ACOUSTIC EMISSION CLASSIFICATION USING SIGNAL SUBSPACE PROJECTIONS

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ABSTRACT

In using acoustic emissions (AE) for mechanical diagnostics, one major problem is the differentiation of events due to crack growth in a component from noise of various origins. This work presents two algorithms for automatic clustering and separation of AE events based on multiple features extracted from experimental data. The first algorithm consists of two steps. In the first step, the noise is separated from the events of interest and subsequently removed using a combination of covariance analysis, principal component analysis (PCA), and differential time delay estimates. The second step processes the remaining data using a self-organizing map (SOM), which outputs the noise and AE signals into separate neurons. The algorithm is verified with two sets of data, and a correct classification ratio of over 95% is achieved. The second algorithm characterizes the AE signal subspace based on the principal eigenvectors of the covariance matrix of an ensemble of the AE signals. The latter algorithm has a correct classification ratio over 90%.

1. INTRODUCTION

The increased reliability and safety standard of engineering structures requires the detection of the precursor or onset of failures. A promising technique in addressing this challenge is acoustic emission (AE), or the transient energy spontaneously released by incremental crack growth. Compared to other nondestructive testing (NDT) techniques, AE has the advantage of real-time continuous monitoring of in-service structures [1]. A major issue in applying the technique, however, is how to differentiate the events of interest, i.e., those due to crack growth or imminent failure, from noise of various nature in a large dataset. Often the real AE events are measured in the presence of noise due to vibration, fretting, and electromagnetic interference etc, and automatic noise rejection is required before correlating AE activities with crack initiations or progressive failures. This essentially falls into a problem of pattern recognition and classification for random waveforms. In many cases, traditional signal processing techniques such as filtering, energy analysis, spectrum analysis etc, are insufficient to separate the two, as the noise often has similar temporal and frequency features as the AEs due to crack activities, and new alternatives have to be explored. One approach is to use neural networks that are capable of automatically discovering features and patterns in a larger collection of almost random observations [2].

This article presents a novel, efficient algorithm for automatic clustering and separation of AE events based on multiple features extracted from the original test data. The algorithm consists of two steps. First, the noise events are separated from the events of interest and subsequently removed, using a combination of covariance analysis, principal component analysis (PCA), and differential time delay estimates. The original data is reduced by up to 70% after this step. The second step processes the remaining data using a self-organizing map (SOM), which clusters AE signals and noise signals to separate neuron outputs. To improve the efficiency of classification, short-time Fourier transform (STFT) is applied to retain the time-frequency characteristics of the remaining events, and reducing the dimension of the data. The algorithm is verified with two sets of test data and a correct classification ratio over 95% is achieved. Furthermore an AE signal subspace, i.e., a set of orthogonal basis retaining the features of AE signals, is computed from the separated AE's. When applied to data from new tests, signals of similar features, i.e., AE events of the same origin, are selected automatically. The example in this study shows a correct selection ratio of 90%.

2. CLUSTERING OF AE EVENTS FROM THE TEST DATA

In this section, a system that removes the non-crack events and applies a Kohonen network to cluster the potentially crack-related AE signals is shown in Fig. 1.

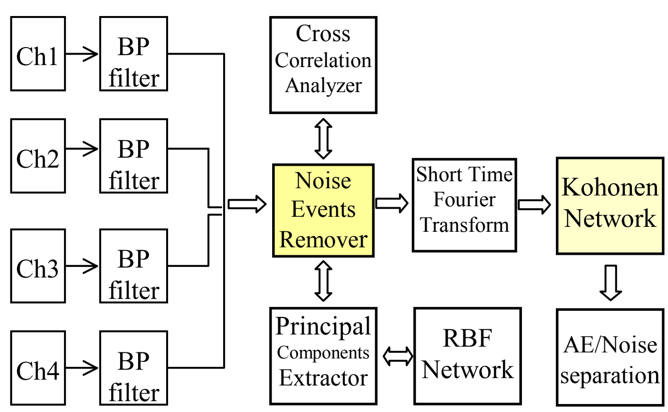

Figure 1. System for acoustic emission clustering

Two sets of data (Test1 and Test2) have been used for verifying the performance of the system. Three techniques are employed to remove the noise events. The first used a bandpass filter 20Kz - 1Mhz, after collecting signals from four channels (sensors), to remove low frequency noise, i.e., events whose ratio of energy in the frequency band to the whole energy is below a certain threshold. Second, using the first and second principal components (PCs), (a larger number of PCs, e.g. 5, can be used if needed) we remove clusters that correspond to the high frequency mechanical signals such as those generated by the grips that hold the sample, with a radial basis function (RBF) network. In the third technique, cross-correlation is used to measure the delays between the sensors to remove events that have relatively large differential delays, i.e., the grip noise. At this stage, a significant amount of noise would be removed from the original test data. Next, a Self-Organizing Map (SOM) is used to process the remaining data for separating the noise and clustering AE signals. To improve the efficiency of classification, short-time Fourier transform (STFT) is used to retain the time-frequency characteristics of the remaining events, and reducing the dimension of the data. Figure 2 shows the results of successive removal of noise from the original data.

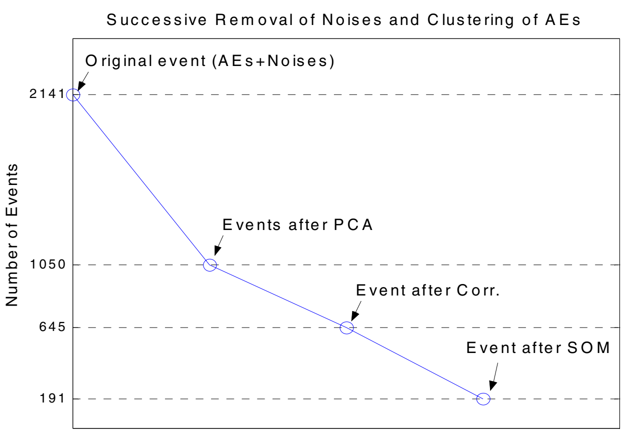

Figure 2. Results of successive removal of noise

3. PRINCIPAL COMPONENTS OF THE DATA

Principal components analysis can be used for separating AE and non-AE signals and the corresponding spaces spanned by the first few principal vectors are denoted as *signal and noise subspace* respectively. In practice, however, the data recorded from an AE test contains both, and an algorithm has to be able to select one type or the other from the mixed data. Using this combined signal and noise data, we performed the principal component analysis. Figure 3 shows the distribution of the first two principal components associated with the output of the RBF network for each of the four sensors. It is noticed that the two principal components are mainly divided into four clusters: the cluster around the origin and three branches. Randomly choosing and plotting a signal from these four regions shows that the center cluster contains mainly AE signals, while the other three branches are noise. This is also confirmed when projecting the selected AE signals to the mixed space, and they overlap with the center cluster.

This result is not surprising. The first two PCs are heavily influenced by the intrinsic features of the grip noise, since they account for more than 80% of the total events used in performing the analysis. When signals of different nature, in this case, the AE signals, are projected to these two directions, it leads to a distribution of PCs around the origin, meaning no similarities exist between the AE and noise. Some overlaps of the two are due to the highly non-stationary nature of the two types of signals. One then can use the clustered PCs to remove a large number of non-AE events, either based on single sensor data or by a validation or voting rule using the PCs from all the sensors.

To separate the clusters explicitly, a simple radial basis function (RBF) network is employed. After this stage, a significant portion of the noise data is successfully removed, and the data set is reduced by almost 50%, i.e., the data is reduced from 3027 to 1506 and from 2141 to 1050 respectively for test 1 and test 2.

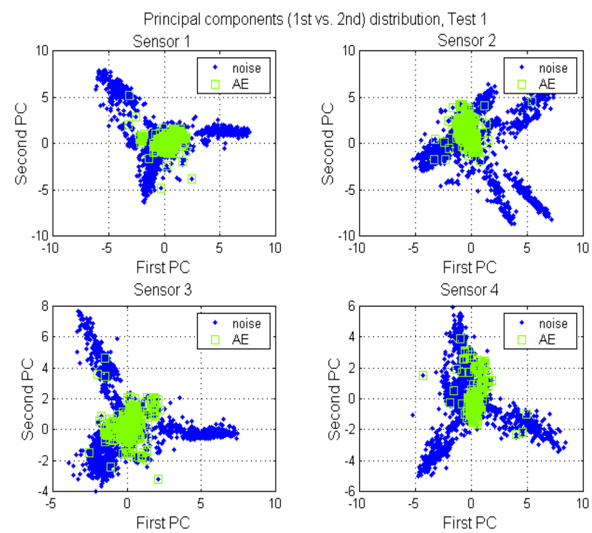

Figure 3. Second PC vs. first PC for test 1 data

4. DELAY ESTIMATION FOR THE MULTI-SENSOR DATA

To further reduce noise from the already halved data, time-delay estimate is used. The estimate is based on the location of the maximum of the cross-correlation between the signals of any two sensors: for a pure delay model of propagation, two data sequences from the same source will have the maximum cross-correlation when the delay between these two data sequences is compensated. The normalized cross-correlation value above a threshold is used as the true delay. Ideally, a high threshold close to 1 is desired. However, due to the presence of noise, this study uses threshold values as low as 0.4, i.e., it is conservative in keeping some noise signals rather than rejecting potential AE's. Figure 4 shows the estimated differential delays between the signals received at 3 pairs of sensors. Using the delay estimation, the two test data are reduced to 500 and 645 respectively.

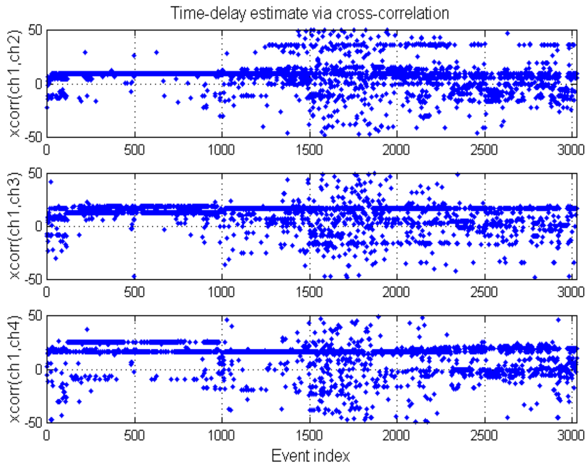

Figure 4. Delays between pairs of sensors for all 3027 events, test 1. (a): Sensors 1 and 2; (b): Sensors 1 and 3; (c): Sensors 1 and 4.

5. CLUSTERING OF AE EVENTS USING THE KOHONEN NETWORK

Some noise events still remain to be separated because of their close resemblance to the AE signals. Since no precise model for AE signals is available, a neural network-based scheme seems to be an appropriate choice. This study uses a 4×4 Kohonen network. The network is an unsupervised, i.e., the network is presented with only the inputs and samples of self-similar are grouped to the same node. The training set consists of 500 128-dimensional vectors of the STFTs of AE signals and noise, randomly chosen from the pool of one sensor. The test set consists of all the remaining data from all the four sensors. Figure 5 shows which event mapped to which neuron.

As crack-related signals have different time-frequency features compared to grip and noise-related signals, it is expected that crack-related signals to be mapped to special neurons. The results show that almost all the AE signals mapped to the neurons 4-6. Table 1 lists the AE's classified by the network.

Table 1. Performance of the Kohonen network.

Test	AE events	AE's clustered	AE's missed	False alarm	% of correct classification
1	385	382	5	2	98.7%
2	192	191	2	1	99.5%

6. EVENT CLASSIFICATION BASED ON SIGNAL SUBSPACE PROJECTION

The scheme described above assumes no a-priori information about the AE signal subspace (or equivalently the noise subspace) is available.

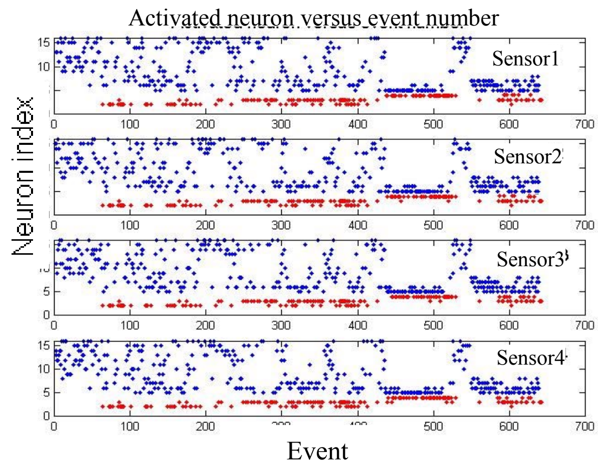

Figure 5. Output of the Kohonen network to all potentially crack-related signals

In AE testing, however, calibration of the system and repeatability of the test have to be ensured before applying the technique to engineering application. Therefore, at least some typical AE's are available. If one is able to characterize the AE signal subspace based on the principal eigenvectors of the covariance matrix of available AE ensemble, or equivalently the noise ensemble, the following possibilities may be explored:

- Having identified the AE signals from one test using the developed system, one can use it as estimate of the signal subspace for the subsequent tests;
- The events prior to the possibility of any measurable crack-related events may be used to estimate the noise subspace; and
- The high correlation among successive events during a rapid rise in the event count may be used as an indicator of a group of potential AE events, and used for estimating the AE signal subspace;

Once the signal subspace has been estimated, data from new test can be projected onto this subspace. The norm of this projection is a measure of the closeness of the data to the signal subspace. In this case a norm of 1 is a perfect fit to the signal. Thus, a threshold, or averaged among several sensors, if necessary, can be set for identifying the potential crack-related AE events. Similarly, noise can be classified.

As an example, a signal subspace of dimension 5 based on AE ensemble of test 2 is computed. Figure 6 shows the results when projecting the complete data of test 2 on the signal subspace. It is noticed that AE's, i.e., cluster with higher values of the projections) are effectively separated from the noise. Figure 7 shows the results when cross-projecting the test 1 data onto the signal subspace of test 2. The result shows 175 correct classifications, excluding 2 false alarms, out of 191 or a ratio of correct classification of 89.4% is achieved. Similarly a ratio of 91.5% is achieved when cross-projecting test2 data onto the test1 AE subspace.

Table 2. Performance of the cross-projection method.

Test	AE events	AE's clustered	False alarms	Correct classifications	% Correct classification
1	385	353	9	344	89.4%
2	192	177	2	175	91.2%

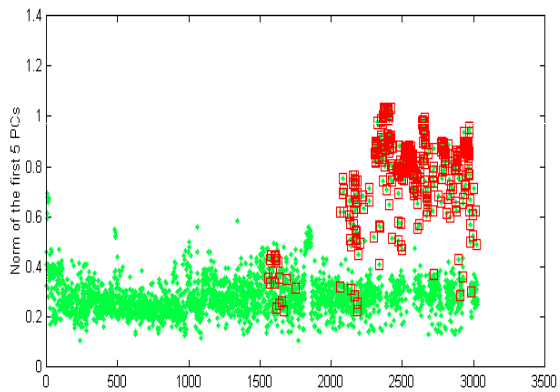

Figure 6. Norms of the projections of test 1 data onto the test 2 signals subspace

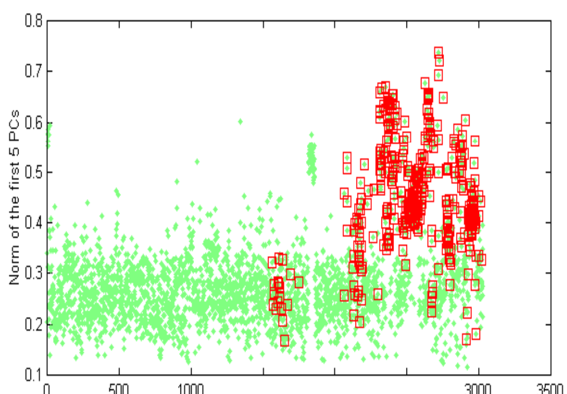

Figure 7. Norms of the projections of test 2 data onto the test 1 signal subspace

7. CONCLUSION

This paper has presented a set of novel efficient algorithms for automatic clustering and separation of AE events based on multiple features extracted from the original test data. The algorithm successfully removes the non-AE noise from the original record using a combination of covariance analysis, principal component analysis (PCA), and differential time delay estimate. The algorithm leads to a reduction of the data by more than 70%. A Self-Organizing Map (SOM) is then applied to separate the AE's from the noise in the remaining data. The algorithm is verified with two sets of data, and a ratio of correct classification over 98% is achieved. Also, an AE signal subspace, is computed from the separated AE's. When applied to data from new tests, signals of similar features, i.e., AE events of the same origin, are selected automatically. The example in this study shows a correct selection ratio of 90%.

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8. REFERENCES

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