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Bayesian Estimation of Acoustic Emission Arrival Times for Source Localization

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Abstract

The onset time of an Acoustic Emission (AE) signal is an important feature for source localization. Due to the large volume of data, manually identifying the onset times of AE signals is not possible when AE sensors are used for health monitoring of a structure. Numerous algorithms have been proposed to autonomously obtain the onset time of an AE signal, with differing levels of accuracy. While some methods generally seem to outperform others (even compared to traditional visual inspection of the time signals), this is not true for all signals, even within the same experiment. In this paper, we propose the use of an inverse Bayesian source localization model to develop an autonomous framework to select the most accurate onset time among several competitors. Without loss of generality, three algorithms of Akaike Information Criterion (AIC), Floating Threshold, and Reciprocal-based picker are used to illustrate the capabilities of the proposed method.

Data collected from a concrete specimen are used as an input of the proposed technique. Results show that the proposed technique can select the best onset time candidates from the three mentioned algorithms, automatically. The picked onset time is comparable with manual selection, and accordingly has better accuracy for source localization when compared to any of the single methods.

Keywords: Onset time, Acoustic emission, Bayesian inference, Automatic picker

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1 Introduction

2 Introduction

Assessment of microcrack network characteristics in cement-based materials is vital to determine the consequences of degradation on its physical behavior, e.g. mass transfer or tensile strength [1–3]. When a microcrack develops, the released energy propagates as stress waves to the surface of the structure. Sensors, usually of a piezoelectric type, are used to detect these acoustic emission (AE) signals generated by extension and coalescence of microcracks. AE activities are localized knowing the differences in arrival times (i.e. when $\mathcal{P}$ waves reach to sensors) of signals at different sensor locations. The technique is known as the time of arrival (TOA) method, which is highly sensitive to the accuracy of the measurement of the AE onset time [4].

AE activities are recorded in the presence of environmental and sensor noise. Detection of an actual AE signal in a noise-contaminated signal environment is critical for robust source localization. Visual inspection plausibly is the most precise way to determine the onset time, particularly for an experienced operator used to seeing AE signals. This method, however, has two main drawbacks: first, considering that the microsecond duration of an AE signal is miniscule compared to the monitoring life of a typical structure, it is not feasible to conduct visual inspections of AE signals for continuous health monitoring of a structure. Second, AE signals are sometimes embedded in the noise with a low signal-to-noise ratio (SNR), whether due to propagation distance, dissipation, or environmental noise.

Automatic pickers are intensively used to find the arrival time that best determines the onset of a signal from the noise. These methods work based on different features of signals such as amplitude, energy, and statistical properties. Fixed and Floating Threshold methods, Akaike's Information Criterion (AIC), Hinkley Criterion [5], cross-correlation based methods [6, 7], CWT based binary map [7] and Reciprocal-based Onset time selector [8] are a few examples of many algorithms developed for automatic onset time detection. The goal of this paper is not to evaluate these algorithms or to propose a new competing algorithm. Studies of these methods confirms that although some methods are in general more reliable than others, there are always cases that other methods could have obtained the onset time more accurately [9]. In this work, we show that several different methods can be used simultaneously to result in a more accurate estimate of source coordinates. To do this, we introduce a Bayesian approach to automatically select the most accurate onset time for source localization from the candidate algorithms' for onset time detection.

The proposed approach is explained by considering three onset time detectors. These methods, including a model for source localization and the proposed approach for onset time selection, are explained and discussed in the methodology section of this paper. Experimental data, generated by a pencil-lead breakage (PLB) test [10], is used to illustrate the method capability. Results are shown by illustrating an example of onset time detection methods on one of the signals, implementation of the proposed approach, and comparison of different sets of onset time on source localization.

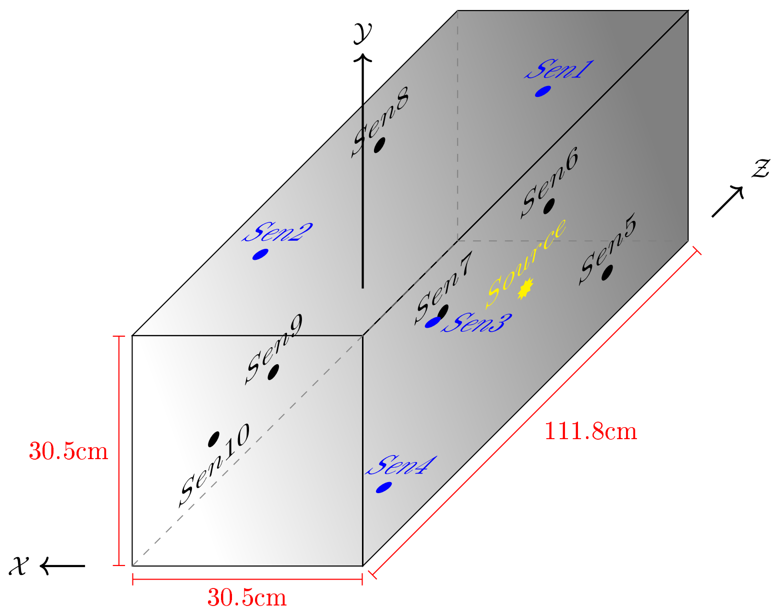

Figure 1: Concrete block and sensors layout

3 Experimental data

The data of this work is collected from a PLB test on a concrete block specimen shown in Figure 1. The AE signals are recorded using ten sensors located on different faces of the concrete block. The source is located in the $\mathcal{ZY}$ face of the concrete block as shown in Figure 1.

The AE signals are recorded using ten sensors at different faces of the concrete block. Source is located in the $\mathcal{ZY}$ face of the concrete block as shown in Figure 1.

4 Methodology

This section is organized in to three parts. In the first part, three different methods to detect the onset time of AE signals are introduced. In the second part, the shortest path method which is used to obtain the $\mathcal{P}$ wave travel time is explained. In the third part the proposed approach to select the best onset time among those onset times obtained by the three methods is introduced.

4.1 Automatic onset detection algorithms

The three onset time selectors, or automatic pickers, are used in this paper are: I) Floating Threshold picker, II) AIC picker, and III) The Reciprocal-based picker.

4.1.1 Floating Threshold

The Floating Threshold algorithm is one of the most common and simplest picking algorithms. Onset time is the moment when signal amplitude passes a threshold calculated as a factor of the root mean square amplitude for the first portion of each time series, known to be before the signal onset. In this work, we consider four times the noise standard deviation as the threshold. It is assumed that noise follows a zero-mean normal distribution, and it is therefore very unlikely that a sample of the noise distribution falls out of the interval specified by four standard deviations from zero. Therefore, the first point of a signal that passes this threshold is classified as an AE event, yielding the onset time. Although the Floating Threshold algorithm is used intensively due its simplicity, it is not very useful when SNR is low or sudden spikes exist in the signal. The Floating threshold can be expressed mathematically by Equation 1.

$$t_{onset} = argmin(t_i | abs(X[t_i]) > X_{tre}), \tag{1}$$

where t_{onset} is the first arrival time, obtained by finding the smallest time (t_i) correspond to samples ($X[t_i]$) with absolute value greater than the threshold (X_{tre})

4.1.2 AIC picker

Auto-regressive algorithms are another class of pickers which use statistical properties of a signal to find the onset time. These algorithms are threshold independent and insensitive to random spikes in time-series [11]. The Akaike's Information Criterion (AIC) is commonly used for onset determination of AE signals. The AIC function of an AE signal reaches its minimum at the onset time. The AIC algorithm has been compared to many other auto-pickers, and it is proven that it has a reliable onset determination [12,13]. Equation 2 shows a fitness function which is used in the AIC method. The time corresponding to the minimum of this function is considered as the onset time of an AE signal.

$$\begin{aligned} AIC(t_i) &= t_i \ln(\sigma^2(X[1, t_i])) + (t_N - t_{i+1}) \ln(\sigma^2(X[t_{i+1}, t_N])) \\ t_{onset} &= argmin(AIC(t_i)) \end{aligned} \tag{2}$$

In Equation 2 t_i is the time corresponds to the i^{th} sample and N is the total number of samples in signal X, $\sigma^2 s[p, q]$ is variance of the portion of signal X from sample p to q. The onset time is considered as the moment corresponding to the minimum of the fitness function shown in Equation 2.

In an interesting study, the AIC and Floating Threshold methods are compared when onset times were obtained manually using visual inspection as the metric. It was shown that AIC outperformed the Floating Threshold method generally. However, in some cases the latter identified the onset time more accurately [9].

4.1.3 The Reciprocal-based picker

This method is conceptually similar with the AIC method, the point of difference is its fitness function which is shown in equation 3.

$$\begin{aligned} REC(t_i) &= -\frac{i}{\sigma^2(X[1,t_i])} - \frac{N-i}{\sigma^2(X[t_{i+1},t_N])} \\ t_{onset} &= argmin(REC(t_i)) \end{aligned} \tag{3}$$

In research by Babjak et al., the AIC and Reciprocal-based picker were compared, and it was shown that the Reciprocal-based picker could detect onset time more accurately than the AIC picker for their structural health monitoring problem [8].

4.2 The shortest path model

The shortest path model is used to obtain the traveling time of a $\mathcal{P}$ wave from source to sensors. This model is not the most accurate model for a heterogeneous material like concrete. The distance between the source and a sensor divided by the $\mathcal{P}$ wave speed, models the time of arrival for each sensor. Equation 4 shows the mathematical expression of this model [14].

$$\Delta t_i = \frac{\sqrt{(X_0-X_i)^2+(Y_0-Y_i)^2+(Z_0-Z_i)^2}}{V} - t_0 \tag{4}$$

Where $\Delta t_i + t_0$ is the time that an AE wave reaches to the ith sensor from the source. Source coordinates are shown by X_0, Y_0, and Z_0 and coordinates of the ith sensor are shown by X_i, Y_i, and Z_i. The last parameter of the model is V which is the $\mathcal{P}$ wave speed.

4.3 The proposed Bayesian picker

Bayesian methods are intensively used for model updating inverse problems [15–17]. Equation 5 shows the mathematical expression of the Bayes theorem,

$$P(\theta|D) = \frac{P(D|\theta)P(\theta)}{P(D)}, \tag{5}$$

where our initial belief about parameters, i.e. prior $P(\theta)$, is updated by seeing new evidence, D, conditioned on the model parameters in the likelihood function $P(D|\theta)$. Here, the updated belief, known as the posterior, is shown by $P(\theta|D)$.

Obtained onset times from an automatic picker can be used as input data, but since the onset times obtained from different methods are not exactly the same, the posterior for source location shows different amount of uncertainty and bias. Our data may be structured as a matrix of $n \times m$, which n is numbers of sensors and m is numbers of candidates for an onset time. Here m is three since we used three methods to identify the onset times. Considering that we used ten sensors in our test, the data $D = [d_{ij}]_{n\times m}$ will be a 10 by 3 matrix.

Obviously, one of the suggested onset times for each signal is closer to the unknown *true* value of the onset time. Of course, we do not know which one is the most accurate without doing some kind of independent visual inspection. However, intuitively the most accurate onset times leads to the least amount of uncertainty in the inference of source coordinates. We propose to let the Bayesian model pick the onset times from the pool of data by introducing a new latent parameter, denoted by α. The new parameter is a categorical parameter consists of one outcome out of m possible outcomes. Here, since m is three, the possible outcomes of α would be $0, 1$, or 2. Each of these numbers represents one of the automatic pickers, i.e. 0 for AIC picker (d_{i0}), 1 for the floating threshold (d_{i1}) and 2 for the reciprocal-based picker (d_{i2}). Then the data is fed to the model using the Equation 6:

$$d_i = 0.5 \times d_{i0}(1-\alpha)(2-\alpha) + d_{i1}(\alpha)(2-\alpha) + 0.5 \times d_{i2}(\alpha-1)(\alpha) \tag{6}$$

When we run MCMC algorithm, each time only one of the obtained onset times is selected for each sensor. For the prior of this parameter, we can assign the probability of $\frac{1}{3}$ to each method if our initial belief about them has no preference. However, based on the literature, generally in most of cases AIC picker gives us more accurate estimation of the onset time than floating threshold method [9]. Furthermore, in another work is was implied that the Reciprocal-based picker arguably gives better estimation of onset time than AIC picker in most of the cases [8]. The power of Bayesian inference is that we can consider this information in our priors before observing the data by assigning subjective probabilities to each automatic picker as we did in this work.

Priors for source coordinates are assigned uniformly distributed over the known block dimensions. Similarly, a range of variation is selected for the wave speed prior. Finally, using our prior about the $\mathcal{P}$ wave speed and considering the dimensions of the block, a positive-valued distribution is assigned to t_min.

Categorical Gibbs Metropolis method is used for inference about α, and No U-Turn Sampler (NUTS) method is used for other parameters [18]. After implementing MCMC a chance of success is assigned to each picker for each sensor considering numbers of related α value in each chain (e.g., counts of the value "1" in the MCMC chain of α for the Floating Threshold method). Finally, the onset time with highest probability is selected for each sensor, and the model is run again by considering only the chosen onset time.

5 Results

Figure 2 shows an example of the implementation of the three methods. It illustrates that these methods may identify the onset time differently. From visual inspection it seems in this case that the Reciprocal-based picker

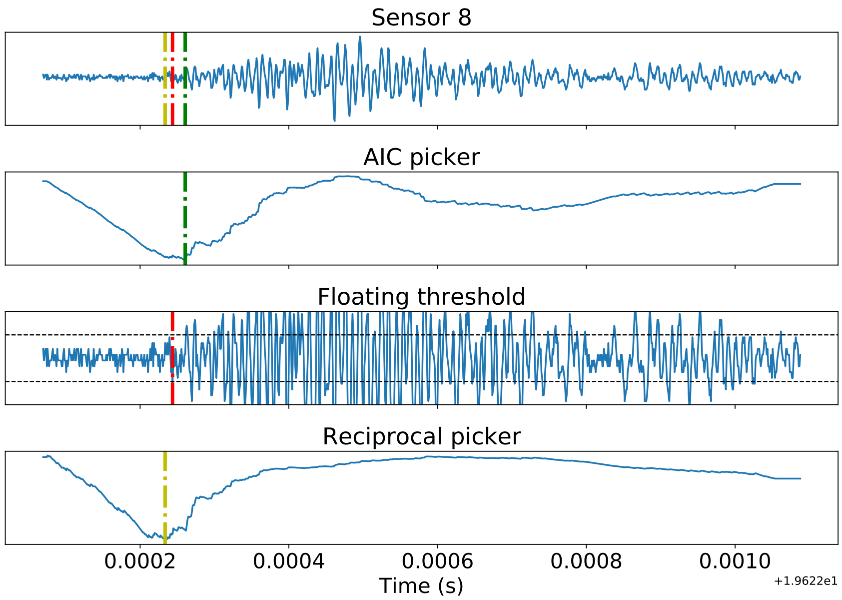

Figure 2: Comparison of onset time detection using three methods for sensor 8

detects the onset time more accurately than other two, and Floating Threshold method is more accurate than AIC picker. Implementing the proposed approach, the posterior for the categorical parameter, shown in Figure 3, reflects a similar expectation. Even though in the prior, based on the literature, we assigned more chance of success to the AIC picker than Floating Threshold; our method for sensor 8 suggested a higher probability for the Floating Threshold onset time in comparison with AIC picker, and the highest probability is obtained for the Reciprocal-based picker as expected based on visual inspection shown in Figure 2. The categorical parameter sometimes shows a very similar chance of success for two of pickers (e.g. AIC and reciprocal-based picker for sensor 1). Checking their corresponding onset times, we found that these values are almost the same, and then a similar posterior probability is expected intuitively.

To study the effect of onset times on source localization, each set of onset times is used for source localization using Bayesian inference and performing MCMC sampling. Then, results were compared with the selected onset times using the proposed method. The source obtained by those onset times which are selected by the proposed approach shows less amount of uncertainty compared to when only onset times from one of the other methods are used. Figure 4 shows the joint Bayesian inference for two coordinates of the source in comparison with that obtained using the chosen onset times by the proposed approach.

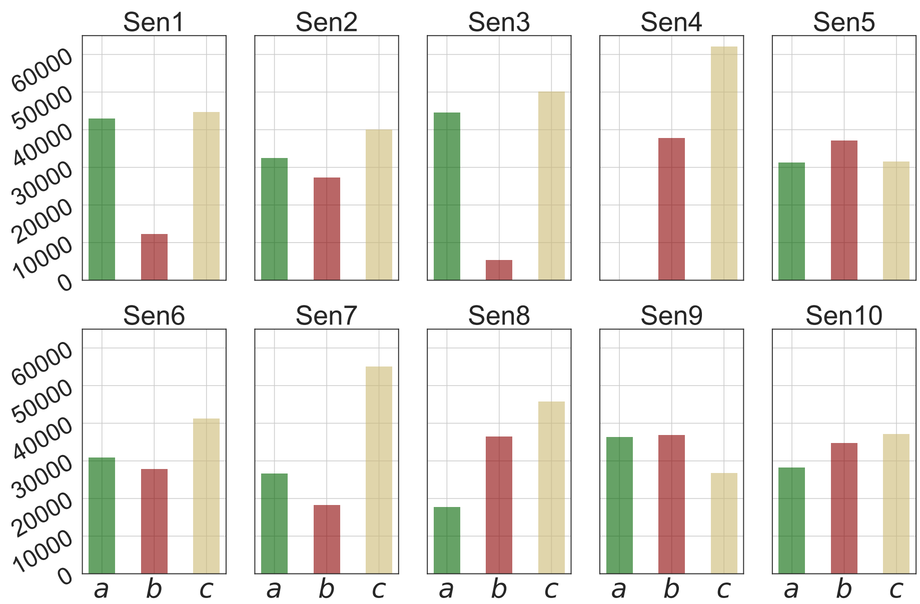

Figure 3: Histogram for Bernoulli parameter indicating posterior probability of selection a) AIC Picker, b) Floating Threshold Picker, c) Reciprocal-based Picker

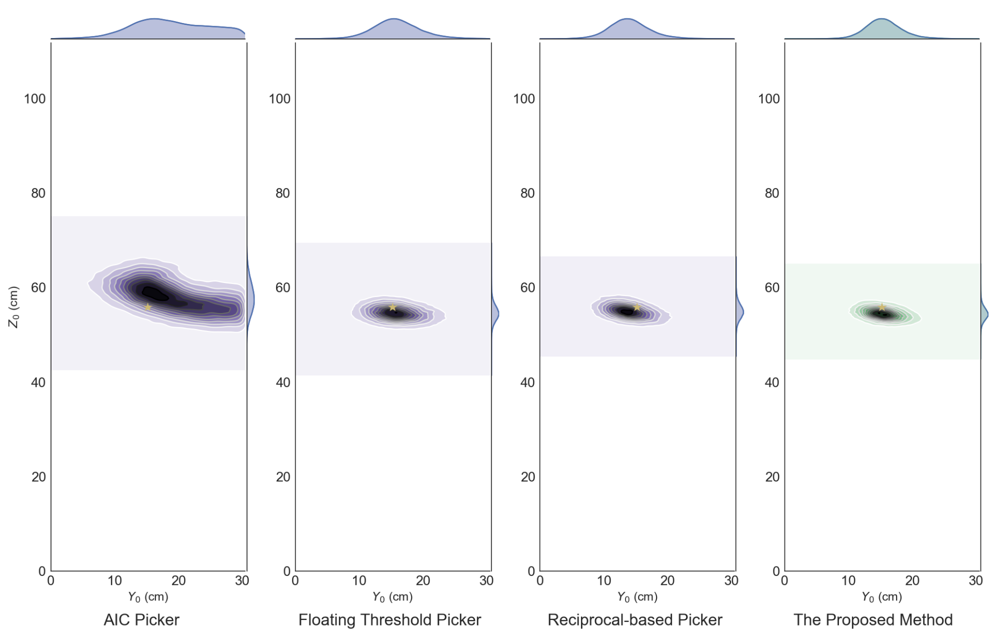

Figure 4: Comparison of source

6 Concluding Remark

In this paper, a Bayesian model selection process was formulated for optimal AE signal onset time detection for the purpose of source localization. The selection process works by choosing the most accurate onset time from a population of onset times identified by using different established algorithms. Here, three methods of AIC Picker, Floating Threshold and Reciprocal-based method were used as a suite of well-known, mature, widely-used onset time detectors. The proposed method was implemented on a set of experimental data obtained from a PLB test. Results showed that the posterior probability obtained for each picker is in accordance with our expectation concluded from visual inspection. Moreover, onset times obtained from each method were used for source localization. Bayesian source localization using the selected onset times by the proposed method was less biased in comparison with the use of each set of onset times separately. The proposed approach implementation is straightforward and fast, showing strong potential to be used for continuous monitoring of structures using AE methods.

7 Acknowledgment

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