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Hit Detection and Determination in AE Bursts

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1. Introduction

This chapter presents a methodology for detecting and determining Acoustic Emission (AE) hits in AE bursts, i.e. signals with large number of overlapping transients with variable strengths. The methodology is designed to overcome important limitations of threshold-based approaches in determining hits in this type of AE signal; for example, when the signal's amplitude between transients does not fall below the threshold for a predetermined period of time. The threshold-based approach is a special case of the proposed methodology. The methodology, and the associated algorithms, were presented in *Acoustic Emission-Based Fatigue Failure Criterion for CFRP* by Runar Unnthorsson, Thomas P. Runarsson and Magnus T. Jonsson [17] and used in four articles by the same authors [15, 16, 18, 19].

The chapter is organized as follows. Section 2 provides the reader with an overview of Acoustic Emissions, what they are, how they are acquired and the various factors that can affect them from when they are emitted until they are digitized by the AE system. Majority of these factors will change the originally emitted AE waves so that the digitized representation will be different. In Section 3 an overview of the AE processing techniques is given with emphasis on conventional methods of determining AE hits and the corresponding hit parameters. The section also introduces the problem of determining AE hits in bursts. Section 4 then introduces the methodology and presents the algorithms. In section 5 an experimental AE signal is used to demonstrate the methodology. The chapter ends with section 6 which concludes the chapter and provides suggestions for future research into this topic.

2. Acoustic Emissions

Acoustic Emission (AE) is a term used for transient elastic stress waves generated by the energy released when microstructural changes occur in a material [9, 21]. The energy

is provided by an elastic stress field in the material. The stress field can be generated by stressing the material, for instance using mechanical, thermal, pressure and chemical stressing. These types of stress all contribute to fatigue failure and are commonly encountered in-service. As the stress waves propagate from the AE source they are influenced by a variety of factors. These factors include propagation velocities, attenuation, reflection, refraction, discontinuities and the geometry of the material. Furthermore, the propagation velocity of an elastic stress wave depends on the wave type, material properties and frequency. When the stress waves reach the surface they cause it to vibrate and the vibration can be measured. The minute surface displacements are measured using sensitive transducers which respond to surface displacements to the order of several picometers. Several types of transducers can be used for this: piezoelectric, capacitance, electromagnetic and optical. The last two are non-contact, but electromagnetic transducers are considerably less sensitive than piezoelectric transducers. Optical sensors, e.g. laser, are free of resonance and can be absolutely calibrated by measuring the correct amplitude of the AE [8].

Piezoelectric transducers are the most popular and are either of a broadband or a resonance type. The transducers are made by using a special ceramic, usually Porous Lead Zirconate Titanate (PZT). Figure 1 shows a schematic view of a piezoelectric transducer and how an AE is converted into an electric representation. The transducers are pressed up against the surface of the material and the vibration is transferred to the PZT inside the transducer through the wear plate. When the PZT element vibrates it generates an electric signal. The transducer's signal is, therefore, a 1D voltage-time representation of the 3D displacement-time wave that it senses.

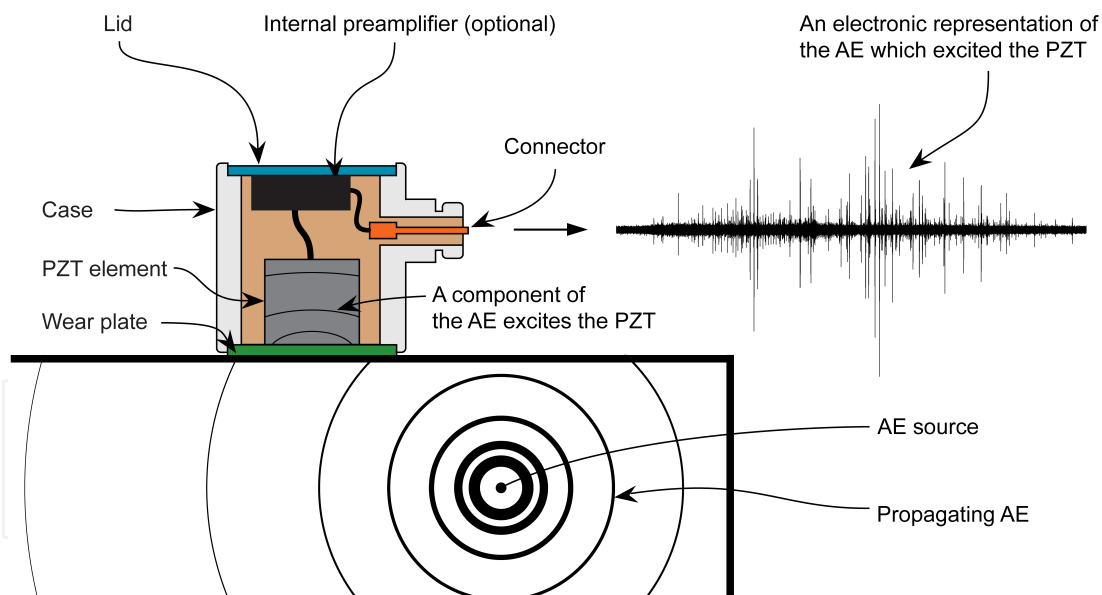


Figure 1. An illustration of a typical resonant piezoelectric AE transducer and how an AE is converted into an electric representation.

Measurements using piezoelectric transducers are sensitive to how the vibration is transferred to them. The main factors that affect this are: the material's surface, the transducer's pressure against the material, and the coupling medium [5]. The presence of a transducer affects the vibration; however, this is unavoidable when using contact transducers. The direction of the waves also affect the transducer's response. This is because AE transducers are nearly always designed to measure the components of the AE waves that

are normal to the surface [1]. Although the stress waves typically have components in the normal direction this directionality means that the response to identical waves arriving from different directions will not be the same.

The selection of transducers is most often based on their frequency response curves, also known as calibration curves. These curves can be absolute or relative. The most typical calibration curves are relative displacement and pressure response curves. Relative curves are useful for comparison of transducers. At Vallen Systeme GmbH pressure and displacement curves are generated by connecting an exciter face to face with the corresponding transducer [20]. In both cases continuous sine waves are used for excitation. Pressure curves are generated by exciting the sensing area uniformly, but displacement curves are performed by using an exciter with small aperture size. The displacement calibration is an attempt to simulate line excitation of a travelling displacement wave. Figure 2 demonstrates the difference between these two calibration methods. The red curve is the result of a pressure calibration and the green curve is the result of a displacement calibration. The resulting response curves are more relevant for continuous and long duration AE signals than for transient AE signals. Some authors have deconvolved the AE signal with the frequency response of the transducers as an attempt to minimize the effect of the rugged frequency response of resonant transducers [7, 11]. The transducer's response to transient signals is, however, different from the response to continuous waves. Hence, the convolution may not work as intended or even make things worse.

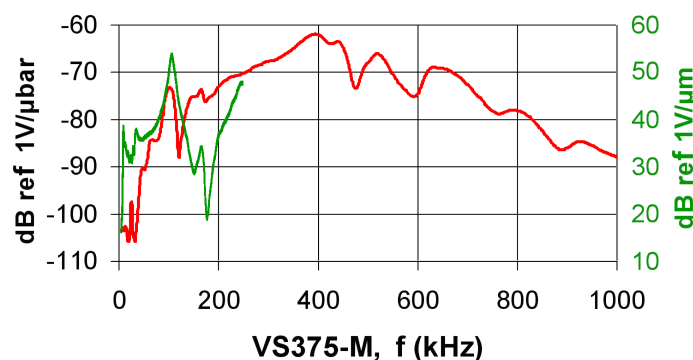


Figure 2. Two calibration curves for the same resonant AE transducer. The red curve is the result of a pressure calibration and the green is the result of a displacement calibration (reproduced with permission from Vallen GmbH).

3. Conventional AE processing and hit detection

Due to all the influencing factors listed above, the digitized representation of the AE will be different from the original emission. Despite this, and somewhat surprising, acquired AEs have been successfully used to detect, monitor and distinguish between several damages, e.g. delamination, matrix cracking, debonding, fibre cracking and fibre pull-outs in fibre-reinforced polymer composites [3, 4, 10, 12, 21, 22].

Acoustic Emission signals can be roughly divided into three types: bursts, continuous and mixed [6]. Bursts are transient signals generated by the formation of damage, e.g. fiber breaking and delamination. Continuous AE signals are generated when multiple transients overlap so that they cannot be distinguished and the envelope of the signal amplitudes becomes constant. Continuous AE can be generated by electrical noise and rubbing. The

mixed type signal contains both bursts and continuous signals and it is the type which is normally encountered in-service.

Over the years many research projects have been conducted with the aim of extracting useful information from AE signals. The extracted information is stored in n-dimensional data structures, known as features. A number of techniques can be used for extracting the AE features. A popular method is to identify transient waves in the signal and extract the features from them. These transients, also called hits, are therefore portions of the measured AE waveform which satisfy a given detection criterion. The purpose of the detection criterion is to detect the presence of transient AE and discriminate it from background noise, or continuous AE. Because AE are mainly transient stress waves, the term AE hit is usually understood as an isolated, and separated, transient from the acquired waveform.

There are many detection techniques which can be used for detecting and determining AE hits. A common technique used in realtime commercial parameter-based AE systems is to compare the AE signal against a certain threshold. The threshold is typically set on the positive side of the signal, just above the noise, and held fixed. The threshold is sometimes floating, i.e. it is adjusted regularly so that it is just above the noise. A hit is detected by comparing the AE signal against the threshold and if the signal surpasses the threshold a hit is detected. Figure 3 illustrates the threshold based hit detection and shows how few well established features are computed.

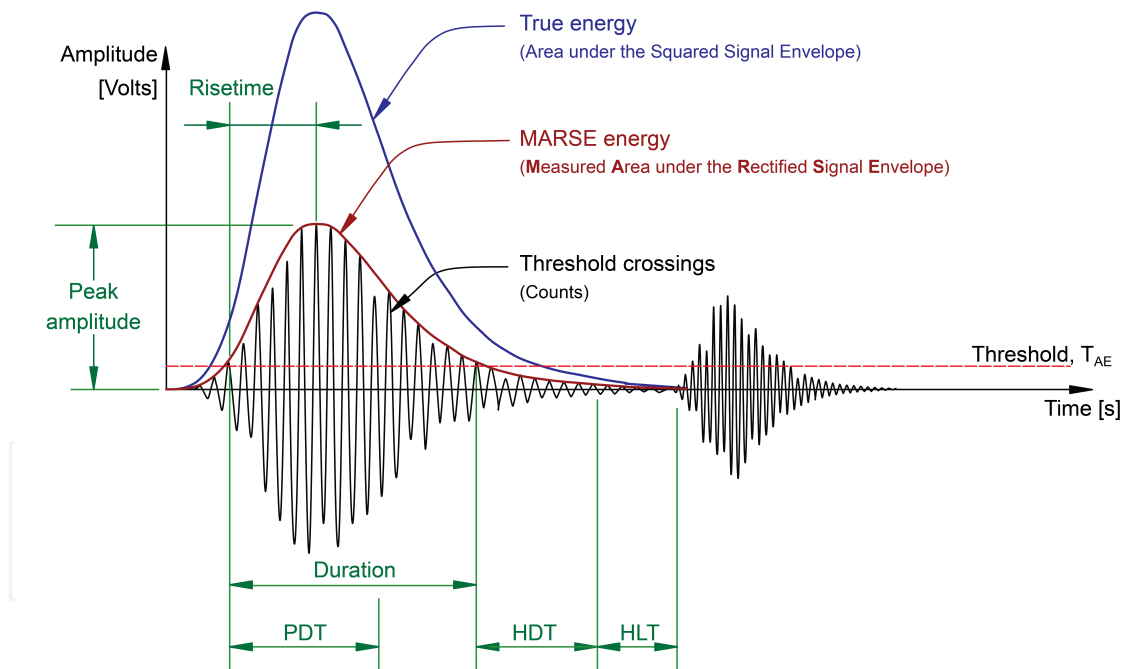


Figure 3. Illustration of the threshold based hit detection and the AE features extracted from each hit.

After an AE hit has been detected it is determined. Three parameters are commonly used with the determination of AE hits: the hit definition time (HDT), the hit lockout time (HLT), and the peak definition time (PDT). These parameters are illustrated in Fig. 3. The HDT parameter specifies the maximum time between threshold crossing, i.e. if no crossing occurs during this time then the hit has ended. If the HDT is set too high then the system may consider two or more hits as one. If the HDT is set too low then the system may not fully

capture the AE hit and possibly treat one hit as multiple ones. The HLT parameter specifies time which must pass after an hit has been detected before a new hit can be detected. If the HLT is set too high then the system may not capture the next AE and if it is set too low then the system may capture reflections and late arriving component of the AE as hits. The PDT parameter specifies the time allowed, after a hit has been detected, to determine the peak value. If the PDT is set too high then false measurements of peak value are more likely to occur. It is recommended that the PDT should be set as low as possible. However care must be taken not to set it too low because that may result in the true peak not being identified.

Once the AE hit has been determined hit-based features can be extracted. Conventional AE hit-based features include amplitude, duration, energy, number of peaks above certain threshold (ring-down count) and rise time [2]. Figure 3 illustrates how these and other common hit based features are related. New features can be designed by processing existing ones. The processing includes, but is not limited to: adding, subtracting, multiplying, and dividing two or more features. New features can also be made by filtering and extracting statistical information from the features in the set; e.g., variance, skewness and kurtosis.

Trend analysis of hit-based features is widely used. Sometimes trending is carried out by plotting the cumulative sum of the feature. In some applications trending can be sufficient; e.g. when monitoring of the AE signal's power alone is of interest. In many cases, however, further analysis is required. In some cases more information about a feature can be gleaned by studying its statistical parameters and its correlation with other features.

The threshold based hit technique is suitable when the background noise level is either constant or changes gradually. The threshold level is then set at the beginning of monitoring and if a floating threshold is used then the threshold is updated regularly. The technique, however, does not perform well when the AE signal contains strong temporal bursts of high AE activity. Such bursts consist of overlapping transients with varying strength, duration, shape and frequency. For this reason, the burst threshold based technique cannot determine the exact start and end of individual hits as the AE burst never drops below the threshold. Bursts with these properties occur in CFRP assemblies subjected to dynamic loading; e.g., the CFRP prosthetic foot Variflex [14, 17].

Figures 4 and 5 show the AE acquired at two different times while the Variflex was subjected to multi-axial cyclic loading. Figure 4 shows the measured AE signal during one loading cycle early during testing. Also shown, is the threshold which was set just above the noise.

Figure 5 shows the AE signal few thousand loading cycles later. The two strong bursts contain AE from many sources such as damage growth, rubbing of crack surfaces and friction between the fibres and the matrix due to their different material properties. As can be observed, the threshold based approach is not able to separate the transients in the bursts. In the next section a technique designed to overcome the abovementioned limitations of the threshold based hit detection.

4. A new methodology for detecting and determining AE hits

Transients in AE signals acquired from complex systems are often difficult or even impossible to separate using a conventional threshold based approach. There can be several reasons for this such as variable amplitude of the continuous AE within a loading cycle and overlapping of transients, which can be simultaneously emitted from the many AE sources in the material;

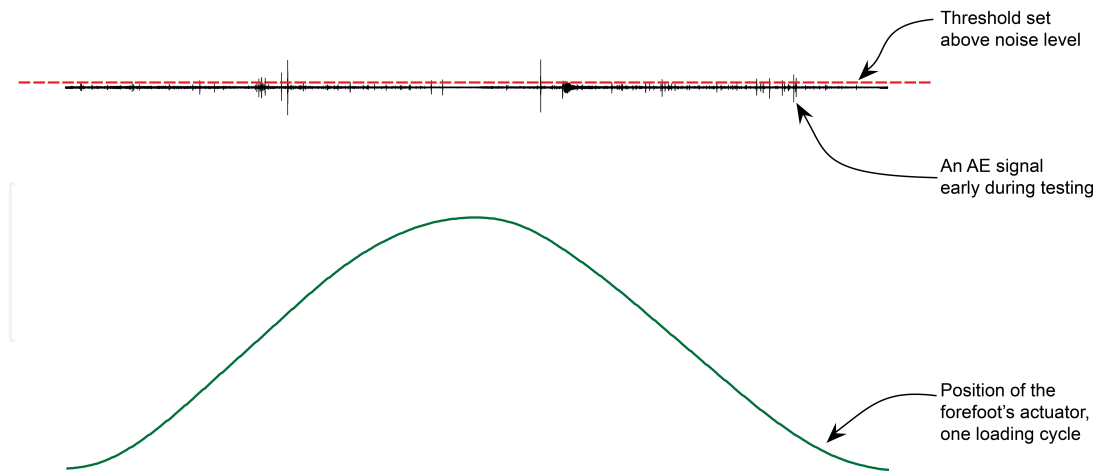


Figure 4. AE signal in one fatigue cycle early during cyclic testing of an assembled CFRP.

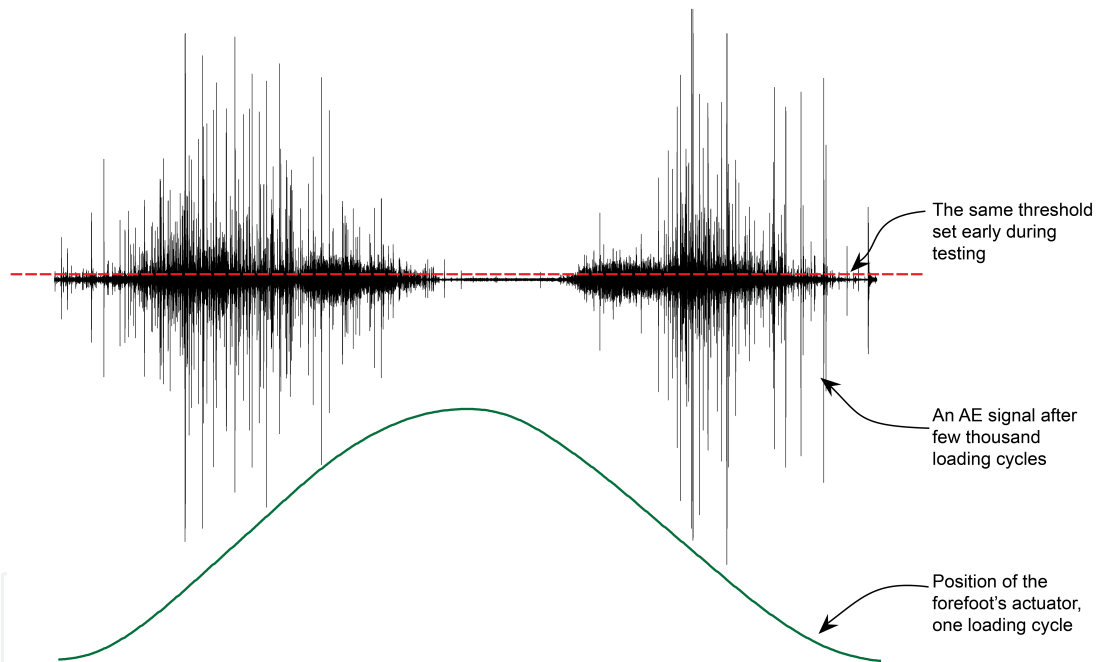


Figure 5. AE signal in one fatigue cycle few thousand cycles into the cyclic test of an assembled CFRP.

e.g. in CRFP composites subjected to dynamic loading. These transients have varying strength, duration, shape, and frequency. Hence, as the complexity of the AE signal increases, more advanced signal processing methods are required to detect and separate transients.

In this section a new methodology for detecting and determining AE hits is introduced and explained. Figure 6 shows a flow chart of the procedure. In the first step, the acquired AE signal is processed in order to extract descriptive features for detection. The resulting signal is called a detection function, or novelty function, and can be in any suitable domain of interest; e.g., time and time-scale/time-frequency domains. For detecting and locating hits, the detection function is input to a peak-picking algorithm which automatically detects

hits based on the trough-to-peak difference of local troughs and peaks. In the final step, the detected transients are compared against a threshold both to locate the hits more accurately, as well as to filter out weak hits; e.g., from background noise.

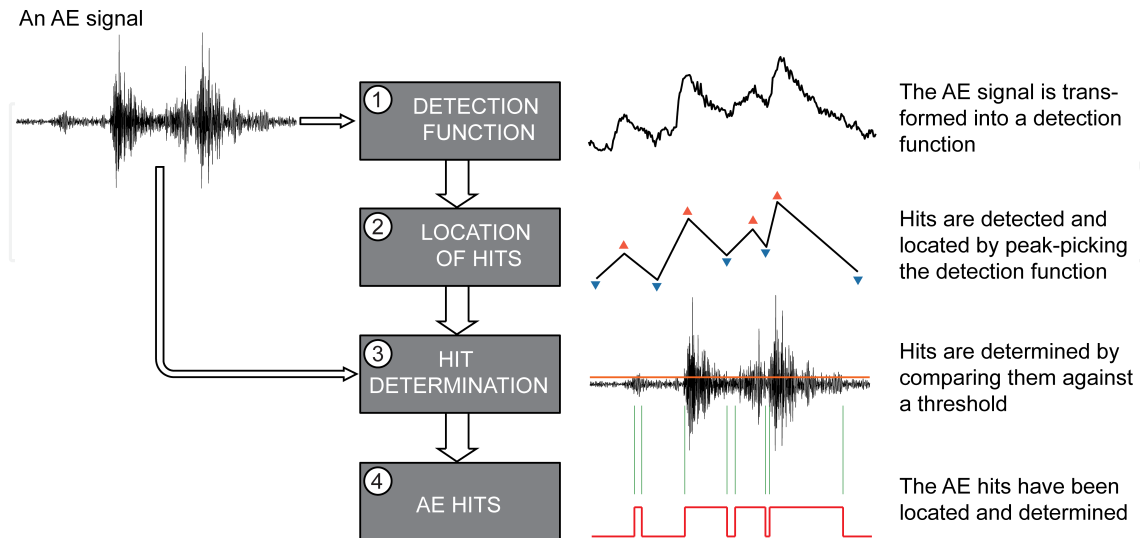


Figure 6. Flow chart of the AE hit determination procedure.

4.1. Detection functions

Two detection functions based on the signal's power will now be introduced, one in the time domain and one in the time-frequency domain.

4.1.1. Time Domain

Assuming an acceptable signal-to-noise ratio (SNR), most transients can be detected in the time domain using the temporal characteristics of the signal; e.g., the amplitude. Temporal amplitude increase is one of the key properties of transients and is, for an example, used in threshold based hit detection and determination. The signal's power can also be used for generating a detection function. In digital signal processing it is customary to refer to the squared values of a sequence as power and to the sum as energy. Hence, the power can be calculated by squaring the amplitudes:

$$P[i] = \frac{|x[i]|^2}{R} \quad (1)$$

where x is the voltage of the acquired AE signal, R is the equivalent resistance of the transducer and amplifiers and the use of square brackets serves as a reminder that the values are discrete. In acoustics, the energy is commonly expressed in base-10 logarithm scale, known as the decibel (dB). The logarithm transformation changes the dynamic range of the signal by enhancing low values, while compressing high values. The logarithmically converted energy can be expressed by

$$P_{\log_{10}}[i] = 10 \log_{10} |P[i]| = 10 \log_{10} \left| \frac{|x[i]|^2}{R} \right| = -10 \log_{10} |R| + 20 \log_{10} |x[i]| \quad (2)$$

Because the hits will be determined by peak-picking the detection function, both the negative constant involving R and the multiplication by 20 can be omitted. Furthermore, in order to ensure that the detection function will be positive and to eliminate the need to deal with numbers less than one, whose logarithms are negative, the rectified signal values are incremented by one. The resulting detection function is:

$$DF[i] = \log_{10} |1 + |x[i]|| \quad (3)$$

This detection function has the shape of the the signal's power envelope. In some instances the detection function may be too jagged to accurately perform peak-picking. In order to improve the peak-picking the detection function can be filtered but, with the cost of higher computational load and a time-lag of peaks. Figure 7 illustrates the process of generating the detection function.

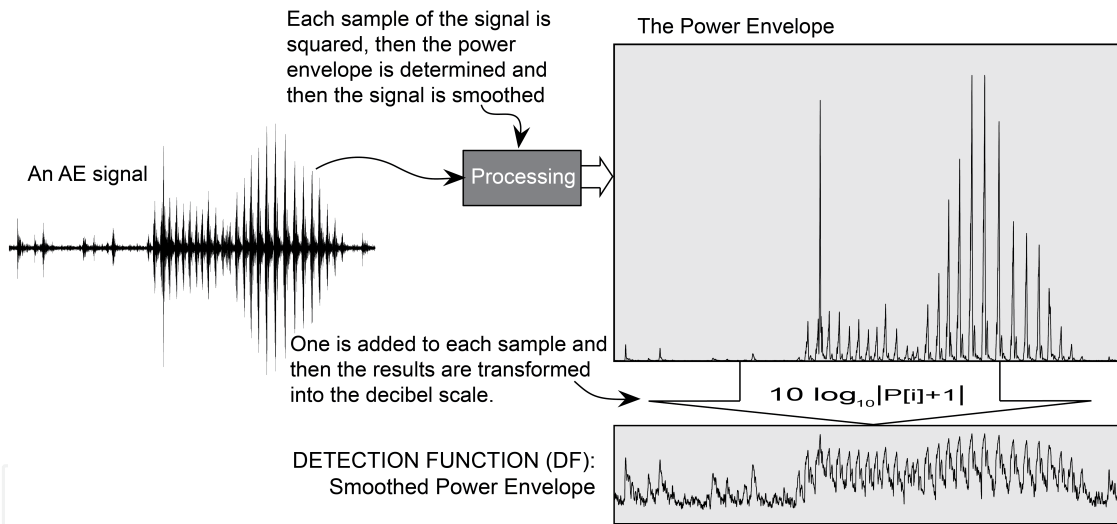


Figure 7. Illustration of the procedure for generating detection function in the time domain. In the chapter, a simplified version of this procedure is used.

4.1.2. Time-Frequency Domain

AE signals are mainly transient stress waves with a broadband frequency response. This property can also be used to detect transients. Power spectrum analysis, for instance using FFT, only shows which frequencies exist in the signal and how they are distributed. This is because the FFT is not designed to analyze transient signals, but rather continuous signals. Time-frequency representations are methods designed to analyze time-varying signals. Among the methods that have been used for this task is the Short-Time Fourier Transform (STFT).

The STFT is an enhanced version of the standard FFT. The idea behind the STFT is to divide the signal into portions where it is stationary. A window function is used to extract the portions from the original signal. The portions are then processed using FFT. Hence, the STFT is basically a FFT with a window function. The time-frequency localization obtained is from the location of the window functions. The frequency localization suffers due to the limited size of the window. For a given window size, the STFT has a constant localization resolution at all times and frequencies. By increasing the window size, the frequency localization can be improved, but then the time localization gets worse, and vice versa. This problem is related to the Heisenberg's Uncertainty Principle, which can be applied to time-frequency localization of signals. Basically what it says is that we cannot know both the exact localization of time and frequency.

In the time-frequency domain the power of the signal can also be used to detect and isolate transients. For this purpose a function based on the short-time Fourier transform can be used to generate the detection function. Figure 8 and Algorithm 1 describe how the STFT based detection function is computed.

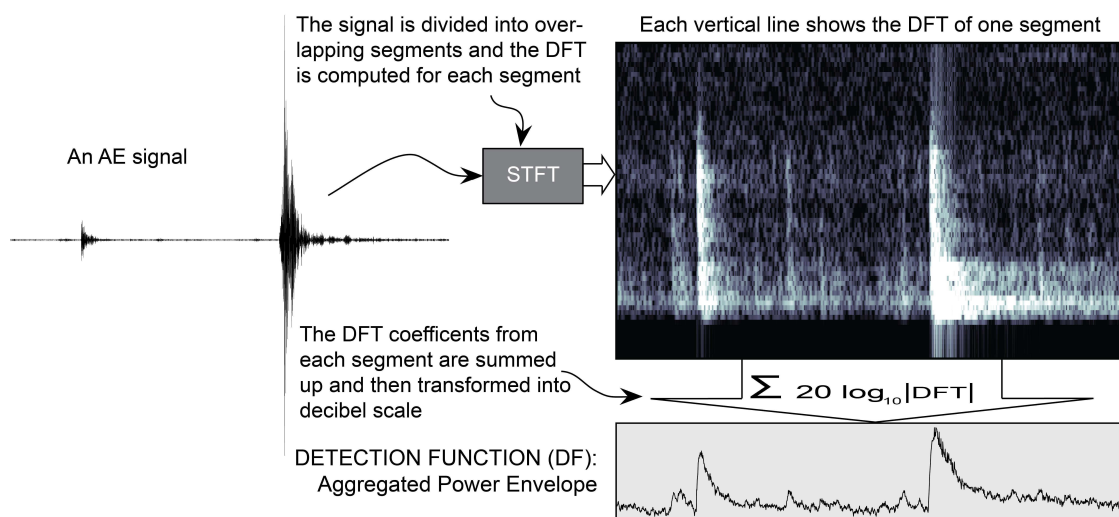


Figure 8. Illustration of how the time-frequency based detection function is generated.

The computation procedure starts by dividing the AE signal into segments of k samples. The segments overlap by d samples. For each segment, the discrete Fourier transform (DFT) is computed using k samples; i.e., no zero padding is used. Then the results are converted into the decibel scale by applying logarithm (base 10) to the complex modulus (magnitude) of the DFT coefficients. The coefficients for each segment are then summed up. Each coefficient is multiplied by a 20. The multiplication can be omitted because it only scales the detection function; i.e., the peak-picking results will be the same with adjusted parameters.

The number of elements in the detection function, DF , is equal to the number of segments. Consequently, the elements are mapped to the corresponding data points in the AE signal, the mapping is stored in a vector MAP . The time resolution is controlled by the length of the segments. The additional information obtained by using overlapping, is obtained by interpolation.

Algorithm 1: *STFT based detection function***Data:** signal, k, d**Result:** DF, MAP

```

1 Segments  $\leftarrow$  signal divided into k sample segments with d sample overlap;
2 MAP  $\leftarrow$  map the segments to corresponding data points in the signal;
3 for  $i=1$  to number_of_segments do
4   | DFT  $\leftarrow$  Calculate Discrete Fourier Transform of segment  $i$ ;
5   | DF [i]  $\leftarrow$  sum ( $20 \log_{10} (|DFT|)$ );
6 end

```

Given the reduction in the time resolution and the computational cost involved, the STFT based detection function does not compare well against the previous detection function, which was in the time domain.

4.2. Peak-picking the detection function

In order to locate hits from the detection function a peak-picking procedure is used. The procedure is illustrated in Fig. 9. The small troughs and peaks in the detection function are incrementally removed until it contains only troughs and peaks which have trough-to-peak difference above the trough-to-peak threshold, T_{tp} . The hits are then located from the remaining troughs in the detection function. The threshold controls the sensitivity of the approach. If the sensitivity is increased; i.e., T_{tp} is lowered, then smaller pulsations in the AE signal will be detected as hits. This procedure can be split into two algorithms: Algorithm 2 and Algorithm 3.

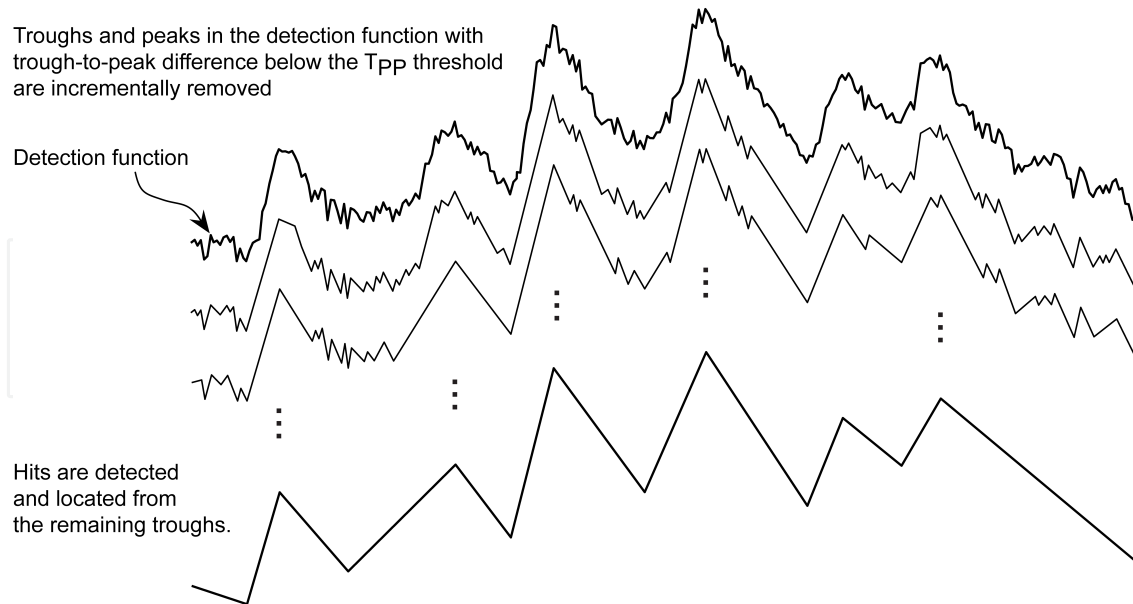


Figure 9. Illustration of the incremental peak picking procedure.

Algorithm 2 is used for locating troughs and peaks in an input signal. The algorithm starts by creating an empty vector, *Locs*, of the same length as the input signal. This vector will be

the output of the algorithm and contains the locations of all detected troughs and peaks. The derivative, or slope, of the input signal is used to determine troughs and peaks. The slope is computed by subtracting a time-shifted version of the input signal from itself. Peaks are detected by first finding all samples which have zero or positive slope. If the next sample in time has negative slope then a peak is detected. The procedure for finding troughs is similar, in this case all samples with zero or negative slope are first found and when the next sample in time has positive slope then a trough is detected. The end points are treated separately. In both cases, it is first checked if a peak or trough have been determined at the ends. If not, then a trough is determined if a peak is closest to the end, and vice versa.

Algorithm 2: *Trough and Peak Picking Algorithm*

Data: signal
Result: Locs

```

1 Locs  $\leftarrow$  zero vector of the same size as signal;
2 peaks:
3 tmp_indices1  $\leftarrow$  indices of all samples with positive slope (and 0);
4 tmp_indices2  $\leftarrow$  indices of samples in tmp_indices1 for which the adjacent samples with
   indices tmp_indices1 +1 have negative slope;
5 Locs [tmp_indices1 [tmp_indices2 ]+1]  $\leftarrow$  (+1);
6 valleys:
7 tmp_indices1  $\leftarrow$  indices of all samples with negative slope (and 0);
8 tmp_indices2  $\leftarrow$  indices of samples in tmp_indices1 for which the adjacent samples with
   indices tmp_indices1 +1 have positive slope;
9 Locs [tmp_indices1 [tmp_indices2 ]+1]  $\leftarrow$  (-1);
10 end points:
11 nz_indices  $\leftarrow$  find the indices of non zero entries in Locs;
12 if abs (nz_indices [first entry])  $\neq$  1 then
13 |   Locs [1]  $\leftarrow$  (-1)  $\times$  nz_indices [1]
14 end
15 if abs (nz_indices [last entry])  $\neq$  length of signal then
16 |   Locs [1]  $\leftarrow$  (-1)  $\times$  nz_indices [last entry]
17 end

```

Algorithm 3 is used to remove troughs and peaks which have trough-to-peak difference below a specified threshold, T_{tp} . They are removed incrementally by increasing the threshold, a , from 1 to T_{tp} in steps. The larger the increments, the larger can the hit location error be. Smaller increments, however, increase the computational cost. After each removal step, Algorithm 2 is used to reevaluate the troughs and peaks from the remaining list. The reevaluated list is then used for the next step. The hit locations determined by the peak-picking procedure are the trough locations in the final list.

4.3. Hit determination

After the hits have been located they are compared against a determination threshold, T_{AE} . This threshold is the same threshold as used in the conventional threshold-based hit detection. Here, this threshold is used to filter out weak hits; i.e., only hits which exceed

the threshold are determined as hits. The threshold is also used to extract threshold based features.

Algorithm 3: *Trough and Peak Removal Algorithm*

Data: Locs, signal, T_{tp}

Result: NewLocs

```

1 for  $a=1$  to  $T_{tp}$  do
2   Remove trough/peak entries in Locs which have trough-to-peak difference below  $a$ ;
3   Locs_tmp  $\leftarrow$  Algorithm 2 (signal [Locs ]));
4   Locs  $\leftarrow$  map the entries in Locs_tmp to entries in signal;
5 end
6 NewLocs  $\leftarrow$  Locs;

```

4.4. Summary

Continuous parameter based AE systems commonly use threshold based hit detection with a fixed or a floating threshold. However, in some situations neither may be appropriate. When the fixed threshold is set, it is tuned to the AE signal; i.e., the noise level, at the start of monitoring. As the component under monitoring degrades and the signal level increases, the threshold may not be used to detect individual transients. That is, the threshold based approach may not be able to separate transients if the signal does not fall below the threshold for a sufficient period of time. In some situations a floating threshold can be used to overcome this problem, however, a floating threshold may not be appropriate if the signal level varies. This is because it can be difficult to set the appropriate response time of the floating threshold. If it is set too fast it can be affected by strong transients.

In this section an approach for hit determination has been introduced. This approach is designed to handle the abovementioned limitations of the threshold based hit determination approaches. In order to accomplish this, hits are first detected by peak picking a detection function and then they are compared against a threshold in order to filter out weak ones. Hence, the approach is able to detect and separate transients even though the signal does not fall below the threshold. The separation is accomplished by splitting the transients at the point of lowest amplitude between them, Fig. 10 illustrates this.

5. Experimental study

In this section the approach will be studied by applying both detection functions on the same AE signal. The AE signal was obtained during cyclic testing a CFRP prosthetic foot [17]. The signal consists of 3 AE signals chosen to demonstrates the ability of the approach to work with and detect transients which amplitudes differ by magnitudes.

The AE data was sensed and amplified using the VS375-M transducer and the AEP3 preamplifier from Vallen Systeme GmbH. The preamplifier was equipped with 110 kHz high pass and 630 kHz low pass filter. The gain was set to 49 dB. The analogue AE signal was fed to a 16 bit analogue/digital (A/D) converter for a full waveform digitization using 1.25 MHz sampling rate. After digitization the data was high-pass filtered in order to remove DC and other low frequency disturbances. Phaseless filtering was used on the AE signal in order to

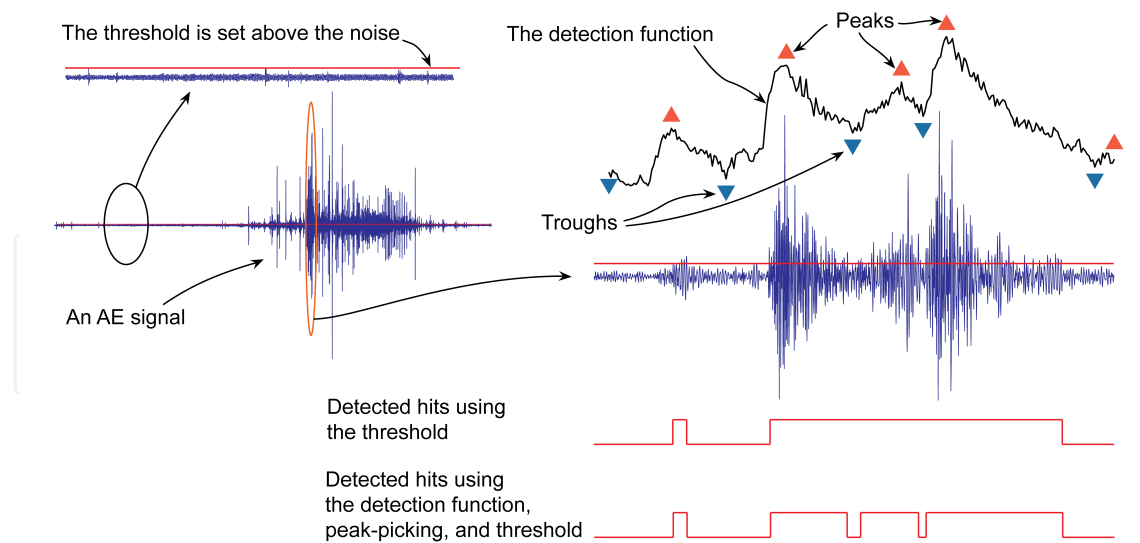


Figure 10. Illustration of how the hit determination approach presented here is able to detect and separate overlapping transients which the threshold based procedure does not.

avoid phase delay. A fifth-order elliptic filter with 1 dB passband ripple and corner frequency of 80 kHz was used. The stopband attenuation was set to 30 dB at 50 kHz. Only high pass filtering was applied to the signal. No corrections were made due to the amplifications made by the preamplifier and the transducer.

The AE signal is depicted in Fig. 11 and consists of weak, intermediate, and strong AE transients. The duration of each type is 5 milliseconds and they are arranged in the order of increasing amplitude. The weak transients are low amplitude transients, all with amplitudes equal to, or less than, 85 mV, the intermediate transients are at most 650 mV, and the strong AE transients are roughly ten times stronger, or up to 6.2 V. The strong transients have been soft clipped by the preamplifier.

In the time domain a 15 sample moving average of the power envelope was calculated before transforming it into the decibel scale. The trough-to-peak threshold, T_{tp} , was set to 13 dB V-s. The resulting detection function, which has the shape of the signal's power envelope, is plotted above the signal in Figure 12(a). The detection function has been offset to fit in the figure.

The STFT detection function described in Sect. 4.1 was used with segment size of $k = 128$ samples and $d = 120$ sample overlapping. The trough-to-peak threshold, T_{tp} , was set to 304 dB V-s. This value was used in [17] to design an AE failure criterion equivalent to a 10% displacement failure criterion. The resulting detection function is plotted above the signal in Figure 12(b)

At first sight the two detection functions may seem to be identical. However, upon close comparison one can see that they respond differently to some transients; e.g., the 3rd transient from the end of the weak transient signal portion (0-5 ms) is better defined in the time-frequency detection function. The reason for the differences lies in the nature of how the functions are generated. In the time domain the detection function is generated by squaring the signal's values, averaging them and then transforming the results into the

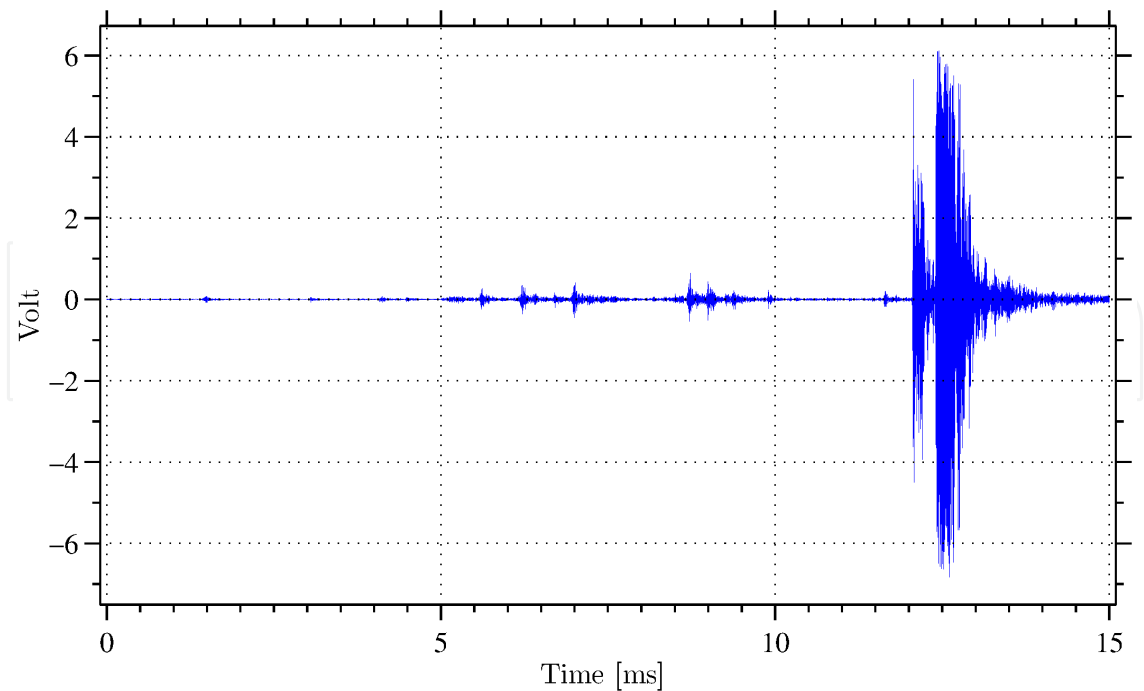
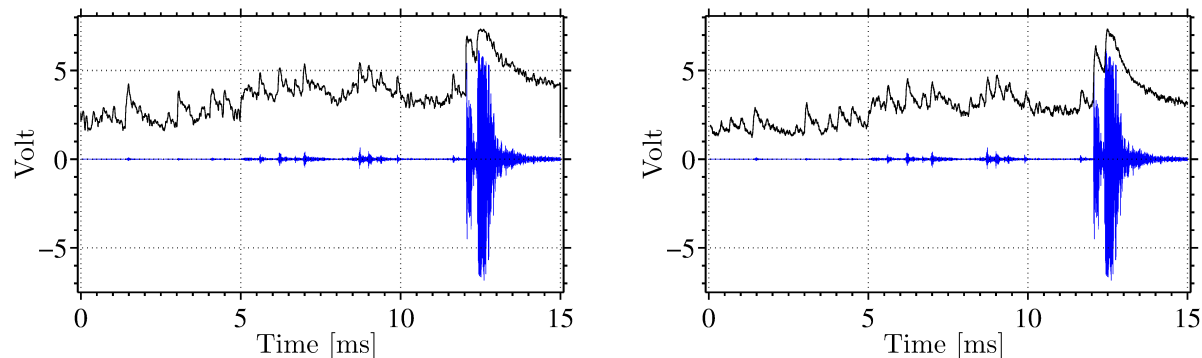


Figure 11. The AE signal that will be used to study the AE hit detection approach. The signal consists of weak (0-5 ms), intermediate (5-10 ms), and strong transients (10-15 ms).



(a) The AE signal used in this study and the corresponding detection function in the time domain. (b) The AE signal used in this study and the corresponding detection function in the time-frequency domain.

Figure 12. The two figures show the AE signal used here. The signal consists of weak, intermediate and strong transients. Above the AE signal are the two detection functions which have the shape of the signal's power envelope.

decibel scale. In the time domain, however, the frequency content of the signal is used for generating the detection function. This means that in order for an transient to have high energy both the amplitude and the frequency content play a role. Hence, the detection function in the time-frequency domain has the potential to be better at detecting the start of transients.

5.1. Weak hits

Figure 13 shows the weak transients, the two detection functions and the results from the peak-picking of the detection functions; i.e., the detected troughs and peaks. The peaks and

troughs are shown respectively by triangles pointing up and down. The figure allows for better comparison of the two detection functions. In the time domain the detection function closely follows the signal's envelope whereas in the time-frequency domain the detection function does not follow the signal's envelope as well. An example is the 3rd transient from the end, located approximately at 3.8 ms. In the time domain the detection function shows the transient as a bump in the curve but, the time-domain detection function responds differently and represents it as a well defined peak. As a result, when the two detection functions are peak-picked the algorithm finds more accurate location of the peak in the time-frequency domain.

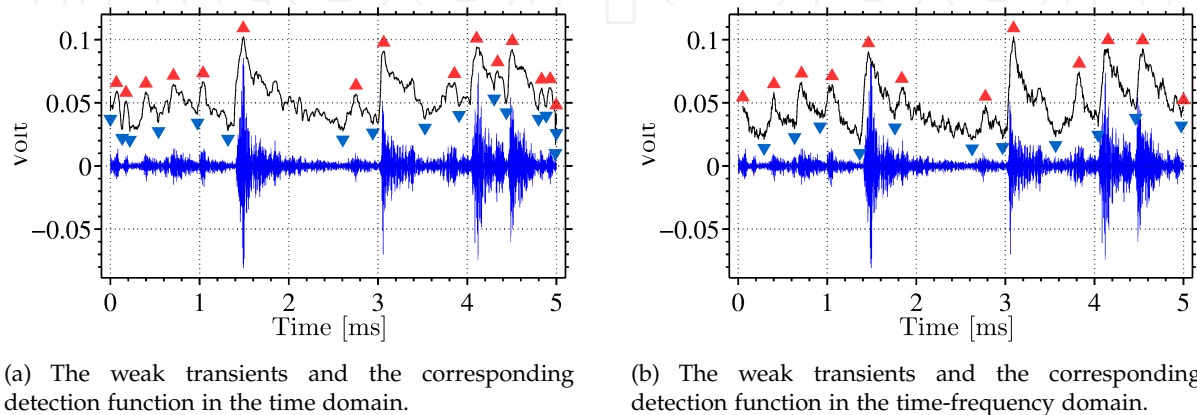


Figure 13. The figures show the weak transients, the detection functions in more detail. Also shown are the results from the peak-picking of the detection functions; i.e., the detected troughs and peaks.

More accurate location of peaks is in general obtained using the time-frequency detection function; e.g., for transients that start at 1.4 ms and 3.8 ms. However, the purpose of the peak-picking is to detect transients. The determination is performed using conventional threshold approaches. Therefore, even though the peak-picking algorithm does not provide exact timing of peaks and troughs it can be used to separate transients.

5.2. Intermediate hits

Figure 14 shows the intermediate transient. The maximum amplitude of the transient in the intermediate signal is approximately 640 mV. The amplitude is 7-8 times higher than the weak transients which are all less than one tick on the Volt axis in the figure.

It is interesting to see that, despite that the same settings are used and the transients are much stronger, the approach handles the AE signal with the intermediate transients quite well. Visual inspection and comparison of Figures 14(a) and 14(b) reveals that the peak-picking results are similar to the results when working with the weak transients.

However, inspection also shows that the detection function in the time-frequency domain can combine two or more transients into one. An example of this is the transients starting at 6.2 ms and 6.4 ms. The detection function in the time domain separates them with two peaks but in the time-frequency domain they are treated as one. This may be of the strong broadband content of the first transient which blends into the second one but, it is also due to the size of the overlapping used in the STFT calculations. The reason why the two transients are not

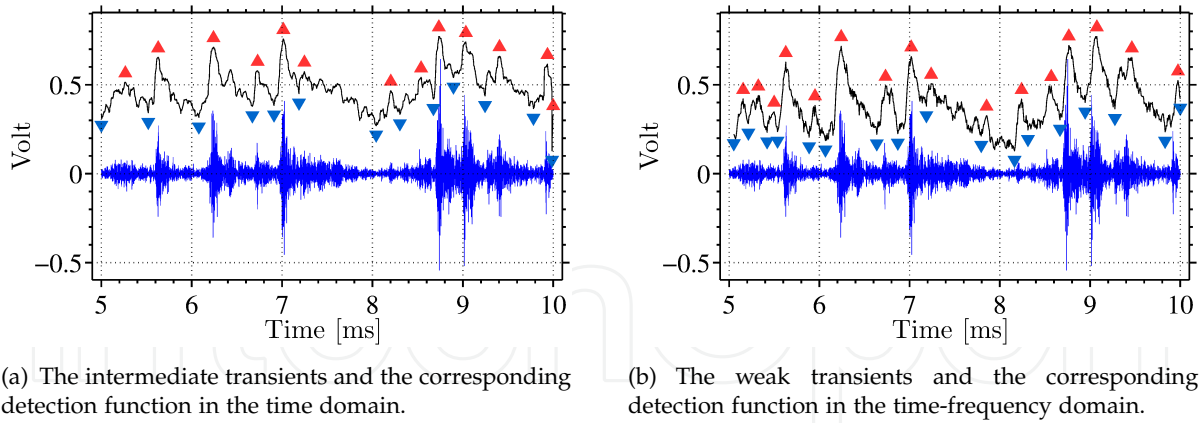


Figure 14. The figures show the intermediate transients, the detection functions in more detail. Also shown are the results from the peak-picking of the detection functions; i.e., the detected troughs and peaks.

identified from peak-picking the detection function in the time domain is the value of the T_{tp} - a lower value will identify the smaller transient.

5.3. Strong hits

Figure 15 shows the strong transients. The transients were soft-clipped by the amplifier but the high-pass filtering of the signal partly restored them. The maximum amplitudes of the strong transients are approximately 10 times larger than of the intermediate transients which are all less than one tick on the Volt axis in the figure. The signal leading and trailing the strong transients is a weak/intermediate signal. As can be observed upon comparing Figures 15(a) and 15(b) the approach is able to tackle the strong transients and identify them. It is interesting to notice that no transients are detected in the transient fluctuations during the decay of the large transient that starts at 11.6 ms. The transients in the decay manage to blend into each other so that they are not represented in the detection functions.

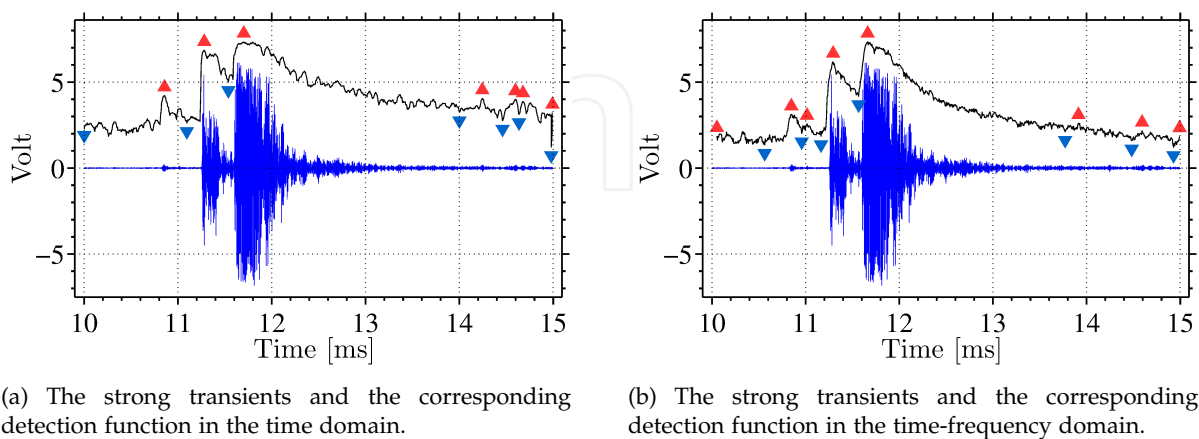


Figure 15. The figures show the strong transients, the detection functions in more detail. Also shown are the results from the peak-picking of the detection functions; i.e., the detected troughs and peaks.

6. Conclusion and future research

The approach presented in this chapter was designed to detect and determine AE hits in AE signals where conventional threshold-based hit detection is not suitable; i.e., using a fixed or a floating threshold. Fixed thresholds are set at the start of the monitoring; i.e., tuned to the noise level of the AE signal. As the material degrades and AE is generated by the cumulative damage, the AE signal level increases and the threshold cannot be used to detect individual hits. Furthermore, neither the fixed threshold nor the floating threshold can be used to distinguish between hits when a burst of strong, slightly overlapping AE is encountered. This type of burst is for example encountered during cyclic testing of assembled CFRP composites. In [13] it was generated by the rubbing of splinters. The overall strength of the AE increased during the test due to cumulated damage, but not noise. For this reason, a floating threshold was not suitable. Furthermore, because the strength of the AE emissions varied within each cycle, it was difficult to set the appropriate response time of the floating threshold. If the response was set too fast the threshold was affected by strong transients.

The transformation of the detection functions into the decibel scale is useful when the transducer cannot be placed at the location of damage and the AE signal suffers from high attenuation. Furthermore, the transformation produces a detection function that makes it possible to use one setting for automatic hit determination of both strong and weak hits.

The resolution of the approach can be fine tuned by adjusting the threshold, T_{tp} . This threshold is used to filter out small local troughs and peaks in the detection function. If a high resolution is required; i.e., to detect pulsations in the signal, then the time domain is the appropriate choice. This is both due to the computational cost and the inherent trade-off between the time and frequency resolution of the time-scale/time-frequency based approaches.

The presented approach has, intuitively, its own limitations. These include the tuning of the parameters used, the required computational load and associated time-lag. The hit determination in the time domain, using the envelope of the signal's energy, has a significantly lower computational load than the STFT-based determination in the time-frequency domain. Although it does not suffer from the time-frequency trade-off associated with the STFT, it will have a slight time-lag if the envelope is filtered; e.g., moving average filters. The main concern is the computational load but, not the time-lag. This is because the detection function and the peak-picking are only to detect the presence of transients. The final determination; i.e., deciding whether it is a hit or not, is performed using conventional threshold approaches. Hence, the exact timing of the peak-picking is not necessary.

Two detection functions were presented in this chapter and used. Numerous of other detection functions can of course be created. The detection functions can be created in the time domain as well as in the time-scale/time-frequency domains. In some instances transients are only separable in the time-scale/time-frequency domains, where wavelets and Cohen's class of time frequency representation (TFR) are used, respectively. Both approaches have been shown to provide a good representation of signals and for this reason, they have been receiving increasing attention in the recent years. The successful detection of transients, using either wavelets or Cohen's class of TFR depends strongly on the choice of the wavelet function and the distribution function, respectively.

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