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Acoustic emission classification by cross-correlation

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ABSTRACT

Acoustic emission signals specific to the incremental advance of fatigue cracks can be detected, cycle after cycle, during crack propagation tests. They were termed acoustic multiplets in reference to repeating earthquakes. Detecting such multiplets would give information about the fracturing process and provide early warnings when monitoring industrial parts in service. We developed a clustering method to extract multiplets signals from all signals and noise of fatigue tests. This method is based on the computation of the cross-correlation function between waveforms. On the distribution of the cross-correlation matrix, signals belonging to multiplets are clearly identified and permit to automatically clustered. This paper developps the steps of the method, presents results obtained on a dataset of a fatigue test and shows its noise robustness.

Keywords : *Acoustic emission, fatigue crack growth, multiplets, cross-correlation, waveform clustering*

1 Introduction

Despite many efforts over the last hundred years to understand its causes and detect its possible precursors, cyclic fatigue of materials remains one of the major causes of failure of industrial parts [1]. The problem is “How to alert in real time when a crack is likely to lead to the ruin of the part ?”. Acoustic emission (AE) is a key method of non-destructive testing, as it enables the recording of transient elastic waves occurring during damage of materials and structures. Numerous works carried out with this method have shown that there is a correlation between the global acoustic activity and damage, including during fatigue [2]. However, this correlation only becomes significant near the final failure and thus far too late [3]. Indeed, the monitoring of slow crack growth from a global measurement is difficult and very sensitive to the signal to noise ratio (SNR). Moreover, the non-specific nature of these AE measurements makes the identification of sources difficult [4].

A new approach, recently proposed [4, 5], allows the detection of acoustic emissions specific of fatigue crack growth, called "acoustic multiplets" in reference to the analogous phenomenon in seismology [6]. These so-called acoustic multiplets are characterized by highly correlated waveforms (figure 1 a), signature of a unique source. They are repeatedly triggered over many successive loading cycles at almost the same stress level (figure 1 c, d and e) and originate from a single location (figure 1 a). They are considered to mark the slow, incremental propagation of a crack at each cycle (see striations on figure 1 b), or the rubbing along its faces (fretting). Being specific to incremental fatigue cracking, they can therefore potentially be used as early warnings of global failure of industrial parts [5].

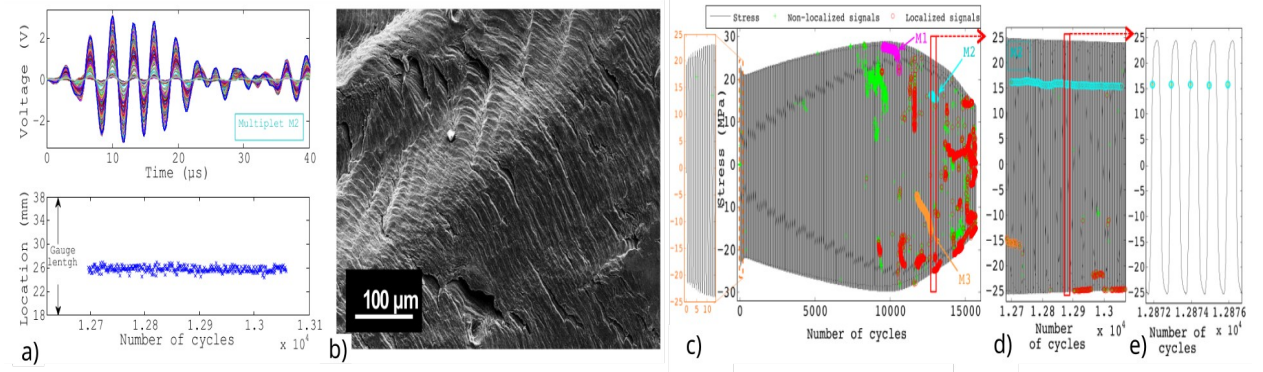


Fig. 1 : Acoustic multipliers as a signature of fatigue crack growth (from [4]) - a) Waveforms of acoustic signal belonging to a multiplet during fatigue of Aluminum at 0.1 Hz, and location of the corresponding AE signals on the specimen ; b) Striations on a post-mortem SEM image of the crack face of the sample ; c) Acoustic activity during a fatigue test on aluminum : stress vs number of cycles. Magenta, cyan and orange clusters correspond to typical examples of multipliers ; d) Enlargement on a specific multiplet and e) on some loading cycles.

A key point in this approach is the choice of an appropriate and robust measure of waveforms similarity. Due to the classical procedure to detect acoustic bursts from threshold crossing and the noise that affect the signal, nearly identical signals can be shifted by a little time delay and are then non-aligned. It means that the method of measure needs to be able to quantify the similarity between 2 waveforms regardless of the delay.

The cross-correlation function is often chosen for this kind of problematic [7,8,9]. In the field of acoustic emission, the cross-correlation function has been sometimes used to improve the localisation of acoustic sources [9]. A cross-correlation matrix over all the AE signals signals of a channel recorded during a mechanical test on concrete has been used to investigate very quickly changes in the physical properties of the ray path of events from one cluster [8]. Another application of the cross-correlation matrix has been proposed to filter noise in fatigue test [10]. This article offers a robust way based on cross-correlation matrix distribution to extract highly correlated populations of signals, in order to identify multipliers in fatigue crack growth tests.

2. Method to extract highly correlated populations

2.1 Cross-correlation function

Cross-correlation consists in the displaced dot product between two signals. It is often used to quantify the degree of similarity or interdependence between two signals [7]. In the case of AE, since all measurements were recorded using digital acquisition systems, signals have been discretized, so that the cross-correlation between two signals v and w with the same N samples length is expressed by equation 1.

$$corr[v, w](t) = \sum_{n=n_0}^N v(n) \cdot w(t+n) \quad (1)$$

When the discrete time series v and w match, the value of $corr[v, w]$ is maximized. We called the maximizing point t_m : it corresponds to the time delay between the two waveforms. This is explained when peaks (positive areas) are aligned, making a large contribution to the summation.

In the case of AE waveforms, the two parameters n_0 and N define a cross-correlation window. Because acoustic waveforms are transient waves and contain a pre-trigger, an impulsive part and

a coda, the choice of this window has to be set precisely for an adequate determination of the maximizing point.

2.2 Cross-correlation matrix

By calculating all cross-correlation functions for each pair of waveforms for a single channel, and searching for the maximum of these functions, it is possible to build a cross-correlation matrix. Hence, the coefficients contain a value in $[0, 1]$ corresponding to the normalized measure of similarity by cross-correlation (see equation 2).

$$M_{xy} = \max_t(\text{corr}[x, y](t)) \quad (2)$$

An example is presented in fig. 2 showing a cross-correlation matrix of 198 signals compared to each others. By construction, it is a symmetrical matrix with a diagonal full of 1. Then, only half of the matrix is computed.

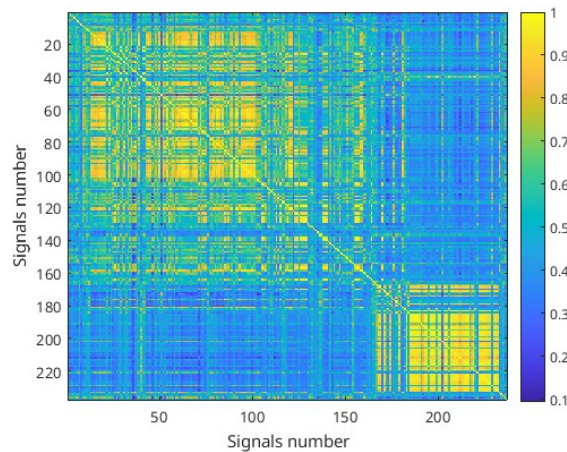


Fig. 2 Example of cross-correlation matrix calculated from a fatigue crack growth test on steel

Since multiplets are groups of highly similar waveforms emitted close in time, multiplets appear as yellow squares on fig. 2. In the rest of the article, for the sake of simplicity, the term 'cross-correlation' will refer to the value taken by a coefficient of the cross-correlation matrix as described in equation 2.

2.3 Distribution of cross-correlation

An operator can visually identify groups of waveforms highly similar in the cross-correlation matrix, but an automatized way is possible by calculating the distribution of the matrix. In a fatigue test characterized by acoustic multiplets, two peaks are expected in this distribution (see fig. 3) : one narrow peak close to 1 containing cross-correlations between waveforms belonging to multiplets, and a wider one corresponding to uncorrelated source signals. The remaining correlation of these uncorrelated source signals results from the resonant nature of the AE sensors. Indeed, due to the acquisition chain, and particularly to the frequency domain of the sensor, the cross-correlation between two totally different source signals is larger than zero. Nevertheless, a distribution of cross-correlations computed on a set of data from an experiment without multiplets would not exhibit the peak of high cross-correlations.

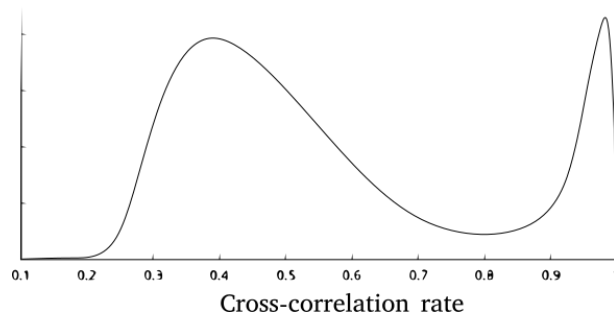


Fig. 3 Schematic cross-correlation distribution for a fatigue test emitting multiplets

From this distribution, it is easy to extract automatically multiplets by setting a threshold on the cross-correlation, e.g. 0.8 for the schematic figure above. All waveforms implicated in cross-correlations above the threshold are collected and labelled as “multiplets”.

4. Application to a fatigue crack growth test

This method has been applied to several acoustic emission dataset recorded during fatigue crack growth tests. Here, results from a load-imposed fatigue test ($R = \frac{\sigma_{min}}{\sigma_{max}} = 0.1$) performed on compact tension (CT) specimen of a 5083 aluminium alloy are presented.

Two nano30 sensors, from PAC, were coupled on the specimen surface as depicted on fig. 4. The PCI2 system triggered recording waveforms sampled at 5 MHz when the signal exceeds the threshold of 43 dB. After the test, no filtering process was applied. Cross-correlation matrices and distributions were directly computed on the waveforms, independently for the both channels.

We selected a part of 1000 consecutive waveforms containing 2 multiplets for this study.

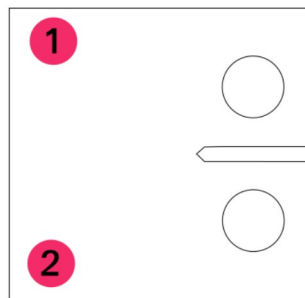


fig. 4 Geometry of CT specimen and sensors locations

4.1 Selection of the cross-correlation window

As explained in part 2.1, a proper window has to be set for the cross-correlation between two AE waveforms. In order to select the starting and ending point of time series, respectively n_0 and N , cross-correlation distributions are computed for different window lengths.

The pre-trigger of 20 μ s is not taken into account in the calculation : n_0 is fixed, while N takes values to select [20, 40, 60, 80, 100, 120, 160] μ s of the waveforms. Fig. 5 show an example of a waveform from the dataset and the different windows used for cross-correlations.

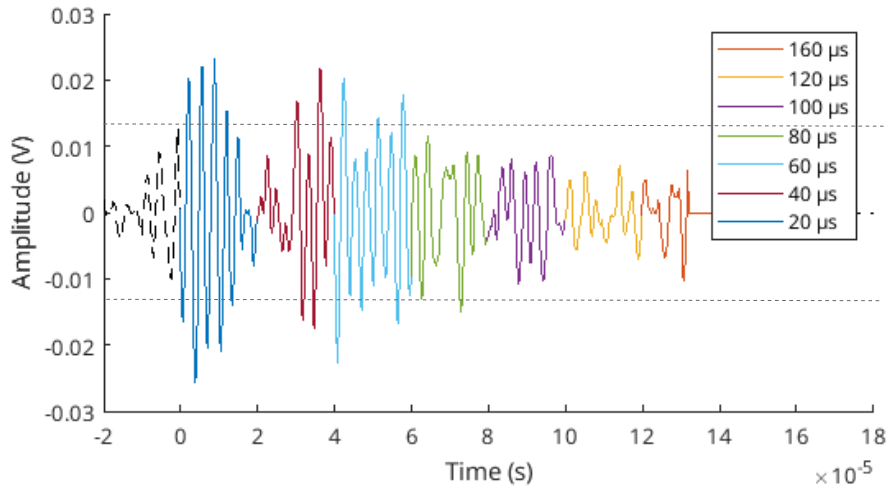


Fig. 5 Example of a waveform and the different cross-correlation windows. Each window starts at $t = 0 \mu s$

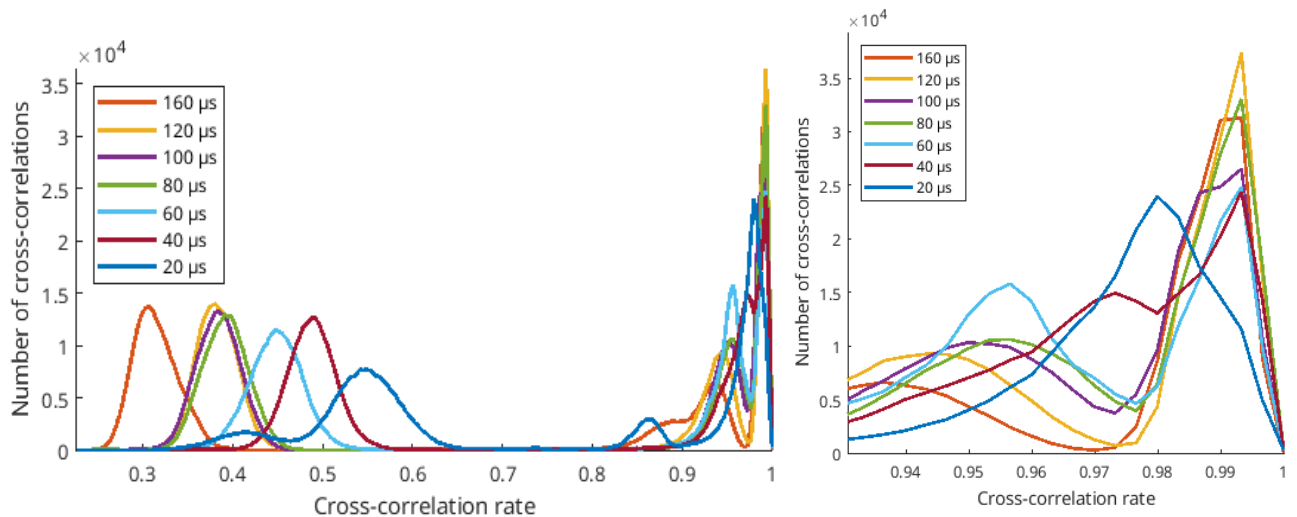


Fig. 6 Distributions of cross-correlation for different windows. Right : Zoom around the peak of high cross-correlations .

The overall shape of the expected distribution presented in section 2.3 for all 7 windows can be found in Figure 6. By extracting signals involved in cross-correlations above 0.8, we clustered, as predicted, multiplets signals into one cluster.

But if the window is too short or too long, some multiplets signals are miss-classified. Extending the length of the cross-correlation window shifts the low cross-correlation peak towards 0 and modifies the large cross-correlation peak level. A cross-correlation performed on too short windows raises the risk to miss the right alignment resulting in an imprecise similarity measure, e.g. distributions computed on windows of 20, 40 and 60 μs whose maximums do not exceed 25 000 cross-correlations.. On the opposite, a too long window contains a large part of the waveforms codas which are less correlated and are characterized by a lower SNR. Hence, the distribution computed on windows of 160 μs has a lower maximum than distributions computed on windows of 80 and 120 μs . That is why the choice of the window is essentially ruled by the level of the large cross-correlation peak : the best clustering performance is obtain by

maximizing the number of cross-correlation in the highest cross-correlation peak. Here, the window has to be set between $[80,120]$ μs .

In addition, one observes that all distributions exhibit three peaks. One in low cross-correlation range and two in the large cross-correlation range. The second peak in the large cross-correlation range between 0.92 and 0.97 in fig. 6, not presented in part 2.3, contains cross-correlations performed between waveforms belonging to different multiplets emitted by the same type of sources. Selecting a threshold between these two close peaks allows to separate different multiplets thanks to an algorithm (not detailed here) by adding information of the signals emission time.

4.2 Noise effect

The noise robustness of our method is evaluated by adding white Gaussian noise to all waveforms. Distributions of cross-correlations are computed for different levels of SNR and are represented on fig. 7.

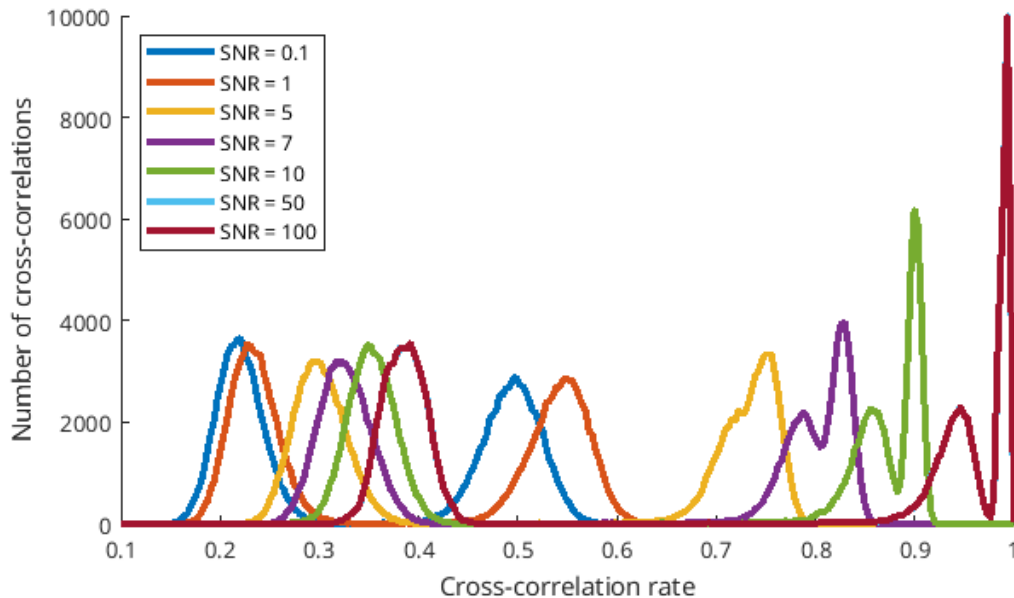


Fig. 7 Cross-correlation distributions for different SNR

From SNR = 100 to SNR = 0.1, the global shape of the distribution including high and low cross-correlations is preserved and shifted towards lower cross-correlation values, as expected. While the shape of the peak of low cross-correlations remains essentially unchanged, the two peaks of high cross-correlations are widening and merge. The method then is still applicable for low SNR, down to 0.1, by moving the cross-correlation threshold to separate highly similar waveforms, belonging to multiplets, from uncorrelated ones. Nevertheless, below SNR = 1 many errors are reported in the classification and below SNR = 5, it is not possible to distinguish the two peaks of high cross-correlations.

6. Conclusion

This paper presents a method to automatically cluster groups of highly similar signals by computing the distribution of the cross-correlation matrix. This matrix is obtained by extracting the maximum of the cross-correlation function of each pair of waveforms from a fatigue test. The selection of the cross-correlation window is discussed and optimized by applying this method on several window lengths. And we show that this method is efficient to extract multiplets, acoustic signature of fatigue crack growth, even if waveforms are polluted by noise.

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