Wavelet Based Approach to Acoustic Emission Phase Picking

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ABSTRACT

One of the most appealing feature of Acoustic Emission (AE) NDT technique is its ability to spatially locate the sources, using times of arrival of elastic waves emitted by the same source, at the antenna of the sensors. The most commonly adopted triangulation procedure for source location relies on the accuracy in the time-localization of the picked phases at each different sensor. To the authors’ best knowledge, all presently available commercial AE systems adopt a threshold based phase detection. Although this process is the most simple, chose the threshold adds another source of uncertainty and it suffers from several major drawbacks, particularly when the testing environment is noisy. This results in false detections, missed events or incorrect time-location detection. The aim of this paper is to propose a novel algorithm for phase detection based on the Wavelet transform. Specifically, we exploit the neighboring concepts that have been found capable of considerably improve the de-noise performance of the wavelet shrinkage method, to construct an Acoustic Emission Activity Detector. Among other beneficial characteristics of the proposed method, preliminary tests conducted in different working conditions have shown a better accuracy in the time-localization of the picked phases.

Key words: Acoustic Emission, Phase Picking, Wavelet, De-Noiseing, Neighboring Concepts.

1. Motivation

One of the key points in the success of AE as an NDT inspection technique is its capability to locate the source of an even so that becomes clear where a certain amount of energy has been released. At the base of this capability plays a fundamental role the ability to exactly locate in time the first arrival of the AE wavefield at each sensor, i.e. phase picking. The uncertainty proper of this procedure fixes a lower bound for the source location accuracy. It is clear that the aim of a phase picker algorithm is to discover when what is acquired by the sensor is no more noise but a proper signal. In the threshold based approach, the most largely adopted phase picker in commercial systems, this distinction is done just looking at the AE amplitude considering noise everything do not overcome the fixed threshold level. Although this method is effective in many application where the S/N ratio is consistently high (e.g. > 10 dB), its false detection rate and time accuracy lowers down soon when this ratio tends to diminish. Another consistent draw back of a threshold based phase picker is its completely arbitrary setup: there exist “good practice” recommendations that experienced practitioners apply when choosing the threshold level but it still remains an arbitrary choice that will affect the entire acquisition process. Those facts motivated us to look for a “data-driven” procedure that could overcome the limitations
stated above attending mostly to the impact on the time location accuracy for low S/N ratio. The proposed solution exploits:

- Time coherence of AE signal
- Resonant nature of AE sensors
- Wavelet block-thresholding [1] de-noise properties

In what follows, we will be focusing on the description of the basis concepts of our approach leaving the details to a successive in-depth publication.

2. Wavelet transform, De-Noise and Neighboring concepts

Wavelet transform (WT), in both continuous (CWT) and discrete (DWT) form, is a popular and powerful tool for analyzing non-stationary data and has been extensively adopted for AE characterization/de-noise [2–6] and source location [7–11]. What makes it so appealing is not only the time-localization property but also the opportunity to do a multi-scale analysis that opens new and sometimes easier paths, to difficult tasks like modal analysis, source characterization etc. [4,5,12]. Before describing the algorithm, it is necessary to remind few important reference works about WT properties and how its de-noise capabilities have evolved from the “classic” wavelet shrinkage [13] to the block-thresholding based shrinkage [1].

In their first seminal paper, Donoho and Johnstone [13] introduced the concept of wavelet shrinkage as the process of shrinking WT coefficients depending on their amplitude compared to a fixed threshold directly estimated from the data (i.e proportional to the estimated noise power). They called this method VisuShrink with two possible variant: Hard and Soft thresholding. For instance, since that time, the same authors and many others have extensively proved [14–19] that the wavelet based approach to function approximation/de-noising is optimal in many sense and outperforms the Fourier transform based one. Another significant step ahead has been done with the introduction of “neighboring concepts” in the shrinking process, following a simple intuition: A coefficient in the wavelet transform is expected to describe the noise or the signal not just depending on its value but also on the values of a certain number of neighboring coefficients (i.e. time coherence). Here’s the introduction of blocks of coefficients in the approximation/de-noise process as first proposed by Hall et al. [20] and successively refined in [1,19,21,22]. Although there exist theoretical justified rules for an optimal choice of the block-size for a large class of signals/functions and affecting noise [1,19], we aim to extend them with something that is specific for AE signals and their acquisition chain. On the other hand, it is straightforward to envision our approach applied to signals of different “nature” (e.g. Voice) but this kind of investigation is outside the scopes of the present work.

For our purpose, we will focus on the “NeighBlock” method (i.e. Cai and Silverman [1]), because it is one of major success between the many that have been developed since [13], even if, potentially, other WT block-based de-noise methods could be adopted as well.

3. Algorithm description

The algorithm is here described in some details however we want to clearly state that it is not in the scope of this paper to report an in-depth analysis of all the steps that are involved in the proposed new method. Indeed, we want to give the reader a precise perception of what have been the ideas behind this work and their basic assumptions.

Let define minimum time-coherent span the duration of the shortest AE signal that we can acquire (i.e. with a certain acquisition chain). It depends on many factors that, unfortunately, we cannot control neither measure in most cases (e.g. source properties and medium properties). However, there exist an upper bound for its “dual” (i.e. in frequency domain) that we can easily
find: the maximum frequency band where we can expect useful information is dictated by the sensor response.

Assuming for simplicity a single resonance sensor and adopting a Gaussian model to describe its response, it is easy to show that the “rise time” (tr) for that system is related to the bandwidth (BW ≃ 0.009σ) by the approximate relation tr ≃ 0.35/BW. Applying this formula we have immediately an estimation of the “minimum” rise time that we can expect for the system under inspection. It is then straightforward to adopt this value to fix a lower bound in the time-coherency (block size) that we impose on the WT transform when applying the block-thresholding. The resulting mask (i.e. equal to 1 for those blocks retained by the block-thresholding rule and equal to 0 for those blocks shrunk) obtained for each decomposition level m will be called “Probability of Presence” at level m (m-PoP). To get a one-dimensional “Probability of Presence” (PoP) we recombine point-by-point (in time), all m-PoP probability curves according to the “cone of influence” definition [23] (i.e. defines the time localization of each coefficient at different decomposition levels) plus this simple assumption: m-PoP are independent for every m and every time t.

This is the simplest form of the proposed algorithm and we will show an example of application in the next section. It must be noticed that, for real problems, the simple Gaussian model doesn't fit really well with most of the response curves of common AE sensor so it has usually been adopted a multi-resonance model plus a second order approximation for the rise-time calculation respect to each resonant point. Moreover, instead of a (0,1) binary mask (i.e. Hard thresholding) in the block-thresholding algorithm we adopted a continuous mask (i.e. Soft thresholding) that admits all the values in the interval [0,1]. About the choice of the mother wavelet we took the Haar wavelet for its (theoretical) arbitrary time-localization accuracy. All the implication of those choices are discussed elsewhere.

4. Application

To prove that the proposed method is effective in the detection of the Time of Arrival (TOA) (a.k.a. Time of Flight) and that it is much less sensible to the S/N ratio respect to other methods, we constructed a set of testing signals taking one frame (4K samples) of a “real” AE signal, reported in Figure 1(a), and summing “real” AE noise, Figure 1(b), (i.e. real colored noise acquire during an AE inspection before starting the loading of the specimen but with the sensors
already attached to its surface) controlling the resulting S/N ratio, calculated respect to the entire frame length. We will consider two examples respectively for 5dB and -5dB S/N ratio. We will also report the result obtained with the proposed method for -10dB, to confirm its low sensibility to the S/N ratio. The sample frequency is fs=3.125 Ms/s and we will compare our performance (i.e. the obtained TOAs) respect to a threshold based method with the threshold fixed to 30dB, assuming a pre-amplifier gain of 20dB and a “dead-time” of 32 μs (100 samples).

5. Remarks & Conclusions

As clearly shown in Figure 2, 3, 4, 5 and 6 mostly, the proposed method outperform the threshold based phase picker and returns almost the same single TOA (i.e. when chosen between TOA_0 that indicates the first sample where PoP ≠ 0 and TOA_1 that indicates the first sample where PoP = 1) even for low S/N ratios. Being the computational complexity of a standard DWT O(n) so less than that one of the FFT O(n log n) and being all the other operations in the algorithm linear in n, the proposed method is potentially capable to work in real-time moreover, without any additional cost, it produces already the de-noised AE signal.
Figure 4: Threshold method S/N -5 dB

Figure 5: Proposed method S/N -5 dB

Figure 6: Proposed method S/N -10 dB
References


