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Wavelet based approach to signal activity detection and phase picking: Application to acoustic emission

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ABSTRACT

Locating the sources of elastic waves during rapid local stress relaxation in solids under load is a central element in acoustic emission non-destructive testing, seismology, etc. The location problem relies heavily on the accuracy of arrival time detection. To increase the reliability of real time signal detection and to ensure precise phase picking of transient waveforms of a low amplitude, we propose a novel Wavelet transform-based algorithm. Benefiting strongly from the neighboring concepts in the wavelet theory, the shortcomings of conventional amplitude threshold-based and Short Term Average/Long Term Average methods are addressed. The proposed method was validated in a variety of acoustic emission tests, demonstrating the excellent temporal localization of the picked phases even for the signals with very low signal-to-noise ratio.

1. Introduction

The correct "phase picking" or the determination of the onset time of a transient signal is of crucial importance in many fields of technology and science such as seismology, non-destructive acoustic emission (AE) testing, ultrasonics, etc. The generic similarity between the AE and seismic phenomenon is that both arise from rapid local stress relaxation events occurring in a solid body under local load. Thus, both deliver unique information regarding the incidence of local fracture or slip events with an unprecedented spatial/temporal resolution. The key point, which has determined the tremendous success of AE in the non-destructive testing practice, is its capability to locate the source of elastic waves in a way similar to that in seismology. For instance, the most commonly adopted procedure for source location in the AE practice is the so-called "triangulation" inherited from quantitative seismology. The temporal and spatial resolution of a vast majority of location methods are interconnected because the source location is computed using the time on the first arrival of the AE wave at each sensor in the antenna network. Thus, the accurate phase picking is central in the source location problem. This problem is however fundamentally complicated by background noise. Therefore, the aim of any signal detector and phase picker algorithm is to distinguish the signal from the noise and to identify the time of its arrival. Various data processing and onset picking algorithms have been proposed in the literature to minimize the localization error and determine the most likely location of the source in different geometries [1–3]. Providing comprehensive reviews to currently available signal detection algorithms Sharma et al. [4], and Küperkoch et al. [5] ended up with a conclusion that despite the vast amount of research in this field, the event picking algorithms had not yet fully come of age. While the AE field is dominated nowadays by the simplest amplitude threshold signal detector, the most widespread algorithm used in seismology for automatic phase detection is

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known as STA/LTA (i.e. Short Term Average/Long Term Average). Sophisticated modifications of this algorithms have been reviewed in detail in [5].

The Wavelet transform (WT), in both continuous (CWT) and discrete (DWT) forms, has been extensively applied in seismology and AE characterization [6], de-noise [7–11] and source location [6,12–15] problems. What makes the Wavelet transform so appealing is not only its excellent time-localization property but also the capacity to perform a multi-scale analysis enabling, for example, modal analysis, quantitative source characterization, etc. [9,10,16]. Jiao et al. [6] have considered the multi-mode and dispersion characteristics of AE signals and used the wavelet-based modal analysis for the arrival time detection. Moriya and Niitsuma [17] have proposed the signal time-frequency representations to enhance the accuracy of the p-wave arrival time detection in the low magnitude seismic waves. Zhang et al. [18] have developed an elegant automatic p-wave arrival detection and picking algorithm based on the combination of the wavelet transform and the Akaike information criteria (AIC). Grosse et al. [11,19] have compared the performance of the autoregressive AIC picker and their original phase picker based on the Hinkley criterion appealing to the partial energy of the whole signal. Karamzadeh et al. [20] have developed a method based on the Continuous Wavelet Transform (CWT) for p-phase arrivals in seismic traces.

Despite all efforts invested into development of a broad variety of signal detectors, the existing paradigm in AE signal detection is footed solely on the simplest amplitude-based trigger. In this approach, the distinction between the “useful” signal and the “useless” noise is made by the comparison of the AE amplitude and the preset threshold level. Although this method has been proven effective in many applications where the signal-to-noise ratio (SNR) is considerably high (e.g. > 10 dB), its accuracy drops sharply as the SNR reduces. The arrival time of an AE transient suffers particularly strongly from the arbitrariness of threshold selection, resulting in irrecoverable errors in the AE source location. Moreover, when the SNR is low the threshold picker simply does not work at all and the low amplitude signals are tacitly not considered in the AE analysis, which can be quite misleading, in our opinion. These issues, which have long been understood but not yet quantitatively resolved [21], motivated us to seek for a “data-driven” procedure capable of overcoming the shortcomings of the threshold-based schemes preserving their efficiency and simplicity when dealing with high SNR signals.

Aiming at increasing the reliability of detection of low-amplitude signals and increasing the accuracy of location of weak AE sources, we propose a new computation efficient, time-frequency-based and noise robust approach exploiting:

- the time coherence of the AE signal;
- the multi resonant nature of the AE sensors;
- Wavelet block-thresholding de-noise properties [22].

The paper is organized as follows. The general block-thresholding concept and our data driven block-size optimization idea is outlined in Section 2. In Section 3, we endeavor to demonstrate that the proper modeling of an AE sensor response lays the groundwork for modifying the block-thresholding strategy for improved phase picking. Then, in Section 4, we validate our approach on both synthetic and real-life datasets. Finally, the results and main finding are summarized in Section 5. For the sake of consistency, the most relevant background remarks on wavelet concepts and related properties are given in the Appendix A, while an example of the proposed procedure for sensor characterization is given in the Appendix B.

2. Methodology: “block-thresholding” concept and its adaptation for AE time-series

Donoho and Johnstone in their seminal paper [23] introduced the concept of wavelet shrinkage as a process of reduction (shrinking) of empirical WT coefficients that are lower than some fixed threshold estimated from the data (i.e. proportional to the estimated noise power). Since inception, the wavelet-based approach to function approximation/de-noising has been proven optimal in many aspects. Particularly, it is superior to the Fourier transform based schemes especially when a transient process is of concern [24–29]. Another significant step forward was made by introducing the “neighboring concepts” in the shrinking process. It follows a simple intuitive logic: if a large coefficient is found in the wavelet transform, according with the shrinkage idea, it “belongs” to the signal. Then, there is an increasing probability that the coefficients in its neighborhood are also describing the signal rather than the noise. The non-overlapping blocks of coefficients were first considered by Hall et al. [30] in the approximation/de-noise process. This concept was extended and refined in a series or successive publications [22,29,31,32] where overlapping blocks were introduced too. Although the theoretically argued rules for an optimal choice of the block-size have been proposed for a large class of signals/functions and affecting noise [22,29], we aim at extending them further with account of specific features of AE signals primarily due to the non-linear resonant type of the AE sensors. The proposed approach *per se* can be straightforwardly applied to the signals of different origins such as seismic traces, voice, etc. However, the analysis of these kinds of signals is beyond the scope of the present work and will be given elsewhere.

For the purpose of this paper, we will confine ourselves to the “NeighBlock” strategy (after Cai and Silverman [22]) which has demonstrated a tremendous success in the de-noise performance although, other WT block-based methods can be potentially adopted.

A great advantage of the proposed modification, is that, except for the “block size”, all mathematical details of the chosen block-thresholding procedure are kept as those in the original definitions [22]. Therefore, the sensitivity and robustness of the proposed approach fundamentally is time-proven. What has to be done actually is the integration of the proposed AE specific block-length optimization with the block-thresholding [22] procedure then verify that it yields reliable and consistent results. This will be shown after detailed algorithm description.