

ANALYSIS OF SIGNAL ACTIVITY DETECTION IN ACOUSTIC EMISSION

Anand, S. and K.Bharathi

Department of ECE, Mepco Schlenk Engineering College, Sivakasi, India,
Email: sanand@mepco.ac.in, bharathikarmegam@gmail.com

ABSTRACT

In recent years, the dynamic behavior of solid structure defects is extremely important as a small defect that is growing may well be more significant than a larger stable defect. Acoustic Emission (AE) is the method used to investigate the behavior of defects under stress. The importance of the AE is to determine the source location when it occurs. It is a real time monitoring technique. Identifying the actual sources of elastic waves during rapid local stress relaxation in solids under load is the major point in acoustic emission non-destructive testing, seismology and soon. This relies heavily on the accuracy of the arrival time detection process. Conventionally block thresholding technique is used to detect the Acoustic Emission, but accuracy is less in this method. The main focus of this work is to increase the accuracy of the real time signal detection and to verify actual phase picking transient waveforms of minimum amplitude, using novel wavelet transform based algorithm. This algorithm relies on the fact that noise commonly manifests itself as fine-grained structure in the signal, and Wavelet Transform (WT) provides a scale-based decomposition. This algorithm was evaluated in different types of acoustic emission tests, demonstrating the excellent temporal localization of the phases picked, even for the signals with minimum signal to noise ratio (SNR) and time of arrival (TOA) of the signal is detected exactly. This method is applied for different signals having different frequency sampling (Fs). In this work signal activity and time of arrival is determined using wavelet transform and block thresholding method. The results are obtained for signal activity and time of arrival for both techniques. From these results the accuracy is high for wavelet transform method when compared to block thresholding algorithm. Comparing to block threshold algorithm the wavelet based approach is applied to the signals with low amplitude and low SNR. These results will be helpful to find whether the signal will intrusive or not.

Keywords: Acoustic Emission (AE), Wavelet Transform, Time of Arrival (TOA), Signal to Noise Ratio (SNR).

I. INTRODUCTION

One of the most widely known applications of detecting acoustic signals is active noise control. Active noise control is used in some headphones and heli-copters to reduce the amount of ambient noise that is audible. The active noise control systems work by using a microphone to input ambient noise data to an analog-to-digital converter where a DSP processor converts it into an inverse signal, which is then out putted through a secondary speaker, causing destructive interference with the ambient noise. Another commercial applica-tion that uses acoustic signal detection is a voice recog-nition system. Microsoft is one developer of voice recognition and has software that allows users to dictate documents and use voice commands to increase productivity. Another application that is similar to speech recognition is voice recognition for security systems. This is done by training a system to recognize a person's natural voice patterns, or their voice print.

This type of system can be used for cell phones, ATMs, vehicle manufacturers, and others to reduce fraud and theft. In order to use analog acoustic signals in DSP, the signal must first go through an analog-to-digital converter where signals are sampled in the time domain to translate them to digital form. After this is done, the signal may either go to an embedded DSP processor or to a PC running DSP soft ware. The DSP software must then distinguish the desired signal from the ambient noise and create the correct output associated with the input signal. To perform acoustic signal detection and improved phase picking of transient wave arrivals of a low amplitude. The

wavelet transform is used perform phase picking efficiently even the signals with verylow signal to noise ratio.

II. PREVIOUS WORKS

Pomponi et al., (2015) proposed we propose a novel Wavelet transform-based algorithm To increase the reliability of real time signal detection and to ensure precise phase picking of transient waveforms of a low amplitude 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. From the concepts in the wavelet theory, the shortcomings of conventional amplitude threshold-based and Short Term Average/Long Term Average methods are addressed

Cai, et al., (1999) introduced a block three-holding estimation procedure which adjusts all para-meters adaptively to signal property by minimizing a Stein estimation of the risk. Numerical experiments demonstrate the performance and robustness of this procedure through objective and subjective evaluations. Removing noise from audio signals requires a non - diagonal processing of time-frequency coefficients to avoid producing —musical noise.!

Serrano, et al., (1996) examine Target Identification Using Wavelet-based Feature Extraction and Neural Network Classifiers. the wavelet characteristic of pro-jecting signal dynamics to an efficient temporal/scale (i.e. frequency) decomposition and extracting from that process a set of wavelet-based

features for classification using a multilayer feed forward neural network for vehicle classification. This effort is part of a larger project aimed at developing an Integrated Vehicle Classification System Using Wavelet / Neural Network Processing of Acoustic/ Seismic Emissions on a Windows PC performed under a Phase II SBIR for the US Army TACOM/ARDEC. The data set used for validation consists of ground combat vehicles (e.g. Tanks (T-62, T-72, M-60), Lightweight Utility Vehicle, Tracked APC and Tank Transporter) recorded at the Aberdeen Test Center, MD. Initial results using wavelet based feature extraction and a feed-forward neural network vehicle classifier employing the Leven berg-Marquardt deterministic optimization learning scheme.

Jiao, et al., (2004) proposed a method called integrating acoustic emission signal and simulated valve motion to diagnose faults in reciprocating compressor valves using the acoustic emission signal coupled with the simulated valve motion. The actual working condition of a valve can be obtained by analyzing the acoustic emission signal in the crank angle domain.

II. PROPOSED WORK

A. Acoustic Emission: Acoustic Emission (AE) is the occurrence of radiation of elastic waves in solid that occur when a material undergoes rapid release of energy within the material. It is one of the Non-Destructive Testing (NDT) techniques. Acoustic Emission is defined as the transient elastic waves. Acoustic Emission can be detected in the frequency ranges under 1KHz, and have been reported at frequencies up to 100MHz, but also most of the released energy is within the range of 1KHz to 1MHz. Rapid stress releasing events generate a spectrum of stress waves starting at 0Hz, and typically falling off at several MHz. The Three major applications of AE techniques are: 1) Source location, which determines the locations when an event source occurred. 2) Material mechanical performance, which evaluate and characterize the material or structure. 3) Health monitoring, which monitor the safety operation of a structure, i.e., bridges, pressure containers, and pipelines, buildings, etc. Most recent research has focused on using AE to not only locate but also to characterize the source mechanisms, i.e. crack growth, friction, delaminating, matrix cracking, etc. This would give AE the ability to tell the end user what source mechanism is present and hence allow them to determine whether or not structural repairs are necessary.

Acoustic emission is a technique that is being used increasingly in the field of structural integrity assessment using fracture mechanics. The dynamic behavior of defects is extremely important as a small defect that

is growing may well be more significant than a larger stable defect. Acoustic emission is the method used to investigate the behavior of defects under stress. The test structure is subjected to a stress (usually slightly greater than the normal maximum load) by mechanical, pressure or thermal means. Under these conditions crack growth, local yielding and corrosion product fracture may occur resulting in a sudden release of energy, part of which will be converted to elastic waves. These elastic waves are readily detected by piezoelectric transducers which, by using methods of triangulation, can give positional information about the emitting defect. The amplitude of the received signals can also be used to give an indication of the rate of growth of the defect. Sources of Acoustic Emission include many different mechanisms of deformations and fracture whilst the detection process remains the same. When the Acoustic Emission wave front arrives at the surface of a test specimen minute movements of the surface molecules occur.

The function of Acoustic Emission sensors is to detect this mechanical movement and convert it into a useable electric signal. The process of Acoustic Emission signal is, the small voltage generated by the sensor is amplified and the raw radio frequency (RF) signal is transferred to the computer. Based on user defined characteristics, the RF signal is split into discrete waveforms. These waveforms are then prescribed by characteristics such as amplitude, rise time, absolute energy based on a user defined threshold. The collected waveforms can then be displayed in two ways. One, the function of waveform parameter and next is as the collected waveform itself. Most AE tests currently only record the waveform, mainly due to the large amount of computing memory it uses.

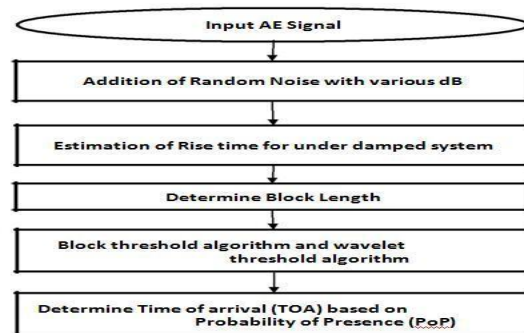


Fig 1: Block diagram

The automated source location capability of AE is perhaps its most significant attraction as a non destructive testing (NDT) technique. The predominant method of source location is based on measurement of time difference between the arrivals of individual AE signals at different sensors in array.

B. Wavelet Thresholding Algorithm: The wavelet thresholding is based on thresholding the DWT of the signal. The method relies on the fact that noise comm.-only manifests itself as fine-grained structure in the signal, and WT provides a scale-based decomposition. Thus, most of the noise tends to be represented by the wavelet coefficients at finer scales. Discarding these coefficients would result in a natural filtering out of noise on the basis of scale. Because the coefficients at such scale also tend to be the primary carriers of edge information, the method of the wavelet coefficients to zero if their values are below a threshold. These coefficients are mostly those corresponding to the noise. The edge related coefficients of the signal on the other hand, are usually above the threshold.

An alternative approach to hard thresholding is the soft thresholding, which leads to less severe distortion of the signal of interest. Several approaches have been suggested for setting the threshold for each band of the wavelet decomposition. A common approach is to compute the sample variance of the coefficients in a band and set the threshold to some multiple of the deviation. Wavelet denoising has wide range of application in signal processing as well as other fields. The signals may be one-dimensional, two-dimensional and three-dimensional. They carry useful information. Denoising (noise reduction) is the first step in many applications.

Other applications include data mining, medical

signal/image analysis (ECG, CT, etc.), radio astronomy image analysis etc. along all coefficients. The noise level is not too high so that we can distinguish the signal wavelet coefficients from the noisy ones. Motivation to the thresholding idea is based on the assumptions that the decorrelating property of a wavelet transform creates a sparse .

C. Algorithm Description: The proposed algorithm consists of the following steps: Sensor characterization from which the minimum detectable signal rise time is taken from the soundsnap.com

Block-size optimization based on the expected rise time Block-thresholding and Wavelet thresholding schemes application with the adapted block length Determination of the time-of-arrival (phase picking!) based on the PoP analysis.

D. Sensor characterization: Properties of AE signals acquired during a test are most strongly affected by the sensor response. The non-linear sensor response typically includes one or several pronounced resonances which determine the useful bandwidth of the entire acquisition chain. In the 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.

IV. EXPERIMENTAL RESULTS

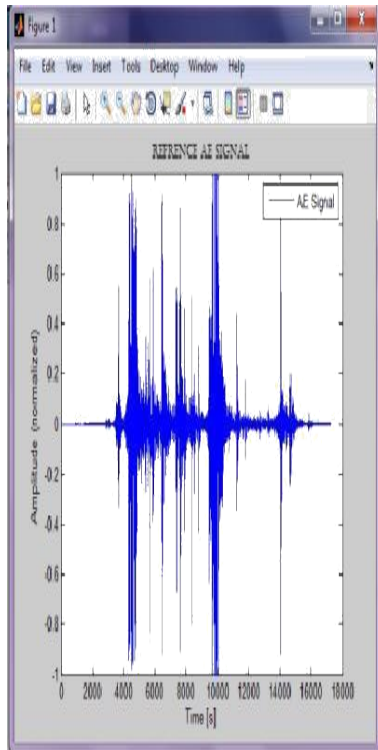


Fig. 2: Rock Crack with 22050 Hz Signal

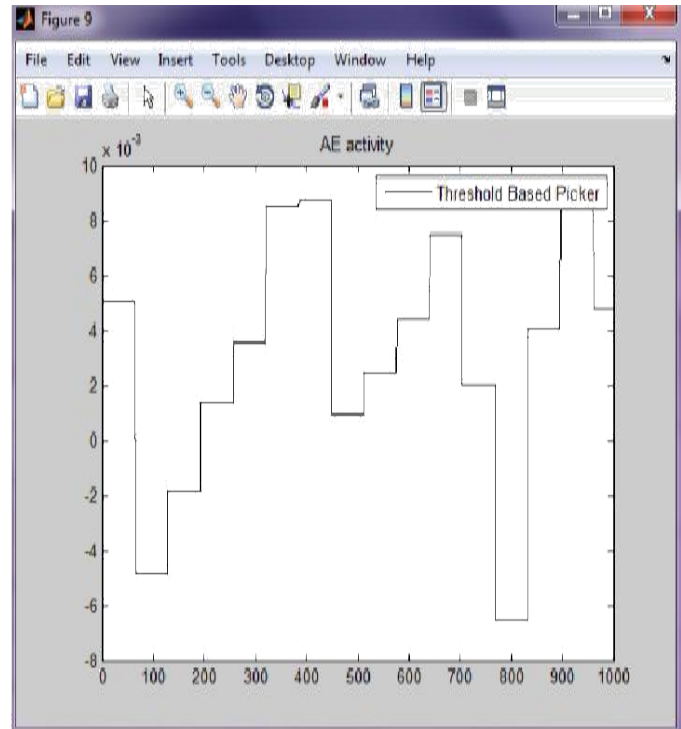


Fig 5: Output of Block Thresholding method

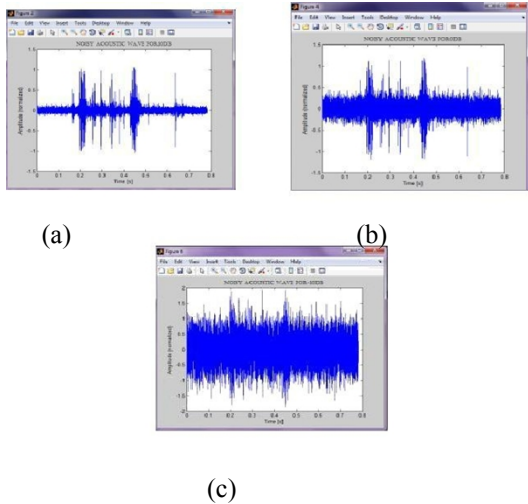


Fig. 3: Noise added for different dB

```

RiseTime =
    1.8117e-05

BlockLength =
    3.3423

DurationofanAESignal =
    3.6233e-05

BlockLengthforanAESignal =
    0.7989
    
```

Fig.4 Parameters obtained

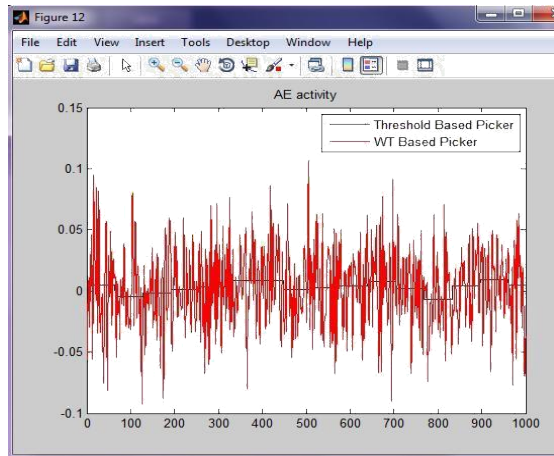


Fig 8: AE signal activity difference

Columns 1861 through 1872	-0.1208	0	0.5588	-0.1442	-0.5886	-0.6715	0	-1.6470	1.3560	-0.8376	1.1212	-0.7478
Columns 1873 through 1884	1.0570	0.2591	2.0675	-0.7353	1.2254	3.9525	-2.0474	0	-0.2892	0	-2.0730	0.0266
Columns 1885 through 1896	0.9112	0.2483	-0.8968	2.1482	0	1.2081	0.5911	-0.3343	0.3423	-0.2388	0	-1.0768
Columns 1897 through 1908	-1.2534	-1.6516	-0.5919	0.9577	0	-1.4552	-0.3913	-0.1650	0.1701	1.9490	0	-0.5083
Columns 1909 through 1920	1.2999	0.9322	0.9525	1.7005	-0.6112	-0.7261	1.9939	-0.7972	-0.3290	1.2061	0.9460	0.4371
Columns 1921 through 1932	0.6268	0.2239	-1.0771	0.0971	-0.5777	0	-1.7369	1.8170	0.2392	-1.0226	-1.2197	0.3393
Columns 1933 through 1944	-1.0408	0.1897	1.1608	2.2302	0	-0.2329	0.1221	-0.4174	1.3426	0.5245	0	0.0368

Fig 6: Output of Soft Thresholding

Columns 2089 through 2100	-1.1225	0.7790	1.3045	-1.3727	0	0	1.4781	0	-1.1254	-1.6099	3.7594	3.8699
Columns 2101 through 2112	2.0090	-1.2542	-1.0092	0	0.7406	-1.0524	-1.9206	0.4700	0.0926	0	-1.6011	-0.4630
Columns 2113 through 2124	0	0	0	3.0661	0	-0.8848	1.0317	0.8406	-1.8102	1.2202	-1.4781	0.7223
Columns 2125 through 2136	0.7371	0.7611	0	1.3004	2.9766	0	1.0518	0	-1.1010	0	2.0645	3.1076
Columns 2137 through 2148	-2.1618	-1.8637	-1.0150	-0.6052	-1.7227	1.1852	0.6675	2.0492	-2.3973	-0.0131	-0.6649	0
Columns 2149 through 2160	1.3628	-0.9498	0	1.2701	-0.4998	0	-1.7992	-1.1939	-1.3289	-1.2899	0.8939	0.8814
Columns 2161 through 2172	0.4600	1.1200	1.0440	1.0004	0	0	-1.0681	0	-0.5202	1.0159	0	2.7970

Fig 7: Output of Hard Thresholding

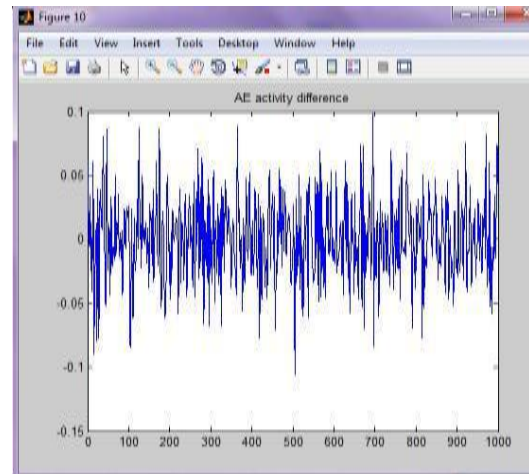


Fig 9: AE signal activity

V. CONCLUSION

The proposed wavelet -based algorithm for improved activity detection and phase picking of transient wave arrivals. The performance of the

proposed algorithm is compared to the most common phase detector: the amplitude threshold adopted in the routine acoustic emission practice widespread in seismology. Testing on various input signal data indi-

cated that all can pick arrival times on AE time series with high signal-to-noise ratio with acceptable accuracy. However, when the data were noisy, the amplitude threshold was not able to recover the most affected while the WT-based phase picking yielded significantly more consistent results than both the amplitude. Moreover, without any additional cost, it returns the thoroughly de-noised signal, which can be a very useful option in the later analysis. The proposed WT-based method is AE-oriented in that it accounts systematically for the specific AE sensor response. However, without loss of generality it can be adapted for a wide range of signal processing and phase picking problems. So wavelet based technique is used to find the exact time arrival of the signal even though it has low amplitude signal or for low SNR signal. Therefore, in future some other algorithm like Short term average and long term average instead of wavelet transform based algorithm is used and comparing those which is best will be found.

REFERENCES

- Cai, T.T. Adaptive wavelet estimation: a block thresholding and oracle inequality approach, *Ann. Stat.* **27**: 898–924 (1999).
- Jiao, J., C.He, B.Wu, R.Fei, X.Wang, Application of wavelet transform on modal acoustic emission source location in thin plates with one sensor, *International Journal Pressure Vessel and Pipes* **81**: 427–431 (2004).
- Pomponi, E., A. Vinogradov and A. Danyuk, Wavelet based approach to signal activity detection and phase picking. *Signal Processing* **115(C)**: 110–119 (2015).
- Serrano, E.P, M.A.Fabio, Application of the wavelet transform to acoustic emission signals processing, *IEEE Transaction Signal Processing* **44**: 1270-1275 (1996).