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ACOUSTIC EMISSION SOURCE IDENTIFICATION IN LARGE SCALE FIBRE REINFORCED COMPOSITES

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Abstract

Within the last decades many approaches have been proposed to perform source identification in fibre reinforced composites. Some of them have been validated using skilled micromechanical experiments or by using reference specimens in combination with imaging methods, leaving strong evidence that these approaches are valid tools to perform source identification tasks. Lately, also numerical methods have been applied to validate the applicability of source identification methods to fibre reinforced composites for reasonably small size specimens as typically used in materials testing. However, the implementation of the same approach for a real composite structure as used in an industrial environment is still challenging. The reasons for this are manifold. To name just a few reasons, the frequency dependent attenuation starts to compromise frequency information with distance of propagation, directivity effects in a composite laminate may cause distinct differences of frequency spectra when detected at different angles to the source and changes in material and thickness will influence the guided wave modes. The aim of this contribution is to present and discuss the current limitations of source identification procedures in large scale composite structures and to highlight the challenges to overcome when attempting to use such approaches. Influence of signal attenuation, directivity effects, laminate stacking and thickness, presence of existent damage, load configurations and component geometry are discussed and recommendations are given how to estimate the applicability of a source identification approach for a specific application.

Keywords: source identification, fibre reinforced composites, acoustic emission

1. Introduction

In acoustic emission of fibre reinforced composites our ability to identify the underlying source mechanisms by signal characteristics has been substantially extended throughout the last decades. Based on the characteristics of the signals, modern statistically driven approaches such as multivariate data analysis and machine learning are now able to reliably classify groups of similar signals [1]–[6]. Modern numerical methods have added the ability to model particular source mechanisms and to obtain corresponding AE signals [7]–[10]. This allows to validate the origin of particular groups of signals as has been shown for various typical coupon test configurations, such as tensile testing, flexural testing, fracture mechanics testing and similar setups [11]–[13]. Despite of these efforts, the direct transfer of established approaches to larger test pieces made from fibre reinforced polymers is still challenging. For typical structural components several items differ substantially to the aforementioned test coupons. The most obvious difference usually is their size. For AE this is linked to three particular challenges. First, the mean source-sensor distance is likely to increase as the sensor spacing is usually chosen larger. Therefore, the effect of frequency specific attenuation is expected to be larger. Second, the influence of dispersion effects increases as well. Third, the sensors are less likely to be mounted in 1D-like orientation (as being the case for a typical tensile test). This causes AE signals to arrive from many different angles to the sensor as seen in Figure 1.
Typically, composite structures also exhibit fairly complex stacking sequences. As with the other effects of wave propagation mentioned above, this may readily be expected to have an

impact on the distinguishability of AE signal groups. Also, the formation of damage within the propagation path of the AE wave is likely to add some disturbance to the amplitude and frequency content of the signal. If any of these factors starts to override the intrinsic characteristics of the AE signals due to their source mechanism, only error-prone source identification will be the result.

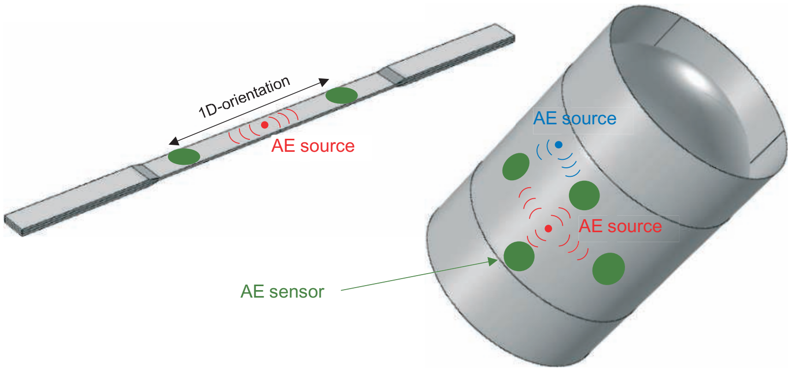

Figure 1. Geometric relation between AE source position and AE sensor position for tensile test setup (left) and component test setup (right).

In the following the author's approach to AE source identification is briefly described and subsequently several factors of influence when applying this to larger structures are elucidated and discussed.

2. Source identification approaches

A general prerequisite of source identification procedures is a suitable data reduction of the acquired AE signals. This comprises elimination of obvious noise signals, and a suitable strategy to focus on the AE signals relevant for material failure. One possibility to aid with the latter is to localize AE source positions and analyze only those signals originating from a specific location (e.g. in the tapered area of a tensile specimen). Subsequently, the detected AE signals are reduced to a number of features calculated from the signals. This comprises an elementary step of AE analysis, but requires some specific attention when dealing with larger structures as outlined in section 3.1. A multitude of those extracted features is then used as dataset and is investigated by an unsupervised pattern recognition method to yield groups of similar AE signals, further denoted as "AE signal clusters".

The overall task of the method proposed in [6] is to detect the most significant clusters of the entirety of AE signals with a minimum of initial assumptions on the cluster structure. Therefore, no assumptions are made on the exact number of signal clusters or the number of AE features or the type of AE features.

Technically, the proposed method is based on a generalization of the clustering approach introduced by [3] and utilizes a two-stage voting scheme adopted from [14]. Based on a list of preselected frequency features, the algorithm calculates all subset feature combinations. For each feature combination, a clustering algorithm yields the partitions for 2, 3, …, 10 clusters, which are evaluated by cluster validity indices. These statistical measures are used to indicate the best partition for the respective feature combination. In the final step, the results of all subset feature combinations are ranked to yield the globally best partition and the respective feature combination (cf. Figure 2).

Compared to signal classification methods based on single features, such pattern recognition methods are computationally intense. But single AE features like peak-frequency or signal amplitudes have significant dependency on the type of sensor or the details of the specimen geometry, stacking sequence and material. Therefore, source classification by static AE feature ranges cannot be generalized beyond certain limits. In contrast, pattern recognition techniques are adaptive to the problem investigated and do not rely on static AE feature ranges.

However, the algorithm by itself is not able to provide more than groups of similar AE signals. Based on the hypothesis that similar AE signals may originate from similar AE sources, the final step consists of an appropriate labelling of the clusters. This may be achieved by microscopic observations (e.g. relative to hot-spots of clusters at particular locations), by comparison to predicted onsets using failure criteria for composites (cf. [12], [15]) or by comparison to modelling results (cf. [11]–[13], [16]–[19]). The latter approach, although being based on modelling results, seems to form the smartest approach to perform such labelling as it does not come with restrictions of specimen type and geometry (other than microscopy). However, it requires a validated modelling strategy to be meaningful. Then it is feasible to either validated signals one-to-one or to compare the resulting partitions directly as done e.g. in [11]–[13], [16]–[19].

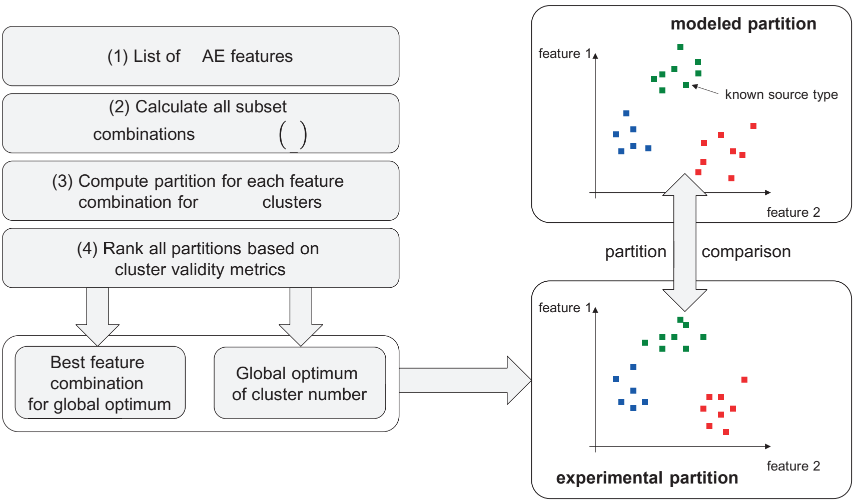

Figure 2. Schematic of pattern recognition approach introduced in [6] including validation procedure using modelling results as proposed in [11], [12].

Regardless how the source identification procedure has been carried out, there is a way to assess the quality of the partition obtained. Based on the corresponding features, an algorithm has been recently proposed to convert the corresponding cluster validity measures into a measure of uncertainty of classification [20]. This is based on the resulting overlap of clusters in their feature space and acts as measure of ambiguity of the cluster labels.

3. Factors of influence

In the following some factors of influence are presented which impact the ability to perform source identification in larger composite structures. In the discussion it is assumed that only transient AE signals are to be interpreted and no noise signals are present in the dataset.

3.1 Extraction of features

One technical difficulty which has seen less attention in the context of source identification so far is the way of feature extraction itself. However, this is of crucial importance and may easily be much more relevant for source identification than the other items listed below. Typical commercial programs either extract features out of the full length of the recorded wave (usually taken as default approach) or allow to extract features from some specific time range (e.g. several µs after first threshold crossing). Considering the dispersive nature of guided wave modes, it may readily be assumed, that the frequency information also changes within the duration of the wave package. Thus it may not be expected to extract similar information at a fixed time window of a wave detected at short distance compared to a wave that has travelled some distance. The signal shown in Figure 3-a is a modeled signals of an inplane dipole source detected at 100 mm distance in a 1 mm Aluminum plate following the approach taken in [21]. The corresponding feature values taken from the first 100 µs after threshold crossing for the features "weighted Peak-Frequency" and "Partial Power 2" are shown as function of the length of the time window used for feature extraction in Figure 3-b.

Here, weighted Peak-Frequency is taken as geometric mean of the classical features "Peak-Frequency" and "Frequency Centroid", while "Partial Power 2" quantifies the fraction of spectral intensity within the range between 150 kHz and 300 kHz (see e.g. [12] for precise definitions).

It is clearly seen, that before reaching 30 µs window length, the frequency information appears to be relatively constant. This corresponds to the time window spanning predominantly the range of the detected S_0-mode as seen in Figure 3-a. This guided wave mode exhibits higher frequencies in this case, thus turning into higher frequency features (500-600 kHz weighted Peak-Frequency). In contrast, the A_0-mode propagates predominantly at lower frequencies. As soon as the extraction time window starts to include a significant portion of that guided wave mode, the frequency features start to be affected as well. With increasing length of the extraction time window this decreases the values and starts to stabilize again for values larger than 75 µs resulting in almost constant feature values. Consequently, the same AE signal could result in fairly different AE features just based on the length of the feature extraction time window.

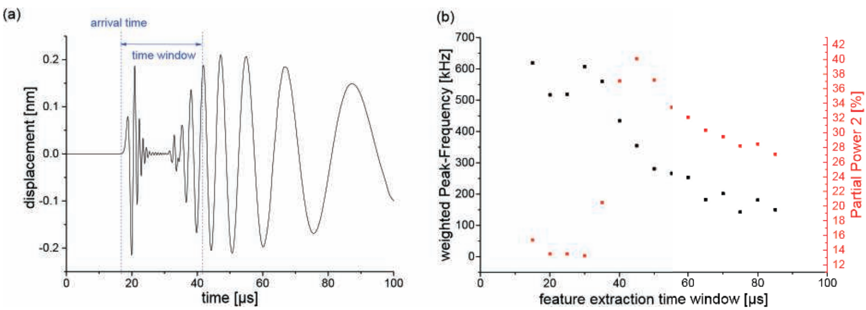

Figure 3. Modeled signal for in-plane dipole detected at 100 mm distance (a) and corresponding feature extraction using different extraction time windows (b).

This finding motivates a first assessment on its relevance to source identification procedures. Figure 4-a present a typical result of the pattern recognition process with accompanying labels derived from numerical modelling results. The dataset itself was collected during four-pointbending of an unidirectional $[0_5]_{sym}$ T800/913 epoxy prepreg material using two WD sensors as described in more detail in [11], [13]. In Figure 4-a the AE features were computed out of the first 100 µs after signal arrival as determined using the AIC strategy (cf. [22]).

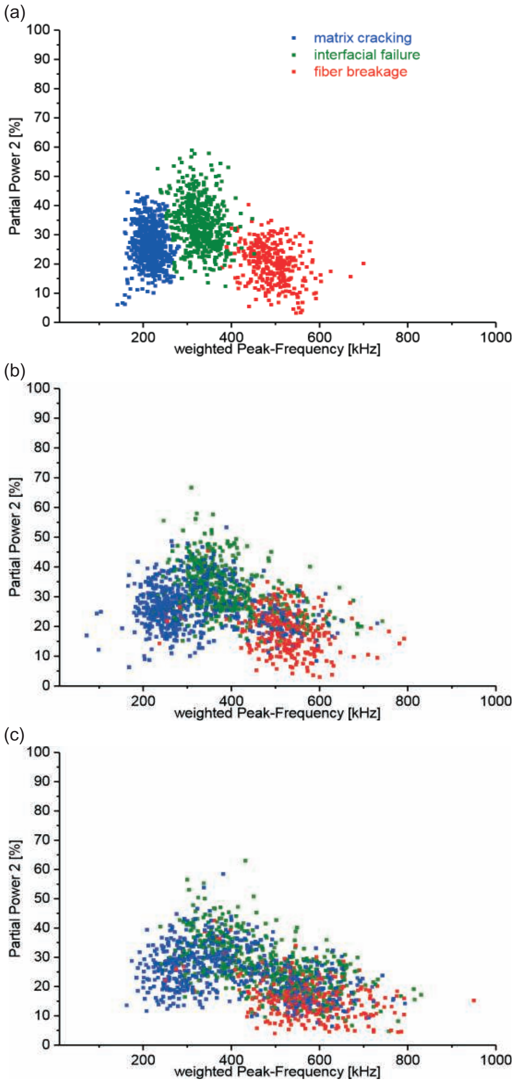

Figure 4. Partition of classified signals using pattern recognition based on 100 µs (a), 50 µs (b) and 25 µs extraction time window (c).

Keeping the labels, the AE features are re-calculated using 50 µs and 25 µs as extraction time window. The resulting partitions are given in Figure 4-b and Figure 4-c, respectively. Obviously, the shortening of the extraction time window results in significant overlap / fusion of the individual clusters. Correspondingly, some of the AE signals move their positions to those of the other clusters (labeling of all data points is kept identical to Figure 4-a). Hence, a different assignment of cluster labels would be expected if the same pattern recognition approach is applied to the AE features seen in Figure 4-b or Figure 4-c.
Therefore, a source identification procedure based on AE features always needs to reflect the full frequency information provided by the AE signal, therefore not restricting itself to just the information given by a single guided wave mode. Suitability of these settings may either be derived from accompanying modelling work, or to some extent, may also be based on the separation seen between clusters. For the latter, the uncertainty of classification may act as a guideline to select an appropriate length of the feature extraction time window.

However, for larger structures, this becomes increasingly difficult as a constant extraction time window will not work for the fairly different arrival times of modes as exemplified in Figure 5. Here AE signals from a study using 0.57 m long double cantilever beams (details in [20]) are shown as located in 80 mm distance (Figure 5-a) and in 280 mm distance (Figure 5-b). Whereas 100 µs would have been sufficient for the short distance to cover significant amounts of both guided wave modes, >500 µs would be required for distances >280 mm. Thus adaptive approaches for feature extraction are required for AE signals travelling to the sensor with fairly different distances.

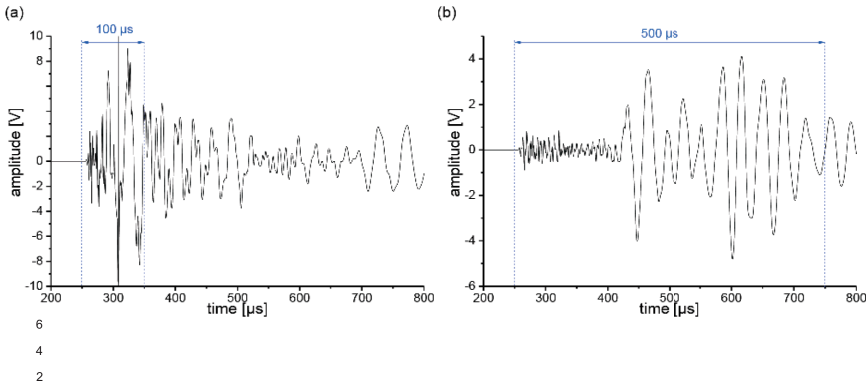

Figure 5. AE signals detected during double cantilever beam tests located at a source-sensor distance of 80 mm (a) and at 280 mm (b).

3.2 Signal attenuation

In addition to the guided wave propagation in thin composite shells, the attenuation of polymer based fibre reinforced materials is also of relevance for the identification of AE source mechanisms. Based on the thermoelastic dissipation effect, higher frequencies are subject to stronger losses of amplitude with propagation distance. Thus, the relative frequency content of AE signals is expected to change even at short propagation distances (< 150 mm). This effect is well known and was investigated in its relevance to AE source identification in [20]. It was found that no substantial reduction of AE source discrimination is expected for propagation distances up to 275 mm. For larger source-sensor distances (up to 500 mm) the study also indicates that source discrimination should still be possible given some rise in the uncertainty of classification. In polymer based composites, for such large propagation distances the signal attenuation starts to significantly affect the overall detectability of weak AE sources. Therefore, this allows to speculate if (i) changes to the AE signal frequencies or (ii) the loss of detectability will be the final limit for successful source discrimination in large composite structures.

3.3 Laminate stacking

On top of the effect of the source-sensor distance, the intrinsic structure of fibre reinforced composites adds some additional challenges. Previous work has already demonstrated the ability of the proposed pattern recognition method to work for different stacking sequences other than unidirectional materials. In general, the added complexity of cross-ply or quasiisotropic layups can well be covered by pattern recognition approaches [12], [15]. Also, the frequency feature based approach was validated for laminates up to thickness values of 15 mm [12]. Special challenges arise in textile architecture materials such as woven or knitted fabrics. Here the additional level of hierarchy as introduced by warp and wefts adds further ambiguity in the damage mechanisms, as e.g. matrix cracking may occur within the warp/weft, in between the same, but also in between the fabric layers. This causes a less distinct separation of the clusters as compared to Figure 4-a for unidirectional materials, therefore reducing the ability to identify particular failure mechanisms. However, several successful attempts using mixed amplitude and frequency based pattern recognition have been proposed in literature [23], [24].

3.4 Formation of damage

During mechanical loading of composite materials, a distinct evolution of damage occurs on several length scales. Therefore, the acoustic properties of the propagation medium will significantly change during the test. In guided wave testing, the change of the signal characteristics is actively monitored to detect the formation of damage within the propagation path between actuator and sensor. In combination with acoustic emission detection this is then usually referred to as acousto-ultrasonics approach [25], [26]. Hence it is easy to conclude, that the characteristics of AE waves propagating through damaged areas will be affected as well. Therefore, a recent study [12] considered this effect by repetitively pulsing an actuator mounted on a tensile specimen. Signals were transmitted throughout the test section of the specimen and were detected with the mounted AE sensors. The result from one measurement using a quasi-isotropic stacking sequence for the Sigrafil CE125-230-39 carbon/epoxy prepreg system is shown in Figure 6. The colour code indicates the clusters identified by pattern recognition methods using the features weighted Peak-Frequency and Partial Power 2. The same feature extraction applied to the signals originating from the pulser (a source that has constant properties during the full test) yields the data points in black surrounded by a black ellipsoid. Choosing a high frequency source for the present case was motivated by the fact that higher frequencies seem to be affect more from damaged areas than the low frequencies [27]. Despite of noticeable changes in the pulser signals detected during the experiment, the extracted feature values stay close together and do not overlap with another cluster. This indicates that the propagation effect itself will not substantially affect the feature values even when massive damage forms within the laminate. This has been confirmed with six typical laminate sequences [12]. Additional evidence is brought in by the fact, that the clusters itself are relatively sharp defined and retain their locations, regardless if only signals from the beginning or the end of the experiment are used (corresponding to almost undamaged and severely damaged specimens).

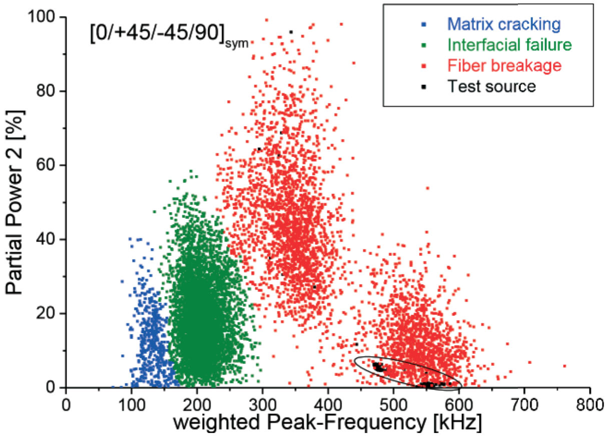

Figure 6. Pattern recognition result from tensile test with superimposed data from pulser signals during test.

3.5 Directivity effects

Another challenge faced in composite structures when compared to coupons was already described in the introduction section. As seen in Figure 1, the direction of propagation from AE source to AE sensor will substantially differ in large scale composite components when compared to the frequently used 1D-like arrangements in coupon testing. As the direction of wave propagation has tremendous effect on the wave velocities and signal attenuation this comes with additional challenges for valid source identification procedures. As discussed in [12], this may cause a strong overlap of signal clusters belonging to one mechanism, just because of the detection direction. Hence it was proposed to compensate for this effect by calculating the mean AE features for several principal directions [12]. This has been found to work for test sources applied on unidirectional, cross-ply and quasi-isotropic plates. However, so far no attempts have been made to bring this to the level of composite structures as the averaging process requires the AE signals to be detected at the principal angles which is hardly the case in practice. Recently, other research groups also proposed an correction procedure of the AE feature values as function of propagation distance [28], [29]. For the complexity in changes to AE features seen in realistic composite structures it still needs to be investigated, which feature compensation technique will perform best to account for this effect.

4. Conclusion

A brief overview on factors of influence to AE source identification as seen in large scale composite structures was given. For some of them, the limits are well established and can be considered in their impact when performing AE testing on this level. Despite of the various challenges it seems possible to apply source identification in large scale composite structures within certain limitations. Apart from cleaned datasets it is necessary to consider the influence of the feature extraction procedure and the directivity effects when judging on the feasibility for a given application. Without further modification to the feature extraction process it does seem only feasible to perform source identification as long as the propagation behaviour stays approximately constant. For general cases, the feature compensation techniques proposed in literature will need to be validated on the structural composite level. If successful, these will form an important contribution to enable reliable AE source identification in large composite structures.

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