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Acoustic emission for monitoring aircraft structures

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Abstract: Structural health monitoring (SHM) is of paramount importance in the aircraft industry: not only to ensure the safety and reliability of aircraft in flight and to ensure timely maintenance of critical components, but also increasingly to monitor structures under test for airworthiness certification of new designs.

This article highlights some of the recent advances in the acoustic emission (AE) technique as applied to SHM, and the new approaches that are crucial for the successful use of AE data for diagnostic purposes. These include modal analysis, enhanced location techniques, and novel signal processing approaches.

A case study is presented on a landing gear component undergoing fatigue loading in which a linear location analysis using conventional techniques identified the position of fracture and final rupture of the specimen. A principal component analysis approach was used to separate noise signals from signals arising from fatigue cracks, which identified and located further fatigue crack positions, subsequently confirmed by magnetic particle inspection. Kernel probability density functions are used to aid visualization of the damage location.

Keywords: acoustic emission, aircraft components, fault detection, fatigue cracks, fault location, signal processing, principal component analysis

1 INTRODUCTION

The theme of this article is an overview of the very many modern applications of acoustic emission (AE), which is now well-established as a reliable technique for monitoring condition and damage in an increasing variety of structures. The article examines the role that AE now plays in monitoring aircraft structures; key technical issues are addressed, major advances are highlighted, and finally, a modern case study is presented from the aircraft industry.

AE is rapidly emerging as a popular, powerful technique in terms of non-destructive testing, condition monitoring, damage assessment, and structural health monitoring (SHM). Its increase in popularity is partly due to recent advances in high-speed digital waveform-based AE instrumentation that permits vast numbers of AE waveform signals to be digitized and stored for analysis. However, the main reason for the increased interest is due to recognition of the role that AE can play in monitoring a variety of machines and structures as part of a more holistic approach. A significant change in the direction of AE came when work was directed at an enhanced understanding of AE signal propagation in terms of guided acoustic modes [**1–4**]. This approach, more recently designated 'Modal AE', offers the potential to depart from the traditional reliance on statistical analysis and significantly improves the structural monitoring capabilities of AE.

The AE technique is often criticized due to the lack of traceability of results; AE measurements are dependent on many significant variables (e.g. wave transmission paths, sensor location and coupling, and sensor and system sensitivity); therefore, results obtained from different systems, different layouts, and even the same system following sensor removal may not be directly comparable. Successful practitioners are fully aware that current commercial methods give a qualitative measure of the source rather than an absolute

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measure of the energy generated at the source and have combined their understanding of source mechanisms and knowledge of wave propagation, together with advanced signal processing techniques to provide an extremely powerful procedure. Researchers are working towards traceable methods [**5**], but in the meantime the AE technique advances and continues to gain popularity in new fields.

2 SIGNIFICANT TECHNICAL ISSUES

AEs are stress waves generated by the mechanical deformation of materials, and the term 'AE' is used to describe both the practical technique and the phenomenon on which it is based. Thus in damage assessment applications, events related to a number of damage types release small amounts of energy that travel through the component or structure in the form of ultrasonic stress waves, which may undergo reflections at boundaries, mode conversions, and may even transfer between components. AE sensors, which respond to surface displacements of the order of picometers, detect the stress waves and convert them into signals that are interpreted by the AE system. Although AE techniques have been widely studied since the pioneering work of Kaiser in 1950 (a comprehensive review of the history of AE is given by Droulliard [**6**] and an extensive coverage of the theory behind AE is given in Miller and Hill [**7**]), significant advances in hardware, especially storage of data and software, have enabled a more in-depth study than was previously possible.

Among the significant and well-known advantages of AE over other techniques, the following features stand out.

1. The detected energy originates from the specimen itself rather than being supplied from an external source (as is the case in ultrasonic testing).
2. AE is capable of detecting the *dynamic processes* associated with damage.
3. AE can detect sources without prior knowledge of the probable location.
4. The extreme sensitivity of the method enables a large area to be covered with a relatively low sensor density.

The major drawbacks, however, are that the technique cannot be used to provide an instant measure of the level of damage present in a structure and more significantly that the identification of the precise event resulting in each stress wave remains a significant challenge.

A vast range of mechanisms generate AE and emission is often classified into two categories: primary and secondary. Primary emission describes emission from sources internal to a material and is commonly associated with microstructural mechanisms such as the dislocation movement and inclusion fracture that can accompany fatigue crack development. Secondary emission originates from sources that are external to a material surface, and describes a vast range of mechanisms, often associated with frictional activity, e.g. secondary sources from fatigue are commonly the result of crack face closure, and include crack face fretting, which can be more useful for fatigue crack location than primary emissions [**8**], which can be difficult to distinguish. The term 'noise' is often used to describe the presence of secondary AE that impedes detection or isolation of primary sources. In fact, the definition of noise as it is widely used in AE practice is more subjective and usually describes the presence of any emission of no interest or relevance to the study. Successful AE monitoring will detect, locate, and identify emission sources (often in the presence of background noise) and provide severity assessment for those originating from damage mechanisms.

Location of AE sources, and thus damage, is normally performed using the time-of-arrival (TOA) technique that develops the arrival delay, based on first threshold crossing, of a particular signal between two or more sensors at different distances from the source. This method uses a measure of the propagation velocity in a material to derive the source location in one, two, or three dimensions. The procedure is well established and is described fully by Baron and Ying [**9**]. Highly accurate source location is a crucial factor in the ability to identify the source of each AE signal. The TOA method is, however, subject to limitations that affect its suitability to certain aspects of monitoring, these are primarily considerations of accuracy, reliability, cost, and logistic complexity. In particular, the use of TOA techniques in composite materials is extremely difficult due to their anisotropy and hence the absence of a single value for wave propagation velocity [**10**].

The process of source identification attempts to determine the origin of an emission source, this is addressed by source characterization techniques. There are essentially two approaches: the deterministic (or fundamental) approach attempts to develop quantitative relationships between source parameters and physical measurements of the AE transducer signal, while the statistical (or stochastic) approach uses distribution, rate, and correlation analysis of AE feature data from a range of different damage sources in samples of interest to compile empirical correlations with measured source properties and behaviour. This information is used to attempt to characterize AE data of unknown origin using a range of methods, from simple filtering and inference methods to more complex computational pattern recognition techniques.

Severity assessment is a particular challenge that depends on the nature of the damage. Qualitative measures of activity and intensity may be made if primary emission can be reliably identified and in some cases, for instance in bridge structures, if crack face closure processes generate sufficient secondary emission, it is possible to estimate crack lengths [**8**]. However, this is a particularly complex task given the difficulty of differentiating between primary and secondary emissions. More quantitative aspects of severity assessment, such as estimation of damage growth rate, remaining life, or failure prediction, are extremely difficult in all but the simplest geometries and are an ongoing challenge to AE researchers. A wide range of studies have examined the correlation between AE feature data and fracture mechanics parameters in an attempt to provide some measure of damage, these are reviewed by Muravin *et al.* [**11**]. The common problem in this approach is that such correlations are highly specific to a particular material, specimen geometry, and loading regime, and are therefore only valid for the conditions in which they were obtained.

Overall, the problem of detecting, locating, and assessing damage in complex geometries remains a significant challenge in all applications, but nowhere more so than for SHM in aerospace structures, where it is highly likely that damage will initiate at joints and locations where the section properties change.

3 RECENT ADVANCES

In recent years, research has been focused on two main areas. The first is to understand the wave propagation of AE through complex geometries; this is a non-trivial problem as the AE source is not controlled by the operator and hence the frequency of propagation cannot be selected as in ultrasonic inspection. The second is to process AE waveforms in an intelligent way, depending on the application, and promising techniques are emerging.

The identification, location, and characterization of fatigue cracks in plate-like structures in particular are crucial for aerospace applications. However, before propagation in complex structures can be understood, it is vital to obtain characterization of the elastic waves resulting from fatigue cracks in simple plates. Many previous studies have either had limited results due to the use of small specimens (which have adverse geometrical effects), or used simulated sources that do not address the issue of a complex, real source. Recent approaches have shown promising results, e.g. Lee *et al.* [**12**] have used a two-dimensional FE model to model AE from fatigue crack growth in a large aluminium plate and partially verified the model experimentally, and Wilcox *et al.* [**13**] have proposed a systematic modelling framework and achieved accurate simulations of experimentally received waveforms from a Hsu–Neilson source.

Treatment of AE waves as guided waves (termed ‘modal AE’) has undoubtedly led to a greater understanding of the behaviour of AE in complex structures. Geng [**14**] presents a good account of the importance of such modern AE approaches and in particular the relevance of this for aerospace applications, where the thickness of each plate-like structure is less than the signal wavelength and describes a landing gear control fatigue test that proved the effectiveness of this approach.

The modal AE approach has also led to advances in both source location and source length estimation. In large structures, most sources of AE produce a wave that propagates in several modes travelling at different velocities. It is therefore important to determine the exact arrival time of different wave components and their relative attenuation. This allows spatial reconstitution, which involves examining the temporal separation of the signals to identify the wave mode velocities [**1**, **4**, **15**]. This applies to plane waves and is thus appropriate for larger structures because separation becomes clearer with the distance from the source.

Pullin and Holford [**16**] used this to good effect during the investigation of a fatigue crack initiated and grown in a steel I-beam under controlled laboratory conditions to a length of 35 mm. AE signals arising from the crack tip were recorded as digital waveforms and the presence of flexural and extensional plate modes was observed. The dispersive behaviour plate wave propagation was used as a means of establishing the location of crack growth using a single sensor (accuracy 1 per cent) and the separation of the wave modes was used to estimate sensor-to-source distances. Furthermore, it was also possible to obtain an estimation of the amount of crack growth from the comparison of wave modes between signals detected at periodic intervals.

Shehadeh *et al.* [**17**] have used a linear array to locate and reconstitute the time-domain and frequency-domain signatures of AE sources in pipes. They demonstrate methods for automatically separating and determining the wave velocity of components in experimental signals and investigate a range of techniques, including a wavelet transform technique, a cross-correlation technique, and a filtering and thresholding technique, to obtain arrival times for various modes and proposed an automatic source location technique with an accuracy of 5 per cent.

Baxter *et al.* [**18**] have developed a novel technique for solving the problems arising from using a single wave velocity in conventional TOA location. The method does not require knowledge of sensor locations or wave speed and initial results indicate a location accuracy of <2 per cent.

In terms of source characterization, it is very tempting to attempt to learn the characteristics of all crack-related AE; but this approach is not robust because each AE waveform is strongly dependent on many transfer functions in the process from source to signal, including geometry, sensors, and amplification hardware. One approach that is proving successful is to provide a coherent signal processing strategy based on patterns and trends within and between groups of data that are physically related to AE mechanisms. In this approach, proposed by Hensman *et al.* [**19**] and demonstrated for detecting fatigue fractures in a landing gear component, it is accepted that waveforms will in general contain much more information than is necessary for the identification of the source event. The data must therefore be transformed into a lower-dimensional set that retains the information of interest but eliminates irrelevance and redundancy. Furthermore, they use feature novelty, previously identified as a useful tool in vibration of structures [**20**], as an additional indicator or the emergence of a fracture.

4 CASE STUDY ON A LANDING GEAR COMPONENT

4.1 Background

Every landing gear fitting is required to complete an airworthiness certification test, which can typically last for 5 years with over 15 months spent in NDT. AE has the potential to monitor such tests continuously, resulting in a substantial saving in time and money for each test. However, using conventional processing techniques, source identification has proved to be challenging, due to the complex propagation paths and numerous sources of noise.

Principal component analysis (PCA) is a mathematical procedure that transforms a number of (possibly) correlated variables into a (smaller) number of uncorrelated variables called *principal components*. PCA is a classical method of multivariate statistics and its theory and use are documented in any textbook from that field, e.g. reference [**21**]. In simple terms, the first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible. PCA, therefore, will simplify high-order data sets to lower dimensions and thus permit a simple analysis.

A brief mathematical explanation follows. The principal components algorithm seeks to project by a linear transformation, the data into a new q-dimensional set of cartesian coordinates $(z_1, z_2, \ldots, z_n)$. The new coordinates have the following property: z_1 is the linear combination of the original x_i with *maximal* variance, z_2 the linear combination that explains most of the remaining variance, and so on. It should be clear that if the p-coordinates are actually a linear combination of $q < p$ variables, the first q principal components will completely characterize the data and the remaining $p - q$ will be zero. In practice, due to measurement uncertainty, the principal components will all be non-zero and the user should select the number of *significant* components for retention.

Calculation is as follows: given data $\{x\}_i = (x_{1i}, x_{2i}, \ldots, x_{pi})$, $i = 1, \ldots, N$, form the covariance matrix $[\mathbf{C}]$

$$[\mathbf{C}] = \sum_{i=1}^{N} (\{x\}_i - \{\bar{\boldsymbol{x}}\})(\{x\}_i - \{\bar{\boldsymbol{x}}\})^{\mathrm{T}} \tag{1}$$

and decompose, so

$$[\mathbf{C}] = [A][\Lambda][A]^{\mathrm{T}} \tag{2}$$

where $[\Lambda]$ is diagonal. (Singular value decomposition can be used for this step.) The transformation to principal components is then

$$\{z\}_i = [A]^{\mathrm{T}}(\{x\}_i - \{\bar{\boldsymbol{x}}\}) \tag{3}$$

where $\{\bar{\boldsymbol{x}}\}$ is the vector of means of the x-data.

Considered as a means of dimension reduction then, PCA works by discarding those linear combinations of the data that contribute least to the overall variance or range of the data set.

4.2 Experimental procedure

A landing gear lever link component was studied while undergoing post-airworthiness testing to failure. The lever link is manufactured from aerospace grade steel, which has very high strength and good fatigue properties that can support significant crack growth; however, it should be noted that in landing gear applications the structures are optimized to such a high level that only small cracks can develop before catastrophic failure occurs, typically <0.6 mm. In this test, the component was loaded below the maximum design load. Ten Physical Acoustics Ltd (PAL) resonant sensors were attached, as shown in Fig. 1, using magnetic clamps

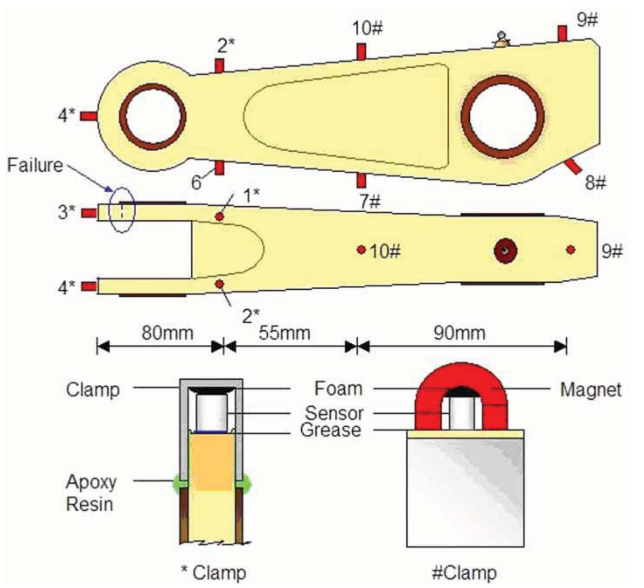

Fig. 1 Test instrumentation and clamping methods

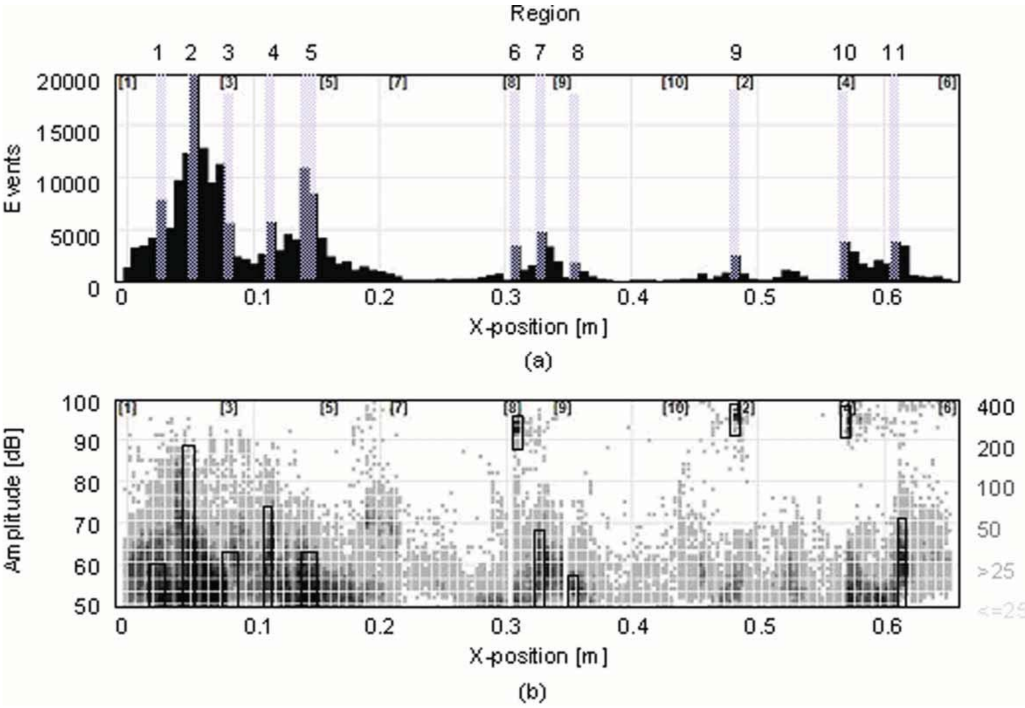

Fig. 2 Location of detected signals (a) in terms of events and (b) amplitude of located events

or aluminium 'U'-shaped clamps that were glued into position, with foam inserts in both methods used to prevent sensor grounding. Grease was used as a couplant and the installed sensor sensitivity was verified using the Hsu–Nielsen source (pencil lead fractures) technique. Feature data (amplitude (dB), counts, duration (μs), energy (atto-J), and rise-time (μs)) were recorded using a 16-channel PAL DiSP system.

4.3 Results and discussion

A conventional linear location analysis was performed on the detected AE between pairs of sensors for the entire test duration; the results of this are presented in Fig. 2. It should be noted that this is a 'wrapped' linear location around the edge of the component consistent with the sensor positions in Fig. 1. Sensor positions are shown by numbers in brackets at the top of each plot. Figure 2(a) presents the location of cumulative events, the peak of which coincides with the position of the fatigue fracture and final rupture region; however, further peaks can also be observed. The amplitude of the detected signals is shown in Fig. 2(b) on a scatter plot; a grey-scale key is shown on the right of the plot.

To assess the suitability of the PCA method to distinguish between AE sources, groups of signals were selected that correspond to the locations of the highest peaks of cumulative events throughout the test. These 11 groups are marked at the top of Fig. 2(a), with the amplitude ranges of the signals contained within each group shown in boxed regions in Fig. 2(b).

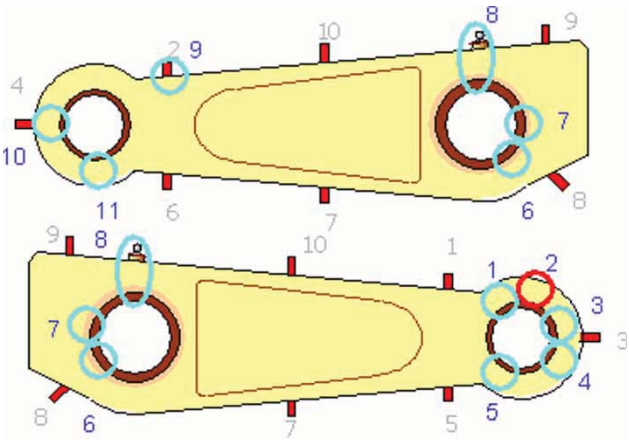

Fig. 3 Location of detected groups mapped onto component

The criterion for selection of each group was that it would contain a minimum of 2000 events within a 6.7 mm section (which is the resolution of the location plot). The relative positions of each of these on the link are shown in Fig. 3. The final 2000 events in each group were selected to ensure that signals from fracture growth were included.

Feature data for each individual signal were extracted, and assigned a number corresponding to the group it came from. A PCA of all grouped signals was then completed irrespective of group number and location. The result of the PCA showing the greatest variance in the data is shown in Fig. 4. The plot clearly shows an overlapping of certain groups of data, with

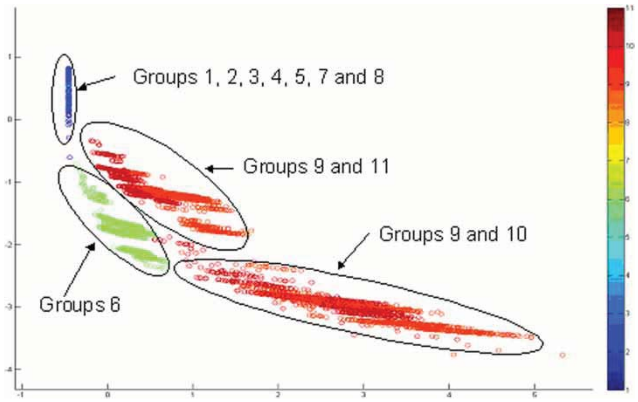

Fig. 4 PCA of all signals irrespective of group number or position

only group 6 clearly separable. This demonstrates that the PCA is not relying on the amplitude of the detected signal as groups 9 and 11 also have high amplitude and are completely separate from group 6.

It is evident from Fig. 4 that the fracture region, group 2, is separated from the high-amplitude groups; however, this is not very powerful as a data separator;

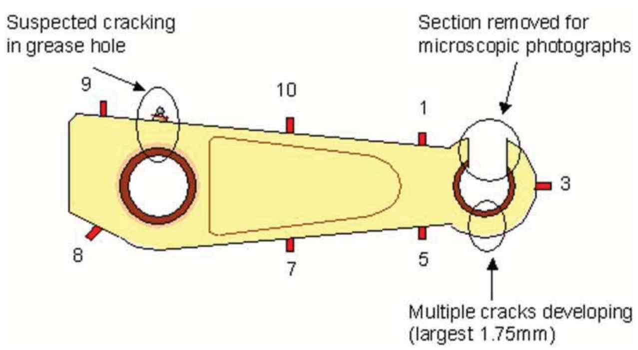

Fig. 5 Outcome of the magnetic particle investigation

a simple data filter during recording could be used to eliminate high-amplitude signals. However, group 2 is not separable from groups 3, 4, 5, 7, and 8. Following the completion of the PCA, the paint was removed from the component and a magnetic particle inspection (MPI) was completed, the results of which are summarized in Fig. 5.

When the cracks identified during MPI, as shown in Fig. 5, are compared with the regions in Fig. 4, it is evident that the PCA technique separated all groups associated with fracture from groups associated with noise, with the exception of group 7. Possible reasons for this are fracturing in the bush, which was removed prior to the MPI investigation, or an error in the location of the signals at the grease nipple as signals from the source could be located between sensors 7 and 8 or 9 and 10. It is not possible to confirm either possibility.

A further aspect to any SHM system is data visualization. Figure 6 shows a conventional planar (two-dimensional) location plot of the completed investigation for the upper section of the component. Each data point represents the position of a location, while its colour represents the number of signals located at that position. The position of damage is not readily identifiable (upper grease nipple) and does require interpretation. The use of kernel probability density functions (KPDF) can significantly improve data visualization. KPDF allows the density of signals and therefore damage to be readily visualized as shown in Fig. 6(b).

KPDF does not have to be solely used in source location; Fig. 7(a) shows a PCA analysis from an AE investigation. The plot appears to show no distinct clustered regions of interest that could be identified as a single source; however, by using KPDF on the same data a distinct source can be identified (Fig. 7(b)).

The completed investigation has demonstrated the usefulness of the PCA technique; however, the

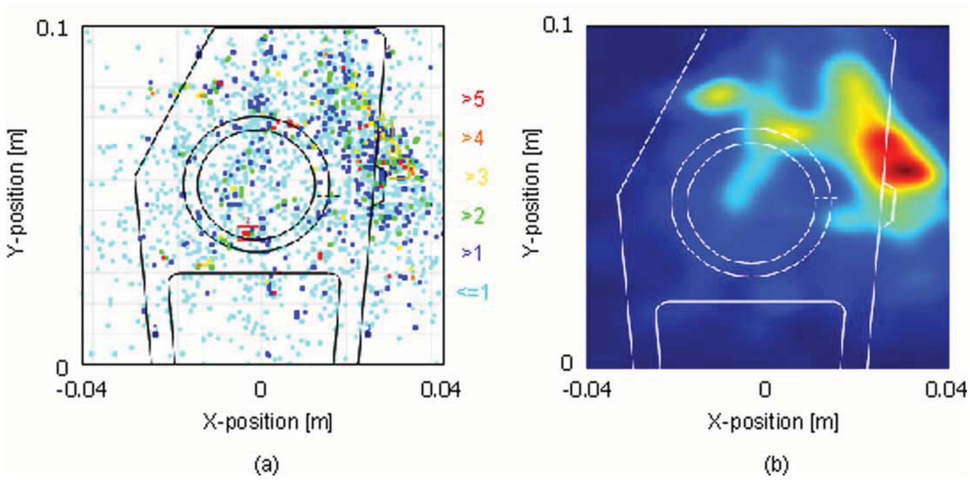

Fig. 6 Planar location of signals from test component; (a) traditional visualization and (b) KPDF visualization

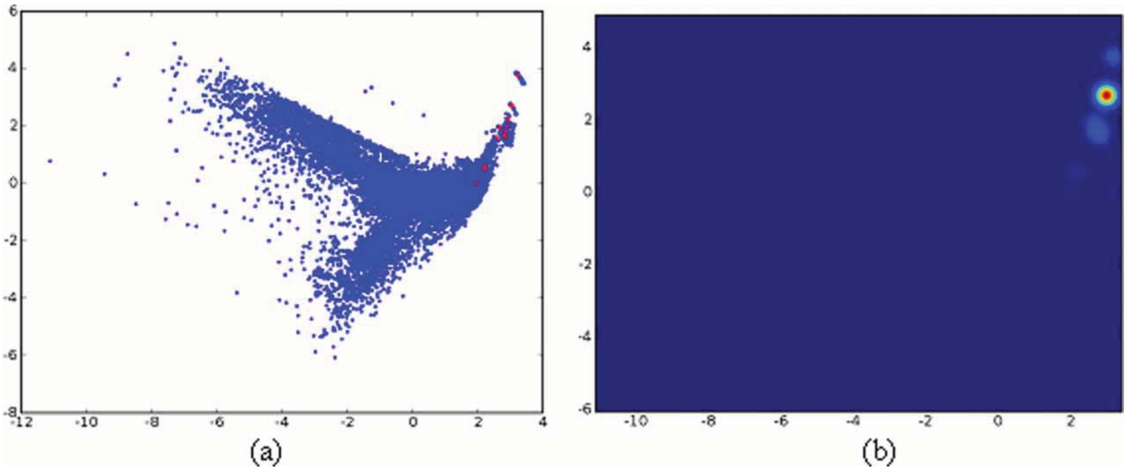

Fig. 7 PCA of collected data; (a) traditional visualization and (b) KPDF visualization

detected noise in this uni-axial test is lower than that found in the multi-axial environment of a full landing gear module airworthiness investigation. It is extremely difficult to demonstrate the technique in the full environment because landing gear structures are designed not to fracture, and in order to validate the approach a fracture needs to be occurring during the test. In addition, the paper has highlighted the need for effective visualization in any NDT application.

5 CONCLUSIONS

This article has provided a mere snapshot of some of the current approaches to the use of AE in SHM applications, in particular as applied to aircraft structures. The examples chosen have highlighted some of the particular problems associated with the AE technique and moreover have illustrated the solutions being developed.

A simple case study has been used to illustrate the importance of integrating novel signal processing approaches with conventional AE analysis. The investigation demonstrated the ability of the AE technique to identify fatigue fractures in a landing gear component. Eleven groups of signals were identified based on AE source location. The feature data of the signals were extracted and a PCA analysis was performed, the result of which separated the group associated with final rupture from the groups of high amplitude and another group possibly related to pin noise. An MPI investigation showed that all groups that could not be separated from the final rupture and fracture source were indeed from fractures. KPDF was also demonstrated as a useful technique to aid visualization of damage locations.

During the past 20 years, AE has come of age, with modal (waveform) analysis replacing the old approach based on waveform parameters. The emphasis on developing an in-depth understanding of the factors affecting the signal from its generating source, through its propagation and on to the effect of the sensor and system, has proved to be hugely beneficial. The recent advances in microprocessors, in particular speed and storage capacity, have enabled a new generation of signal processing strategies and these techniques are able to make full use of the extensive information available in AE signals to provide extremely powerful data analysis strategies.

It is evident that there are significant technical challenges associated with the use of AE; however, it is also strikingly clear that the technical difficulties are being overcome by researchers using a modern approach to the subject. This leads to the conclusion that AE is an extremely powerful technique with enormous potential for addressing a fundamental concern of the aerospace industry, which is the ability to provide robust SHM solutions, both during testing of components and also in flight. As the next generation of aircraft will demand increased weight saving and thus will involve taking the designs to lower factors of safety, one of the keys to survival for aircraft manufacturers will be to ensure increased performance with confidence, to reduce cost of ownership, and to maintain safety standards.

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