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.

1. Introduction

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 elastic 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. The AE signals are always buried in flow noise. The aim of any phase picker algorithm is to distinguish the signal from the background noise and to identify the time of its arrival. Various data processing algorithms have been developed and proposed in the literature to minimize the localization error and determine the most likely location of the source in different geometries. In the threshold based approach, the most largely adopted phase picker in commercial systems, the arrival time is determined as the first threshold crossing, i.e. as the time at which the envelope of the AE signal crosses a preset threshold. 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 drawback of a threshold based phase picker is its completely arbitrary setup: A good practice guide for choosing the threshold level has been produced by experienced practitioners, but only as a "rule of thumb". Thus, it is still an arbitrary choice affecting strongly the entire acquisition and processing chain. 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 basic concepts of our approach leaving the details to a successive in-depth publication.

2. Background on 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 the time-localization property and 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].

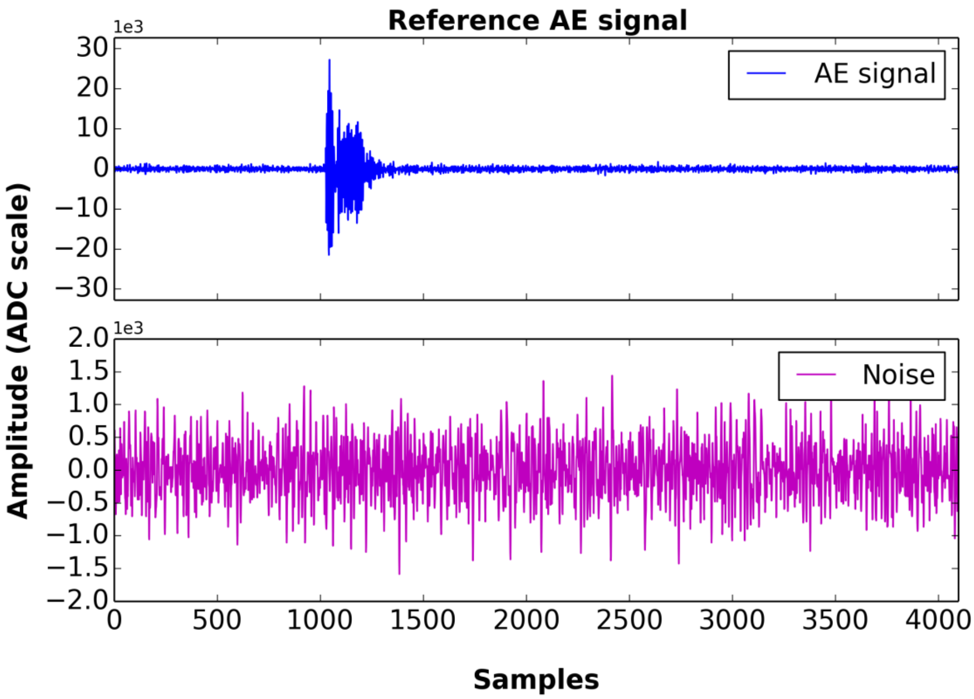
In their first seminal paper, Donoho and Johnstone [13] introduced the concept of wavelet shrinkage as the process of shrinking WT coefficients depending on their amplitude compared to a fixed threshold directly estimated from the data (i.e. proportional to the estimated noise power). They called this 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 crossing a threshold but also on the values of a certain number of neighboring coefficients (i.e. time coherence) doing the same. 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 (best de-noise performace) 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 perception of what have been the ideas behind this work and their basic assumptions.

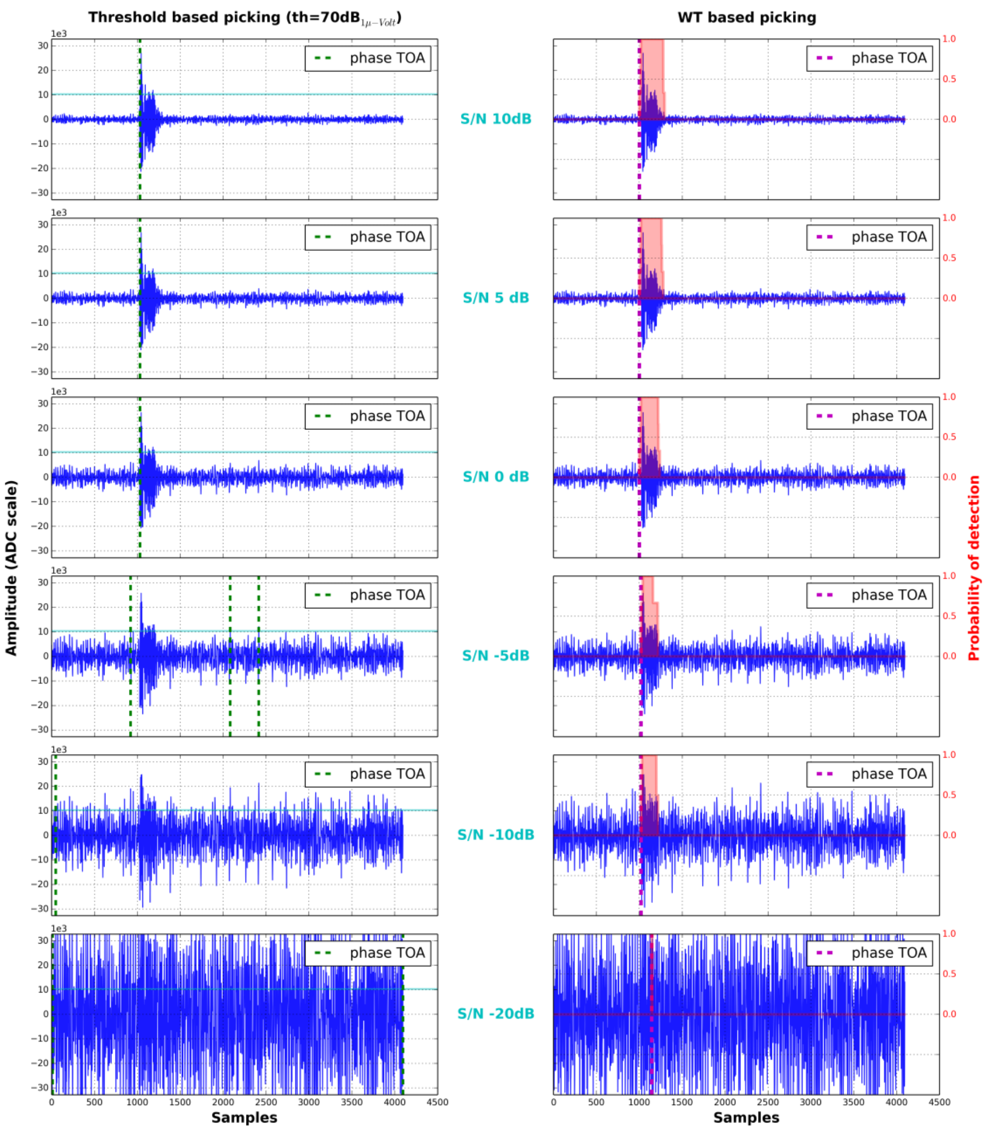
Properties of AE signals acquired during a test are constrained, through other factors, by the properties of the acquisition chain and, most of all, by the sensor response. In modern systems where most components like cables, amplifiers etc. are intrinsically broadband, the strongly non-linear sensor response determines the useful bandwidth of the entire acquisition chain. In time domain, due to the time-frequency duality principles, this means that the sensor response sets a lower bound for the minimum duration of a signal that can be observed.

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 ($BW \simeq 0.674\sigma$) by the approximate relation $tr \simeq 0.35/BW$. 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 bond 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 normalized "*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. The Time of Arrival (TOA) (a.k.a. Time of Flight) is then chosen between TOA_0, that indicates the first sample where $PoP \neq 0$ and TOA_1, that indicates the first sample where $PoP = 1$.



Pic. 1. Acoustic Emission (AE) signal (top graph) and noise (bottom graph) adopted to create synthetic AE events with controlled S/N ratio.

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] (i.e. it explains the existence of TOA_0 and TOA_1 that otherwise coincide in the hard-thresholding scheme). 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.



Pic. 2. Direct comparison of the picking results obtained with the threshold method and with the proposed WT based one. We report the results obtained for different S/N ratio. Noticed that even when the S/N=-20dB the proposed algorithm is still capable to sense the presence of the AE signal while the threshold method produces false detections already when S/N=-5dB.

4. Application

To prove that the proposed method is effective in the detection of the Time of Arrival (TOA) 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 Pic. 1.top, and summing “real” AE noise, Pic. 1.bottom, (i.e. real colored noise acquired 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 compared our performance (i.e. the obtained TOAs) respect to a threshold based method with the threshold level fixed to $70dB_{\mu-Volt}$, assuming a pre-amplifier gain of $60dB$. A “dead-time” (a.k.a. Hit Dead Time) of 100 μs (320 samples) has been imposed on both approaches. Due to the signal length definitely shorter than the frame size, the S/N reported for the synthetic signals is actually lower than what it “really is” respect to the AE signal power. This fact adds a bias in favor of the threshold method that should be taken into account. We report the result obtained for S/N equal to 10 dB, 5 dB, 0 dB, -5 dB, -10 dB and -20 dB. The sample frequency is fs=3.125 Ms/s. The sensor adopted to acquire both the AE signal an the noise is the AE 900S-WB from NF Electronics (Japan).

5. Remarks & Conclusions

As clearly shown in Pic. 2, the proposed method outperform the threshold based phase picker and returns almost the same single TOA 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 the complexity of 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 already produces the de-noised AE signal.

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