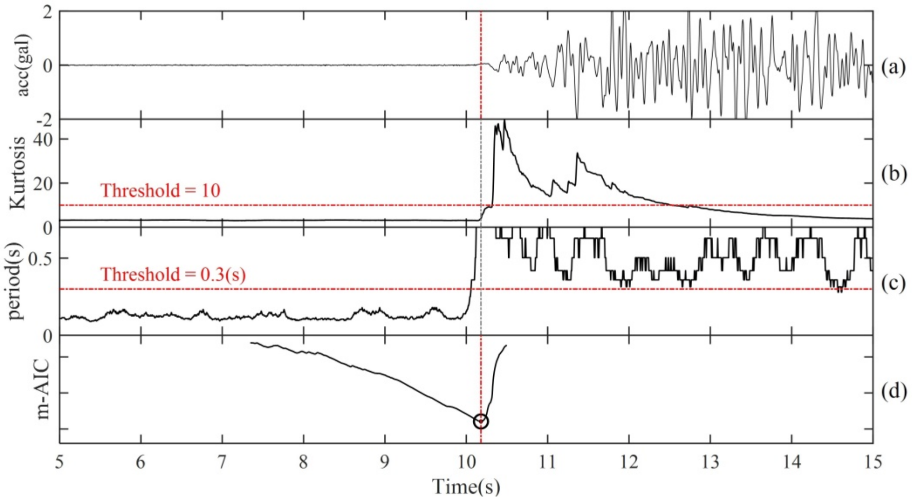
The second seismic trace is obtained from Wenchuan Ms 8.0 earthquake which is a typical trace with a large amplitude and high frequency ambient noise. If we obtain the cursory onset by only amplitude based variable such as kurtosis or STA/LTA, the threshold will be exceeded by the large amplitude ambient noise. If we make the judgment by both amplitude and frequency, then the erroneous cursory onset will be avoided because frequency of the ambient noise cannot exceed the frequency threshold value. This is the second beneficial of introducing the frequency into automatic picking as shown in Fig. 5.



(a) Seismic time series; (b) kurtosis function; (c) apparent period

Fig. 5 example diagram of picking the onset of noisy time series

The third seismic trace is obtained from a moderate earthquake from Eryuan China Ms 5.1 earthquake. This is a typical high quality trace which is general seen from near-field of moderate earthquakes. Both merely amplitude dependent algorithms and the proposed algorithm can pick the P-wave's first arrival with high precision as shown in Fig. 6.



(a) Seismic time series; (b) kurtosis function; (c) apparent period; (d) modified AIC

Fig. 6 example diagram of picking the onset of high quality time series

4. Conclusions

Accurately picking seismic P-wave onset is a crucial technique for real-time systems and offline data analysis. We have proposed a P-wave onset automatic picking algorithm which can be applied to both offline data analysis and real-time systems. The proposed algorithm inherited the merits of both kurtosis function for its high sensitivity to energy change and AIC function for its high precision on separating different set of data. The combination of energy and period information take the advantage of decreasing erroneous trigger.

5. Acknowledgments

This research is funded by National Key R&D Program of China (No. 2017YFC1500802, No. 2018YFC1054004)

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