ADVANCES IN CLASSIFICATION OF ACOUSTIC EMISSION SOURCES

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1. INTRODUCTION

During the last few decades, the Acoustic Emission (AE) NDT technique has experienced considerable growth both in terms of sheer number of inspections and users, and in terms of range of applications. The capabilities of the technique have been proven or are under investigation for a vast number of materials, processes, applications and structures. The complexity of modern AE applications ranges from simple to very complex, while, at the same time, the users of the technique include universities, research institutes, industries and NDT companies. Thus, the demand for advanced AE data analysis tools is constantly increasing. Over this broad range of AE applications, in many occasions, the user wishes to discriminate the various AE sources, which are detected during loading of structures. However, in some cases, complicated AE signatures are present (high level of background noise, different damage mechanisms initiated or ceased at different load levels and at different sections of the structure etc.). In such cases, conventional, graphical AE data analysis and AE source location analysis may not be adequate for effective AE source discrimination. This fact has led towards the development of methodologies such as Unsupervised Pattern Recognition (UPR) for the classification of the AE data.

With UPR, the AE data are separated into "families", by means of clustering algorithms, based on the similarities of their AE features. The separability of the various material-failure mechanisms by means of UPR analysis of the corresponding AE data has been demonstrated as UPR has been applied for the segregation of AE data obtained during various different applications[1]-[4]. It has been proven that the understanding of the damage evolution on structures under loading is enhanced by means of combined application of traditional AE analysis techniques and UPR. Furthermore, it is now evident that application of Supervised Pattern Recognition techniques can lead towards the automation of AE data analysis and evaluation procedures. The present paper outlines the basic features of UPR for AE data and reports on some successful application examples of the technique.

2. BASIC FEATURES OF UNSUPERVISED & SUPERVISED PATTERN RECOGNITION

The main function of UPR, as applied in AE, is to mathematically segregate AE data, based on their AE features. An AE data set will normally contain a number of AE hits arising from the AE activity of the tested structure during loading. Each hit is described by means of its AE features[5] and some non-AE features (e.g. time of hit arrival, channel, etc.). In UPR software, mathematical algorithms[6] (clustering algorithms) are applied in order to divide the set of AE hits into groups (called classes or clusters) based on the similarity of their features. In this context, it is necessary to clarify the meaning of "similarity" among AE hits. Mathematically speaking, each AE hit is treated as a multi-dimensional vector, its dimension being the number of its AE features, and its coordinates being the actual AE features' values. Therefore, AE hit similarity actually implies "close distance" of the corresponding vectors. The clustering algorithms that are used to create classes of AE data, actually, identify families of vectors, which fall close to one another, within the same data set.
UPR is a purely mathematical function. Numerous clustering algorithms exist in the literature[6], each one comprising its own unique parameters, such as the distance calculation method, the vector similarity criteria etc.

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It is up to the user to select such parameters, so as to come up with a classification that has a physical importance. In view of the above, specially designed software is needed, in order for the user to have multiple options that can modify the classification results. The basic stages towards a successful UPR of AE data are the following[7]:

I. ***Import and preliminary analysis of the AE data file***
During this stage, the user should load the data set into the UPR software, select the channels of interest, perform traditional graphical analysis to assess the quality and structure of the data, and, possibly, perform some filtering of known noise sources.
Figure 1: Example of feature correlation hierarchy dendrogram

II. ***Reduction of the AE Features' Set***
The purpose of this step is to select the AE features that will be used for UPR. Not all of the information describing the AE hit is usually used to form these vectors. For instance, it is a common practice to exclude features which do not physically pertain to the AE hit description (Time, Channel number etc.). Additionally, it is desirable to exclude features which exhibit very strong correlation with other features, in order to avoid biasing of the classification. Important aids in identifying highly correlated features are the "feature correlation hierarchy dendrogram" (see Fig. 1) as well as Principal Component Analysis of the feature set[7].

III. ***Normalization***
It is essential that all features (the vector coordinates) be normalized prior to any clustering, in order to avoid biasing the classification towards the AE feature that exhibits the largest physical values. There are several ways to perform normalization[7], such as to set the values of all coordinates to "0 to 1 range", or "-1 to 1 range" etc.

IV. ***Application of Clustering Algorithm***
Research in UPR[1]-[4],[6] has proven that there is no universal clustering algorithm optimum for all AE data. Selection of the right algorithm depends on the structure of the data, the separability of the corresponding sources etc. As multiple algorithms exist, each one with multiple parameters and criteria, and since the optimum (mathematically and physically) number of classes is unknown, the UPR problem can become quite complex and needs a lot of experimentation.

V. ***Supervised Pattern Recognition***
Supervised Pattern Recognition (SPR) is, also, a mathematical process for the classification of AE data. Once the user has achieved a satisfactory UPR-classification for a specific data set (e.g. data set "A"), special algorithms can be trained to classify any new data set (e.g. data set "B") based on the classification results of data set "A". This procedure is performed by Supervised Classification Algorithms[7] (Supervised Classifiers). In SPR, the vectors (AE hits) of the new data set "B" are individually classified, based on their AE features, to one of the predetermined classes yielded by the Unsupervised clustering of data set "A".

3. EXAMPLES OF UPR IN AE DATA

In all cases presented in the present work, the commercially available NOESIS™ Pattern Recognition and Neural Networks software for AE Applications has been used.

Test Case I – Segregation of Simulated AE Sources
AE data from known sources were analysed and treated with UPR. More specifically, a Physical Acoustics Corp. R15 (150kHz resonant) sensor, with PAC 1220A pre-amplifier set to 40dB gain, was mounted on a thick FRP plate 800x800 mm in size and the following AE sources were generated and recorded using a PAC MISTRAS-2001 AE system and MISTRAS software:

1. Simulated AE sources produced by lead breaks (0.3mm, 2H), at various positions on the plate (0-116 sec),
2. Mechanical friction sources simulated by sliding a metallic part across the surface of the plate (155-185 sec),
3. Electromagnetic Interference (EMI) signals generated by unplugging the sensor cable (214-322 sec),
4. Mechanical impact sources simulated by impacting the surface of the plate with a metallic rod (350-409 sec).

Clustering was performed by the k-Means algorithm, using Rise time, Counts to Peak, Counts, Energy, Duration, Amplitude and Signal Strength.

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Figure 2: Typical waveforms of lead break, friction signal, E.M.I. and impact (left). Clustering results in the time domain (Amplitude vs. Time scatter plot , upper right) and in a Counts vs. Amplitude plot (bottom right).

As seen in Figure 2 (upper right graph) the vast majority of AE sources was well separated by the clustering algorithms. There is some mixing of low amplitude AE (pencil) and EMI with mechanical friction. But the signals are such that some data in the AE time region have been produced from pencil friction on the plate. Each class is denoted with a different symbol.

Whilst Case 1 is a simple example, it is worth noting that, still, to perform the AE data separation manually would not be a straightforward task, as even the actual typical waveforms of some AE sources might look similar (see lead break and impact waveform on left of Fig. 2), while two-dimensional correlation exhibits some overlapping.

Test Case II - Flapwise Fatigue Loading of a Wind Turbine Blade

A 4 meter long, FRP blade was used and loaded[8] at the Centre for Renewable Energy Sources, in Athens, Greece. The blade was bolted at the root. At 1.78m from root, a stable saddle kept the blade restrained. One hydraulic actuator was mounted at a flapwise position, 3.1 m from the blade's root. Four sensors were mounted at 1.63 m (ch. 4), 1.95 m (ch. 3), 2.44 m (ch. 2) and 2.99 m (ch. 1) from root (see Fig. 3). The blade was loaded at 0.75 Hz for several thousands of fatigue cycles. Every 10000 cycles, 5 slow cycles were performed at 0.2 Hz. AE hits were acquired only during the slow cycles. The blade failed at 2.15 m from the root.

Figure 3: 4m FRP blade, sensors, loading, and damage layout.

UPR analysis yielded three (3) classes of data. Clustering was performed by the MAX-MIN Distance algorithm using Counts, Energy, Duration and Amplitude as vector coordinates.

As seen in the top graphs of Fig. 4, there is overlapping between the three classes. Class 0 exhibits high Amplitudes, Counts and Energy with medium Duration. Class 1 is, mainly, low in all AE features, whereas Class 2 has very few hits with high Duration and Counts and medium Energy and Amplitude. From the bottom graphs it appears that Class 0 has a decreasing trend with time, as if the corresponding damage mechanism slowly fades out. It also appears that Class 0 occurs at high loads of the loading cycle. On the contrary, Class 1 has a constant trend in time and it occurs throughout the loading cycle.

As seen in Fig. 5, events classified in Class 0 were sharply located at 2.15 m from root where the blade actually failed, whereas Class 1 (Fig. 6) is spread over the area from 1.8 m to 2.3 m (extensive delamination and matrix cracks.

Figure 5: Linear location of Class 0

Figure 6 : Linear location of Class 1

Test Case III – Identification of Hydraulic Noise during Loading of Aerial Man-Lift

UPR was used to characterise AE data recorded during certification testing of an aerial man lift device (Fig. 7). The UPR analysis procedure during the regular loading resulted in four signal classes, two of which were considered as structurally significant (classes 2 and 3) and two were attributed to noise from the hydraulic systems and the lift mechanisms (classes 0 and 1). A Supervised algorithm, Back Propagation Neural Network, was, then, successfully trained, using the UPR results and was applied for the classification of AE data recorded

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in extreme hydraulic noise conditions (i.e. while the aerial man-lift device operator performed standard movements of the boom to position it to its normal position).
Upon application of SPR, data was segregated into four classes again, but the vast majority of data was classified in the two classes pertaining to noise (compare corresponding percentages of class hits during normal loading in Table 1). It is, also, worth mentioning that, both in the case of normal loading (where UPR was applied) and in the case of boom manipulation, data corresponding to classes 0 and 1 were located between sensors 9 to 11 where most of the hydraulic mechanisms reside.

Figure 7: Sensor positions and overall assembly of the device.

Test Type	CLAS	CLASS 1	CLASS 2	CLASS 3
Normal Loading (training set)	438	103 (16.2%)	44 (6.9%)	50 (7.9%)
Hydraulic Noise (weight manipulation)	30980	817 (2.3%)	2656 (7.6%)	724 (2.1%)

Table 1: Distribution of number of hits (and %) per class for the two cases of loading.

4. CONCLUSIONS

The ever increasing demand for advanced AE analysis tools with the ability to discriminate the various sources of AE data, has resulted in the development of sophisticated but flexible Pattern Recognition software, combining traditional, graphical AE analysis and advanced UPR and SPR analysis. The application of UPR techniques on the AE data obtained during various test cases has increased the understanding of the damage evolution and the capability of noise discrimination. Future work in the area of the definition of AE signatures for the existing damage and noise types of AE in various applications could, ultimately, lead to the automation of the classification procedure and the establishment of pass/fail criteria for future tests, based on structurally significant classes.

5. REFERENCES

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