AVERAGED ACOUSTIC EMISSION EVENTS FOR ACCURATE DAMAGE LOCALIZATION

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ABSTRACT

Localizing micro cracks in critical components is crucial in the field of continuous structural health monitoring. In this paper, we utilize several signal processing and machine learning techniques such as hierarchical clustering and support vector machines (SVM) to process multisensor acoustic emission (AE) data generated by the inception and propagation of cracks. We present preliminary laboratory results that explore the pairwise event correlation of AE waveforms generated in the process of controlled crack propagation, and use these characteristics for clustering AE. By averaging the AE events within each cluster obtained from hierarchical clustering, we compute super-acoustics with higher signal to noise ratio (SNR) and use them in the second step of our analysis for calculating the time of arrival information (TOA) for crack localization. We utilize a SVM classifier to recognize the so called P-waves in the presence of noise by using features extracted from the frequency domain for accurate earliest arrival detection. Preliminary results show that our method has the potential to be a component of a structural health monitoring system based on acoustic emissions for instance for bridges.

Index Terms— Acoustic Emission, Crack Localization, Hierarchical Clustering, Support Vector Machines.

1. INTRODUCTION

The collapse of the I-35W bridge in Minneapolis, Minnesota USA in 2007, once again highlighted the need for continual health monitoring of structures such as bridges. Harsh loading, rapidly changing environmental conditions and seismic events are significant sources of damage on these structures. In general the damage is characterized as being local such as cracks or global such as abrupt changes or deviations from natural vibration characteristic of the structure. Several systems are proposed in the literature for monitoring the global damage in bridges and buildings by using accelerometers interfaced with wireless sensor nodes [1, 2, 3 and 4]. However, continuous health monitoring process involves the examination of both global and local damages. Currently, the local damages, such as cracks, on critical components are mainly inspected visually. This type of inspection is slow and prone to human error. Therefore, automated, fast and accurate techniques are needed to detect the onset of local damage to prevent failure. Broadband acoustic emission events can serve as a source of information for the localization and characterization of damage, particularly as caused by the initiation and propagation of microcracks [3, 5 and 6]. Accurate detection of these events and the location of cracks with appropriate signal processing techniques may open new possibilities for monitoring the health of critical structures such as bridges and the provision of alarms related to the potential for serious degradation of structural integrity in an automated manner. In this paper, we describe novel signal processing and machine learning techniques based on hierarchical clustering and support vector machines to process multisensor acoustic emission (AE) data generated by the inception and propagation of cracks validated with experimental results. In particular, our signal processing framework targets to capture and process correlated events as being generated by individually localized crack mechanisms rather than randomly generated AEs distributed within the specimen. A schematic diagram summarizing the overall system is given in Fig.1.

The rest of the paper is organized as follows. In the next section we describe our experimental paradigm to record AE waveforms generated in the process of controlled crack propagation. In the following section we summarize our signal processing, feature extraction and machine learning techniques for clustering AE signals and localizing the cracks. Finally we provide experimental results on the spatial distributions of AE events and compare them to real damage locations.

2. ACOUSTIC EMISSION RECORDINGS

In this study the AE events were recorded during a surface instability type of failure. A picture representing the experimental setup is given in Fig.2. A prismatic rock specimen, placed between two rigid vertical side walls and a rigid vertical rear wall, is subjected to axial load applied in y-axis through displacing rigid platens. The material is supported in z-axis such that compressive force is generated

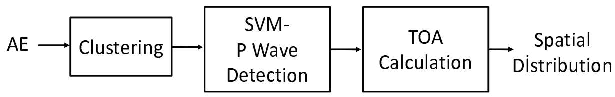


Fig.1. The schematic diagram of the signal processing and classification system.

passively. The rear wall in x-axis ensures that the lateral deformation and spalling take place on the front, exposed face of the specimen.

Four acoustic emission (AE) sensors were attached to the exposed face using cyanoacrylate glue and their positions (x, y, and z) were measured. Four other AE sensors were fastened to the side walls of the apparatus. The eight AE sensors have a frequency response from 0.1 - 1 MHz and a sensor radius of approximately 3 mm. A high speed, eight channel data acquisition system was used for AE recording. The data acquisition system is equipped with four two-channel modular transient recorders with 8-bit resolution and a sampling rate of 20 MHz. AE data were acquired in a more or less continuous fashion until 128 Kbytes of a digitizer memory were filled; then the AE data were transferred to the host computer, with approximately four seconds of downtime. The entire waveforms are stored automatically and sequentially with a time stamp. The signals were preamplified (40 dB gain) and filtered (bandpass 0.1 - 1.2 MHz) at hardware level prior to storage. All recordings are triggered when the signal amplitude exceeded a certain threshold on the first sensor. This sensor is referred to as the "anchor" sensor in the rest of our paper and is used for further processing. A sample recorded signal is presented in Fig.3. In total, 2176 AE events were recorded in the whole experiment. This number includes both real AE and noise events.

3. CLUSTERING OF AE EVENTS

In practice the crack locations are inspected visually by projecting the AE locations on a 2D surface where these locations are computed from the time of arrival (TOA) information at the sensors [7]. The time of arrival is calculated by comparing the signal amplitude to a predefined threshold where the earliest arrival generally related to the

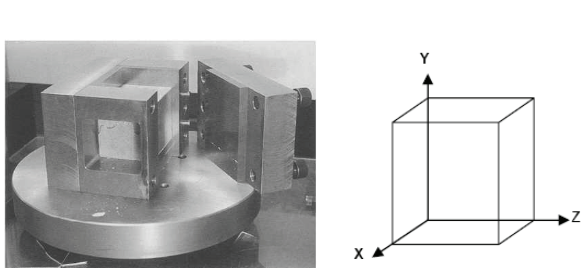


Fig.2. The experimental setup for recording the AE events in a surface instability type of failure.

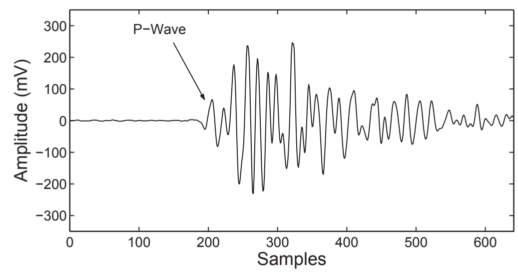


Fig.3. A sample AE event recorded from the first sensor that triggers the whole data acquisition process.

P-wave as shown in Fig.3. This type of method produces misleading TOA information if the signal is noisy, which is always the case in real life situations. Therefore, in our data analysis before applying the amplitude threshold, we aim to increase the signal to noise ratio of the signal by capturing correlated recordings and averaging grouped events. In particular we applied a hierarchical clustering approach that uses the cross correlation function computed between different events.

As a first step we computed the cross correlation function between all events on the signals acquired at the anchor sensor. Then we constructed a correlation matrix that keeps the maximum value of the absolute cross correlation function between all event pairs. This correlation matrix was used to build a hierarchical cluster - dendrogram [8]. The dendrogram represented the nested correlation structure of all AE events. This dendrogram was cut at level 0.3 in order to cluster those events which have cross correlations larger than 0.7. At this level 338 clusters were obtained with two or more members. Acoustic emission events related to a particular cluster are shown in Fig. 4. This step was followed by computing the averages of each cluster to obtain what we call "super-acoustic" signals. Indeed due to averaging, the random components in the data are suppressed and repetitive components will remain the same. Therefore, the super acoustics will have higher signal to noise ratio (SNR) than individual AE events. We also note that a similar approach was utilized for processing gene expression profiles in [9]. It

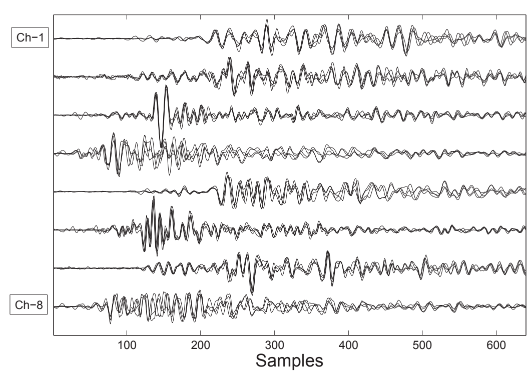
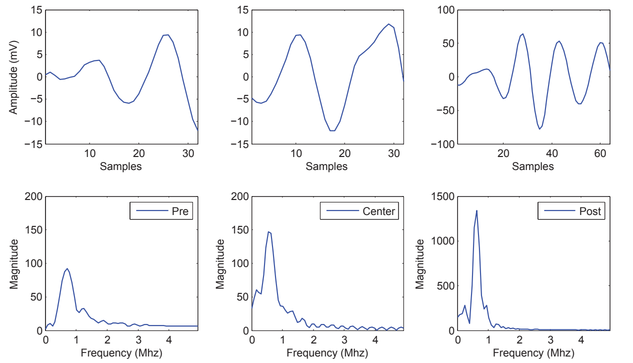
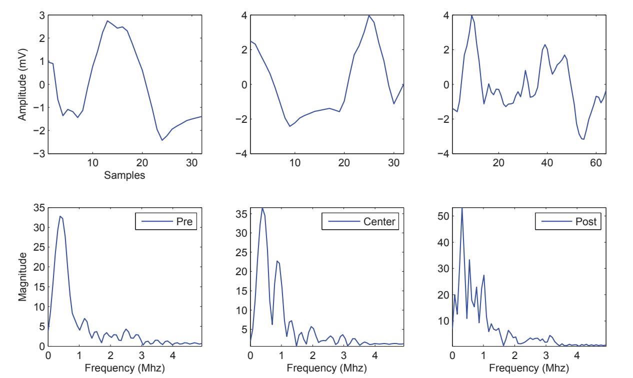


Fig.4. The overlap plot of AE events related to a particular cluster.



(a)



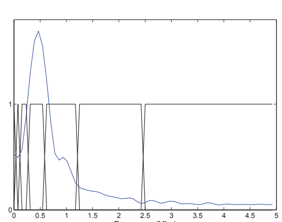
(b)

Fig.5. (a) Sample waveforms and spectra of 32 sample time windows preceding the P-wave, centered around P-wave and a 64 sample window after post P-wave. (b) Sample raw data and spectra of noise segments that may be recognized as a P-wave.

has been shown that averaged gene expression data within clusters have more predictive power than those from individual gene expressions. In our study by increasing the SNR of AE events we expect to localize the arrival times more accurately.

4. P-WAVE DETECTION WITH SVM

As indicated in our crack localization framework, the TOA information is extracted from the P-waves. The detection of P-waves by using simple thresholds becomes difficult in the presence of noise or abrupt spikes in the data. In order to



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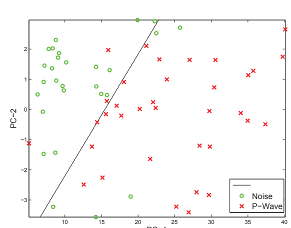

(b)

Fig.6. The subband tiling of the AE spectrum. The bandwidth was wider in high frequencies and narrower in lower frequencies. On the right the scatter plot of the first two principal components.

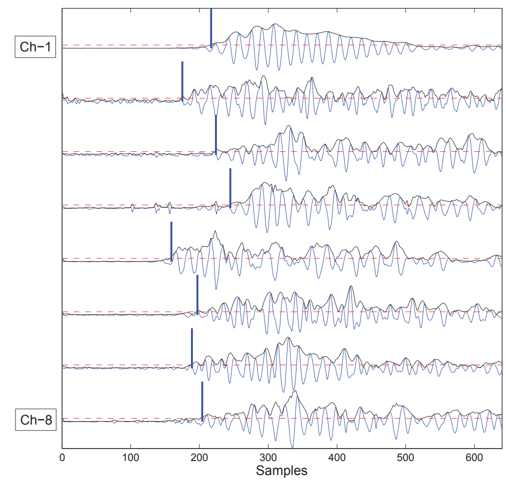

Fig.7. Sample cluster average and detected arrivals from 8 sensors. The TOA is marked with a vertical line on each channel.

localize the P-waves accurately we investigated the time and frequency domain properties of the AE data in short windows around the P-wave location. We observed that the P-waves were generally located in lower frequency bands. This wave is followed by large oscillations. Sample waveforms and spectra related to a typical P-wave (center) and those windows preceding and following this wave is presented in Fig.5. Same analysis related to a segment that may be recognized as a pseudo P-wave is also given. We observed that the pseudo P-waves were not followed by large oscillations. In addition their frequency spectrum indicates that these waveforms had certain amount of energy in higher frequency bands.

Based on these observations 7 subband energy features were extracted from each time window spectrum which was computed with fast Fourier transform. The widths of the subbands were not uniform. The lowest two bands had the same bandwidth and following subbands were twice as wide as the preceding subband. The subband tiling is shown in Fig.6. This setup focused more to the lower frequency bands since the energy of the signal was concentrated in this range. The spectrum of the noise (pseudo P-waves) had jagged spikes. In contrary the spectra of the P-waves were smooth. We also computed the variance of the derivative of the spectrum of each time window as another feature to capture this difference. Together with subband features a 24 dimensional feature vector was constructed. In order to explore the predictive power of these features we applied principal component analysis. The scatter plot of real and pseudo P-waves related to the first two principal components is shown in Fig. 6 (b). On this 2D surface we observed that extracted features were quite informative in distinguishing real and pseudo P-waves.

Computing these features for each time point could be a demanding process. In order to reduce the number of candidate time points that will be tested for P-wave arrival,

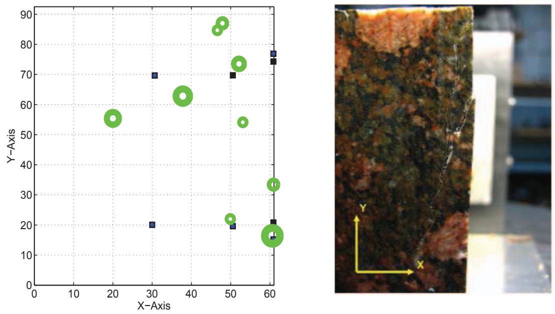

Fig. 8. The estimated locations of the AE events. Each green circle represents the location of a particular cluster. The diameter of the circle is proportional to the number of AE in the cluster.

first the signal was normalized and then the envelope of the signal was computed with Hilbert transform. When the envelope of the signal exceeded a predefined threshold then that time point was tested for P-wave arrival. We empirically found that a threshold value of 0.5 was good enough to localize most of the P-waves. The 24 dimensional feature vector was fed to a linear support vector machine classifier for final decision [10]. The main motivation for using an SVM classifier is based on its robustness against outliers and its generalization capacity in higher dimensions, which is the result of its large margin. The support vector machine classifier was trained by selecting around 25 sample AE events from the non averaged data. The training feature vectors for P-waves and noise sets were constructed from this subset by manually marking the P-wave arrivals and noise events that exceeds the predefined threshold. Sample TOA estimates detected by a SVM classifier for a particular cluster are visualized in Fig. 7. The horizontal dashed lines represent the predefined threshold. Those time points where the envelope of the signal was exceeded the threshold was tested for P-wave arrival. The vertical blue lines represent the detected P-wave arrivals. Note that although several other time points exceeded the threshold the algorithm successfully eliminated them.

5. RESULTS

After calculating the arrival information on each sensor location, the algorithm in [7] was used to estimate the location of the source in 3D. In Fig. 8 we visualize the estimated source locations of the top 10 clusters in the X-Y axis and a picture of the deformed specimen which developed several cracks on the frontal surface. The locations of AE sensors were marked with the black squares. Each green circle represents the location of a particular cluster. The size of each circle is proportional to the number of AE events within the cluster. We note that the locations of the AE events were correlated with the crack locations. Most of the events were localized towards the free surface. Interestingly the largest cluster was localized a few millimeters away from the free surface of the specimen.

6. CONCLUSION

In this paper we introduced novel approaches based on hierarchical clustering and support vector machines for clustering acoustic emission signals and detecting P-waves for crack localization in the presence of noise. We presented preliminary laboratory results that explore some of the characteristics of AE waveforms generated in the process of controlled crack propagation, and use these characteristics for clustering AE and localizing the cracks. By averaging the AE events within each cluster, we computed new acoustics emission events with higher SNR. In the following step the system extracted several features from the frequency domain representation of averaged AE events and used them in combination with a SVM classifier to recognize P-waves for TOA calculation. Our preliminary results show that our method has the potential to be a component of a structural health monitoring system, for structures such as bridges, based on acoustic emission.

7. REFERENCES

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