3rd International Conference "From Scientific Computing to Computational Engineering"
3rd IC-SCCE
Athens, 9-12 July, 2008

ADAPTIVE ANALYSIS OF ACOUSTIC EMISSIONS FOR FATIGUE CRACK GROWTH DETECTION

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Abstract. *Acoustic Emission (AE) signals are collected during well controlled experiments, in order to detect a propagating crack inside a loaded structural component. From the numerous AE signals emitted from the loaded material one has to recognize those originated due to the crack growth. The detection, isolation and modeling of such signals require advanced techniques and experimental setups. Classic techniques such as feature extraction, as well as adaptive techniques, such as multi-model partitioning, are discussed, in an attempt to classify the AE waveforms and identify those related to the propagation of a crack. The aim is the successful estimation of the crack growth rate that may, subsequently, lead to improved reliability estimation and lifetime prediction of the component.*

Keywords: Acoustic Emission, NDE, multi-model partitioning, Pattern Detection, Crack Growth

1 INTRODUCTION

Structural health monitoring applies NDT/NDE methods in order to provide data from the inside of a structure to better understand its structural performance and to predict its remaining life time. Bridges, pressure vessels and other critical steel components, may develop cracks in structural members resulting from a variety of causes. Most NDE methods currently in use can detect, locate, and to some degree size a crack, but they cannot determine if the crack is growing. Acoustic Emission (AE) studies correlate the degree of damage sustained by a material to the cumulative AE counts and its rate of change [1]-[3].

AE testing is a passive inspection technique employed to monitor the behavior of materials under deformation. AEs are defined as "the class of phenomena whereby transient elastic waves are generated by the rapid release of energy from localized sources within a material" (ASTM E1316). AE differs from most other DT techniques in two key aspects: A) the signal has its origin in the material itself, not in an external source, and, B) AE detects movement, while most other methods detect existing geometrical discontinuities.

In fact, Acoustic Emission monitoring has the capability of detecting crack growth in real-time. Only AE has the ability to warn of crack growth and to respond to active flaws. Therefore, Acoustic Emission techniques can play a significant role for the monitoring of civil engineering structures since they are able to reveal hidden defects leading to structural failures long before a collapse occurs.

In order to develop a valid AE detection technique well controlled AE monitoring experiments are required. The primary tasks of the implemented AE system consist of signal detection, denoising, localization and other data analysis or signal characterization techniques. Signals from one or more sensors are filtered, amplified and stored to produce AE data for further processing and interpretation [4].

A collection of such AE data is presented and analyzed in this work. The numerous AE signals emitted from a pressurized steel vessel are collected and classified based on their signal characteristics. Several classic techniques such as parameter analysis and feature extraction, as well as, more advanced adaptive techniques, such as multi-model partitioning, are tested for their ability to identify the different AE signals.

2 THE AE EXPERIMENTAL SETUP

An AE instrumentation system consists of: AE sensors, Preamplifiers, a Data Acquisition system, and specialized Software (Figure 1). The main objectives of the system are the detection, characterization and location of an event. Several methods of AE analysis have been proposed but the most traditional approach is the parameter analysis (PA). The parameter analysis evaluates AE features to identify the AE source and to locate its origin based on the arrival

time of the ultrasonic signal. Most common AE features, as shown in Figure 2, include the signal's Amplitude, Risetime, Duration, Energy, Counts, Peak frequency, Duration, etc.

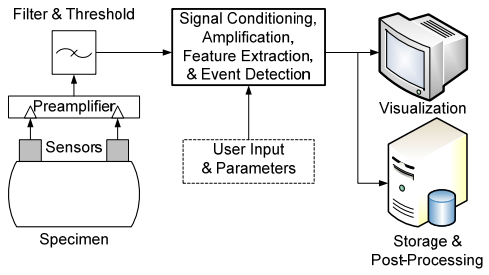


Figure 1: AE detection system.

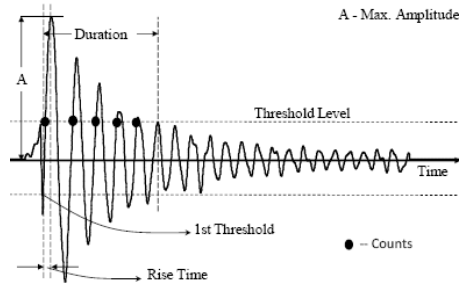
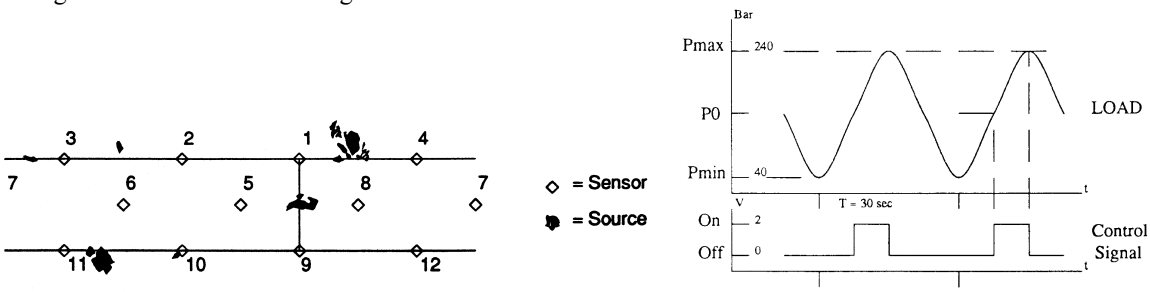


Figure 2: AE signal features

The experimental installation included: the steel vessel specimen, 12 AE piezoelectric resonant sensors magnetically attached on the surface (Figure 3a), the loading mechanism providing a periodic 40-240 bar pressure (Figure 3b), and, the data acquisition and storage systems AEDOS & DATA6000. Acoustic noise at lower frequencies is reduced by applying a 100kHz high-pass filter to the trigger mechanism, while still recording data over the wider 32kHz-5MHz band.

Most AE events occurred repeatedly from cycle to cycle and their waveforms were highly reproducible. The 3-D location accuracy is considered to be most satisfactory. The detected defects are clearly shown in the planar location map of Figure 3a the screenshot in Figure 4.



(a) (b)

Figure 3: (a) AE sensors positioning, and, (b) specimen loading conditions.

Periodically the test was stopped and the specimen fully inspected and it was terminated when a fatigue crack reached the condition of through crack. In total more than 1,600,000 acoustic events were recorded and analyzed during the test.

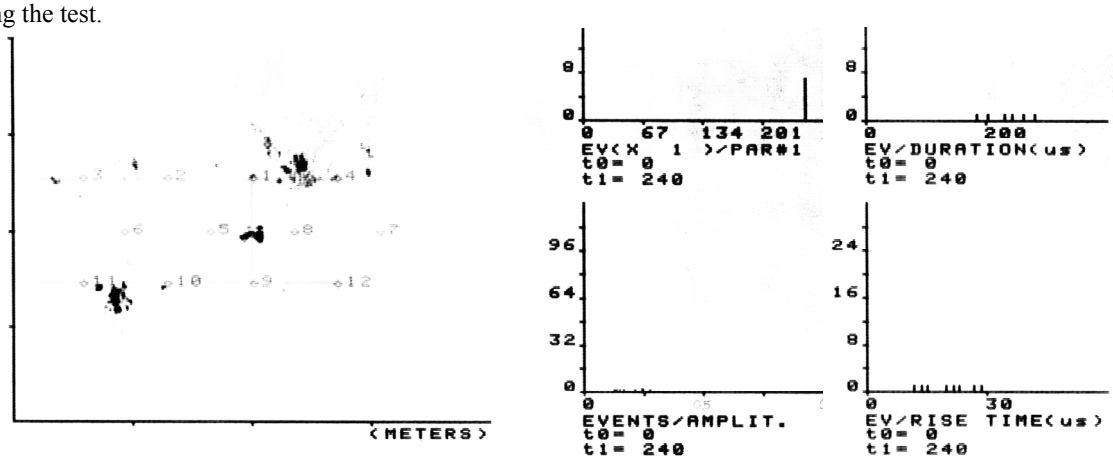


Figure 4: AEDOS on-line AE monitoring screenshot during fatigue test (location, amplitude, duration, risetime).

AE events were detected during the entire fatigue cycle. By considering three main phases on each cycle the events can be divided in three main categories: A) those occurring during pressure fall caused mainly by crack closure, B) those occurring during pressure increase at intermediate levels caused mainly by the widening of the plastic zone around crack tip, and, C) those occurring at pressure values close to maximum (always with dP/dt>0) that may be attributed to crack growth. In order to isolate the AE events emitted at rising pressure and closer to the maximum, a control signal is used that triggered the data acquisition mechanism (Figure 3b).

3 THE AE EXPERIMENTAL DATA

AE results from the above experiment have been selected for further processing. The selection is based on the information provided by the AEDOS system that globally monitors the experiment. A subset of the emitted AE is selected from specific sensors and is forwarded to the data acquisition instrument DATA6000. The following table summarizes the acquisition thresholds and limits.

Sensor No. 5 – Cycles No.:	From: 493930	To: 494115
Pressure Range	220 bar	240 bar
Event Amplitude	125 mV	280 mV
Event Duration	182 μsec	283 μsec
Event Risetime	10 μsec	20 μsec

A representative set of the recorded waveforms for six AE categories follows (Figure 5).

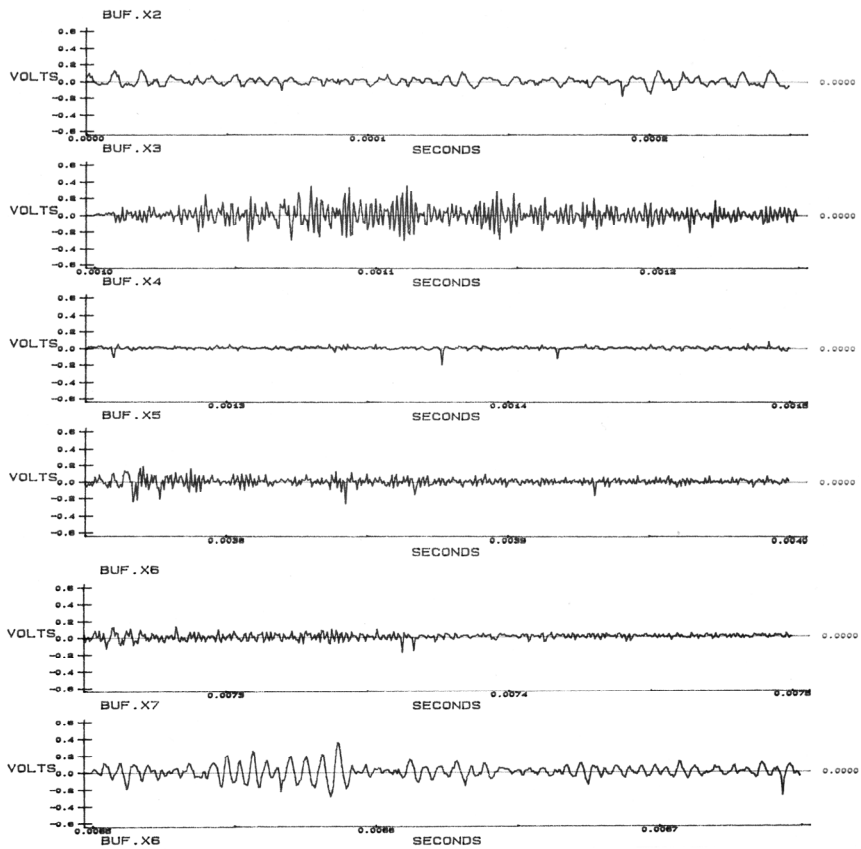


Figure 5: AE waveforms.

The recorded waveforms are analyzed and classified by their characteristics. Using a typical energy-frequency chart for the above six categories of AE signals one can easily group the AE waveforms.

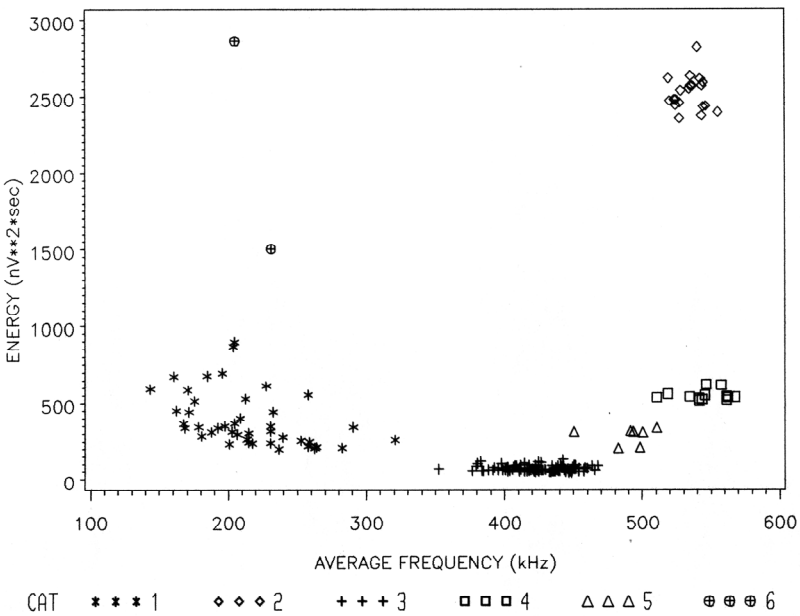


Figure 6: Frequency-Energy chart for six categories of AE waveforms.

By applying FFT we obtain the Power Spectra of these waveforms. For example the "waterfall" plot for the first two categories using 20 signals from each one is shown in the following figure (Figure 7).

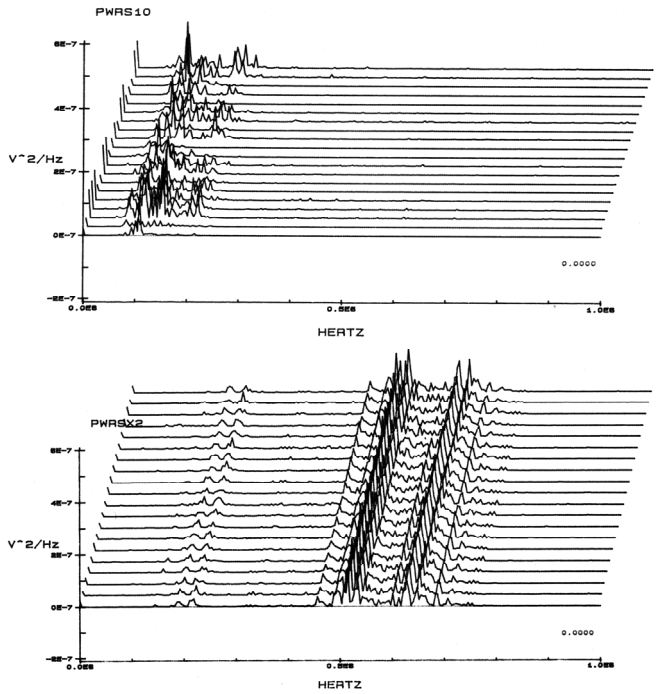


Figure 7: FFT power spectra of 20 AE waveforms (first two catagories).

5 AE RECOGNITION TECHNIQUES

Recognition of a pattern consists of data acquisition, pre-processing, transformation and then training or classifying, depending on the mode of operation. Most pattern recognition (PR) systems use a feature vector for representing the patterns. The greater dimensionality of the feature vector offers more complete description of each pattern. On the other hand, more features add to the complexity of data acquisition and processing.

When only two features are used, the 2-D feature space can be divided by straight lines separating the various pattern clusters. When using more features and higher dimensional spaces, the simple lines become hyperplanes. It is thus necessary, prior to the actual PR analysis, to reduce the feature space and to include only the features that contain the best separation information.

An early approach for the case under consideration, is to select the most significant and characteristic features of the collected AE waveforms such as: the Average Frequency, the RMS value, the Energy, the maximum Amplitude, the maximum Frequency, the Amplitude distribution, the power spectrum, the autocorrelation functions, the mean, etc. Once the feature vector is created, an adequate classification technique is required. There are many statistical techniques that may be applied for the classification decision. Each technique is based on a different set of mathematical assumptions. Examples of such techniques are the linear Discrimination Function, the Empirical Bayes procedure, the K-Nearest Neighbor algorithm, the Least Squares procedure, etc.

Another early approach is to model the AE waveforms as Autoregressive processes [5]. The feature vector can also be created by the AR coefficients, instead of the actual AE waveform features.

Our proposal is to model the different categories of AE waveforms as AR processes and apply other, more advanced classification/identification tools. More precisely the Multi Model Partitioning Algorithm (MMPA) introduced by Lainiotis[6] has the capability to process and classify the AE waveforms using a bank of filters each one tuned to a candidate AR process and consequently the corresponding AE pattern. The structure of the adaptive algorithm is shown in Figure 8.

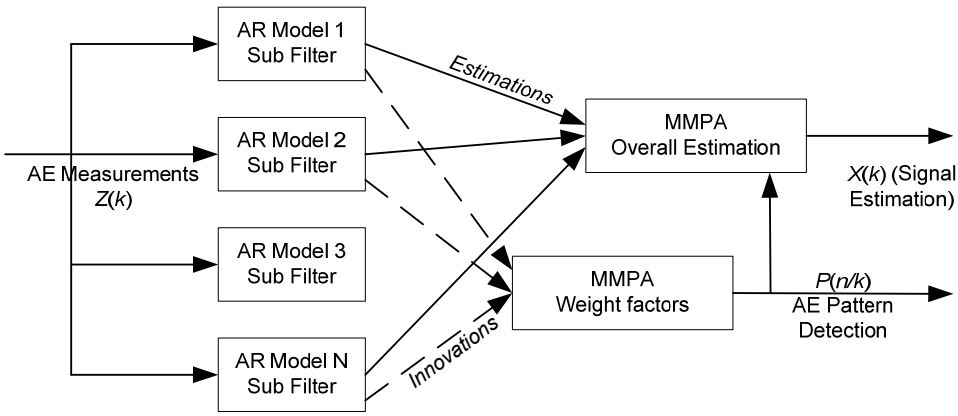


Figure 8: Structure of the Multi-Model Partitioning Algorithm for detedtion and classification.

The above technique is currently under development and a large number of stored waveforms are processed. The aim is to create an adequate bank of models (AR or other) that will represent the majority of the Acoustic Events including those related to the propagation of cracks. The Multi-Model Partitioning technique has been already applied with success to the FCG modeling/prediction problem [7] that is complementary to the AE detection problem.

6 CONCLUSIONS

Acoustic Emission (AE) signals were collected during well controlled experiments, in order to detect a propagating crack inside a loaded structural component. From the numerous AE signals emitted from the loaded material one has to recognize those originated due to the crack growth. The detection, isolation and modeling of such signals require advanced techniques and experimental setups. Classic techniques such as feature extraction, as well as adaptive techniques, such as multi-model partitioning, have been discussed, in an attempt to classify the AE

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