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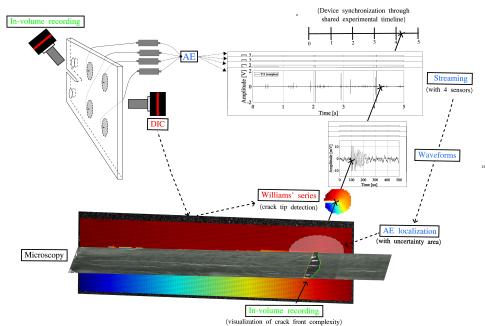
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¹ Graphical Abstract

- 2 Investigation of fracture source mechanisms through full-field imaging and
- **3 acoustic emission**
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5 Highlights

Investigation of fracture source mechanisms through full-field imaging and acoustic emission

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Combining time resolved AE, DIC and in-volume measurements with
 post-mortem fracture surface analysis on transparent PMMA tensile
 cracking experiments. Tools applied for the purpose of AE localization,
 crack tip detection and determination of crack front complexities and
 kinematics within the volume, respectively.

- AE sources and the crack front can undoubtedly be connected for AE sig-
- nals with high amplitudes such as dynamic instabilities.
- Classification of lower amplitude signals remains difficult to connect un-
- ambiguously to a particular source mechanism even for highly correlatedwavesforms.

Investigation of fracture source mechanisms through full-field imaging and acoustic emission

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22 Abstract

The identification and understanding of fracture processes is a vital component in securing engineering structures. By collecting data through experiments or simulations, the identification of material parameters and the understanding of failure mechanisms can be investigated. In the context of inlaboratory experiments, this is done by provoking fracture process through destructive testing (TD) techniques, while collecting data by non-destructive testing (NDT) techniques and postmortem analysis. While NDT techniques are often used individually, increasing interest is given to collective investigations of source activities. Like this, limitations of one method can be compensated by the next. A multi-modal experimental setup is proposed for holistic understanding of source mechanisms. Combined time resolved AE, DIC and in-volume measurements with post-mortem fracture surface analysis are applied on PMMA tensile cracking experiments for the purpose of AE localization, crack tip detection and determination of crack front complexities and kinematics, respectively. Both high and lower amplitude AE signals were captured and respectively associated to localized dynamic instabilities and stable crack advance. Signals are analysed individually using localization, waveform analysis, and AE descriptor classification. Crack front velocity heterogeneities are identified as valuable quantity to correlate with fracture induced AE responses. For dynamic instabilities, a linear relationship between AE absolute energy and crack propagation area was found. While identification and analyses of local and global dynamic instabilities has shown to be rather trivial, difficulties arose with respect to quasi-static related AE events.

23 Keywords: Polymers, Fracture Mechanics, DIC, AE, Source Localization

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24 1. Introduction

To improve the security of engineering structures, one needs to identify 25 and understand different failure sources. The understanding of fracture be-26 haviours, their initiation and propagation, is vital in the field of mechanical en-27 gineering. With the aim of collecting experimental data to support the under-28 standing through simulations, different fracture processes are provoked in lab-29 oratories by destructive testing (DT) techniques (e.g. fatigue, tensile (elonga-30 tion) or torsion experiments), with non-destructive testing (NDT) techniques 31 monitoring the activity. Classical experimental setups present an individual 32 application of NDT methods for data collection. However, combining differ-33 ent NDT methods can provide a more robust and adequate understanding of 34 the phenomenon of interest, due to the particular set of advantages and limi-35 tations of each NDT technique (Wang et al., 2020; Kong et al., 2020). 36

One commonly used technique is the method of Acoustic Emissions (AE). 37 With the material being subjected to external loads, sudden stress redistribu-38 tion take place in the material due to permanent or irreversible damage phe-39 nomena. This causes the release of elastic strain energy in the form of dissi-40 pated heat and elastic waves. The transient elastic waves, as surface motion, 41 are captured by a transducer translating the mechanical to electrical energy 42 through the process of piezoelectricity (Arnau and Soares, 2008). After pre-43 amplification, electrical signals are interpreted and used for the investigation 44 of source activities. Globally, AE analysis can be subdivided into three branches 45 of application: localization, lifetime prediction and damage analysis. The aim 46 of this work is however solely related to AE as a technique for damage analy-47 sis, where AE signals have shown to be highly dependent on the type of source 48 mechanism. In literature, AE has been shown to be applicable to different ma-49 terials – e.g. CFRP laminates (Andraju and Raju, 2023), carbon/glass fiber re-50 inforced composites (Gul et al., 2021), mild steel (Shrama et al., 2015), or con-51 crete (Aggelis, 2011) – and to be sensitive to different physical or chemical phe-52 nomena – material degradation (e.g. cracking (Kong et al., 2020)), reversible 53 processes (e.g. melting or solidification (Wadley and Mehrabian, 1984)), fabri-54 cation processes (e.g. grinding (Jayakumar et al., 2005)), leak and flow (e.g. gas 55 evolution (Cao et al., 1998)) – as potential source mechanisms. The appear-56 ance of these source activities are generally identified – supported by meth-57 ods like machine learning (Almeida et al., 2023; Ciaburro and Iannace, 2022), 58 parameter clustering analysis (Li et al., 2014) or waveform processing analysis 59 (Arumugam et al., 2011) - through the identification of similar waveform char-60 acteristics of repetitive signals. However, the complexity around accurate in-61 terpretation of the AE activity by the user prevails in each considered method. 62

Hence, to support the process of interpretation of AE signals, it seems useful to 63 approach AE analysis through the scope of reverse engineering. Due to direct 64 visible access to the fingerprint of the source activity on the fracture surface, 65 cracking phenomena seem to present a suitable activity of interest for such in-66 vestigation. The complete picture of the link between AE activities, state vari-67 ables, fracture mechanisms and fingerprints on the post-mortem fracture sur-68 face might provide valuable information for the design of robust and reliable 69 NDT algorithms. 70

To achieve a holistic understanding of source mechanisms during fracture 71 experiments of classical quasi-fragile material, this work proposes a multi-72 modal experimental setup combining different NDT tools. With the purpose 73 of AE localization, crack tip detection and determination of crack front com-74 plexities, combined time resolved AE, digital image correlation (DIC) and in-75 volume measurements with post-mortem fracture surface analysis are applied 76 on cracking experiments, respectively. Each technique was considered to by-77 pass the need of blind interpretation, while allowing to tie AE signals to frac-78 ture surface patterns, i.e. enabling traceability of any captured AE signal to 79 the spatial position of the elastic waveform formation on the fracture surface. 80 Model experiments on PMMA are performed under predominant mode I load-81 ing conditions leading to stable crack propagation, where heterogeneous crack 82 fronts generate high density of AE emissions with localized dynamic instabil-83 ities, that are leading to high amplitude AE responses. Compared with proper 84 pure mode I experiments as a baseline and unstable alternate (stick-slip) crack-85 86 ing (previously investigated in (Heinzmann et al., 2023)), the paper discusses the complexity around the ability of correlating AE to local fracture regimes. 87 Such experiments may help the chain of understanding the connection of frac-88 ture mechanisms and their AE signature. 89 The presented work is structured as following: at first, the experimental 90

setup is described by giving detailed information on the applied NDT methods
DIC, AE and crack front extraction. Thereupon, a metrological assessment of
AE source localization and DIC crack tip detection is presented to verify the
applicability of the established inverse problem and detection of the equivalent elastic crack tip position w.r.t. complex crack fronts, respectively. The
presented work is then concluded by a discussion on the PMMA fracturing
through the multi-point view setup.

98 2. Experimental program

99 2.1. Material, sample geometry and AE sensor placement

Tapered double-cantilever beam (TDCB) shaped samples were obtained from 8 mm thick molded PMMA plates (Plexiglas®) through laser cutting (Class-4 laser system). To make intended in-volume recordings possible, only transparent PMMA plates were considered. The sample geometry, as well as AE sensor positions are shown in Figure 1. The coordinates (x; y) of the sensor positions, with the notch tip as origin, are marked in red.

Two types of macroscopically stable crack propagation tests have been per-formed:

a) Smooth quasi-static mode I crack propagation. Pin holes were drilled
 manually to ensure perfect perpendicularity between pine hole axis and
 sample face.

b) Same test as the first, however, the pin holes were machine drilled with
laser cutting. Here, clearance angles in the pin holes induces transverse
loads constraining the crack. The combination of normal axial loads with
supplementary transverse loads provoked cracking with a rough crack
profile and relatively intense AE activity.

With the objective of this work being the investigation of AE and crack growths 116 relationship, the second case has been considered to be a good candidate with 117 the pure mode I crack propagation case serving as reference. In the contin-118 uation of the work, this type of cracking will be referred to as complex, while 119 referring to the reference case as smooth. The considered experiments with 120 their particular cracking type are summarized in Table 1. For discussion, the 121 presented data is combined with AE measurements from previous experiments 122 (?), where unstable crack propagation where analysed though the eye of linear 123 elastic fracture mechanics (LEFM) theory, without presenting the AE measure-124 ments. 125

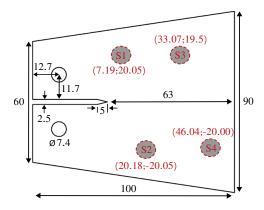


Figure 1: Sample geometry with the AE sensor positions and their coordinates (red) with respect to the notch tip [mm]. Radius of the notch tip is defined by the laser beam diameter of approximately 200 μ m.

Table 1: List of experiments.

Test	Cracking type
Reference	Purely mode I (smooth)
T5, T13	Predominantly mode I with bending (complex)

126 2.2. Loading and test configuration

Experiments were conducted with an ElectroPuls E10 000 Instron device with a load cell of 1 kN maximum loading capacity. The room temperature was controlled at 21°C. With a two staged loading procedure (?), influences of the notch tip on the cracking process were avoided. Extension rates of 0.01 mm.s⁻¹ were applied during the first loading stage initiating an approx. 1 cm pre-crack, while subsequent cracking was driven by extension rates of 0.07 mm.s⁻¹.

133 2.3. Experimental setup and methods

The investigated crack propagation was simultaneously monitored by an 134 AE sytem (MISTRAS Express-8) and a camera system with two high-resolution 135 cameras (Viework VP-50MX-M/C 30). Each of the cameras, having different 136 purposes, faced one side of the sample. One camera was used to perform DIC, 137 while the other was used for in-volume fracture surface recordings of the prop-138 agating crack. This was achieved by placing the camera with an inclination to-139 wards the sample surface. Notice that in-place alignment has been checked to 140 make face-to-face image registration straightforward. Lightning for the cam-141 eras was provided by multiple EFFI-Sharp PWR FF (Effilux) LED projectors. 142

The sample surface facing the camera intended for DIC measurements was 143 coated with a speckle pattern. A form was designed and attached to the surface 144 before coating the surface with regular spray paint, in order to ensure the best 145 AE sensor to surface coupling by protecting the intended sensor positions from 146 paint. Furthermore, consistent sensor placement from one test to the other 147 was eventually achieved. Four AE sensors, positioned as visualized in Figure 148 1, were used to capture AE activities. To improve AE localization, sensors were 149 placed with horizontal offsets. Synchronous triggering of the systems was per-150 formed with a trigger box (R&D vision) being activated by the stage change of 151 the Instron device. Like this, temporal accordance of the devices was achieved 152 to simplify data comparison in the wake. A sketch of the experimental setup 153 with a picture of a mounted sample is presented in Figure 2, while camera hard-154 ware parameters are given in Table 2. 155

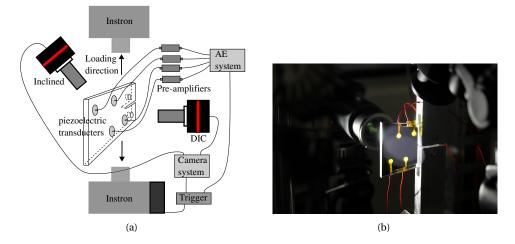


Figure 2: (a) Sketch of the experimental setup and (b) picture of an unbroken sample mounted in the mechanical device.

156 2.4. Digital image correlation (DIC)

By taking sequential images of the deforming sample, displacement fields can be obtained using DIC. It is based on the principle of conservation of brightness between reference (f) and deformed images (g) (equation of optical flow). This ill-posed non-linear inverse problem has the following form:

$$f(\underline{X}) = g(\underline{X} + \underline{u}(\underline{X})) \tag{1}$$

where $\underline{u}(\underline{X})$ presents the sought displacement field. The following ill-posed non-linear problem is eventually solved iteratively (Quasi-Newton method)

Purpose	DIC	In-volume	
Camera	Viework VP-50MX-M/C 30		
Image resolution	7856 × 1300 pix		
Acquisition rate	62.5 fps		
Lens	TOKINA 100 mm		
Aperture	f/2.8		
Field of view	37.18×6.15 mm	49.75×8.23 mm	
Resolution	4.65 μm	6.17 μm	
Patterning technique	Spray paint		

Table 2: Camera hardware parameters

using FE-based quadrilateral elements and bi-linear shape functions. Further-163 more, with the displacement field obtained through DIC and a post-projection 164 of the displacement field onto the Williams' series expansion, fracture param-165 eter can be derived (Roux and Hild, 2006; Réthoré, 2015). Among others, the 166 method allows for the detection of the crack tip position with a sub-pixel ac-167 curacy. For more details on the extraction of fracture mechanics parameters, 168 the authors refer to the Appendix A presenting an extraction from (?). DIC 169 and Williams' series projection has been performed by using the library of the 170 open-source software UFreckles (Réthoré, 2018), while required variables are 171 listed in Table 3. Notice that in the context of this work only crack tip position 172 will be analysed, with the projection zone $(R_{min} \text{ and } R_{max})$ being defined by a 173 parametric study. Furthermore, with DIC techniques working in pixels, a con-174 version variable is needed to find the corresponding metric/imperial data. Tak-175 ing an image of a ruler placed on the sample surface and using an FFT analysis, 176 the pixel to meter conversion value is systematically obtained with a sub-pixel 177 precision. Finally, a Savitzky-Golay filter (Polynomial), with a rolling windows 178 of 50 ms, i.e. 3 frames, is applied on projected data. 179

DIC			
Software	UFreckles (Réthoré, 2018)		
Discretization	FE-based global DIC		
Shape function	Bi-linear quadrilateral		
Shape function	Lagrange element (Q4P1)		
Element size	95 µm		
Post-filtering	Median filter using		
rost-intering	1 st neighbour applied to U		
Williams' series projection			
Е	3.5 GPa		
ν	0.32		
R _{min}	127.8 μm		
R _{max}	1301.6 µm		
2D approximation	Plane-stress		

Table 3: DIC & Williams' series parameters

180 2.5. Acoustic emission(AE)

AE analysis was performed with four resonant piezoelectric sensors 181 (Medium Frequency resonant Miniature sensors Nano30 by MISTRAS). They 182 have been mounted with conductive scotch and super glue. AE data was ob-183 tained by the AEwin streaming option to improve optimal recovery of AE ac-184 tivity by taking advantage of the short experiment duration (5 s). Hence, signal 185 descriptors and waveforms were computed, through in-house Matlab scripts 186 during post-processing. The AE responses were enhanced by a pre-amplifier 187 with a gain of 40 dB, while background noise filtering through an imposed 188 threshold was unnecessary since AE data was retrieved by streaming. The 189 system was calibrated and tested for appropriate coupling before each test 190 through the pencil lead break procedure (Scruby, 1987). 191

192 2.6. Crack front identification

Collecting information from within the volume, one would need CT scan 193 techniques (Crandall et al., 2017) for the investigation of opaque materials. 194 However, with PMMA existing as transparent material, capturing crack front 195 kinematics is feasible with standard imagine techniques. To do so, the cam-196 era system has to be placed with an inclination to the sample surface causing 197 experimental challenges in providing sufficient light and sharpness over the 198 full sample length and thickness. Thus, lens and light settings were defined 199 on a test sample, in which the crack propagated to about half of the sample 200

length. However, already tiny deviations from the crack path of this example
case led to strong local variations and losses in sharpness and light with respect
to each newly propagating crack. Hence, a compromised lens setting and light
positions had to be used to facilitate the recovery of the crack front kinematics for any possible crack path. For post-processing, a crack front extraction
algorithm was built along the following steps:

- Normalization: To begin with, images were normalized to correct for
 light variations between frames.
- 209
 2. *ZOI:* A zone of interest (ZOI) around the crack front was defined, within
 210 which the extraction was performed.
- 3. *Revealing advancement*: To reveal the advance of the crack front, preced ing images were subtracted from the current one. To increase robustness,
 not only one preceding image, but the average of a pre-defined number
 of preceding images was taken into consideration.
- 4. *Binarization:* A pixel threshold, based on the mean and standard deviation (std) of the newly created image (step 3), was defined. This threshold
 was used to binarize the image.
- 5. *Erosion and dilation:* The binary image was eroded (to remove unwanted
 pixels) and dilated (to recover continuous objects).
- Boundary: Tracing the boundaries of each object to define their pixel co ordinates by the MATLAB function bwboundaries, which is based on the
 Moore-Neighbor tracing algorithm modified by Jacob's stopping criteria
 (Gonzalez et al., 2004).
- *Exclusion:* Excluding tiny objects with a minimum amount associated pixels.
- 8. *Reconstruction:* Rebuilding the crack front mask based on the different objects.
- 9. *Finishing*: Recovering a clean crack front by only considering the most
 advanced position of the rough crack front mask.
- 10. *Smoothing:* Applying a moving median filter to reduce periodic trendsfrom outliers along the crack front.

It is worthwhile mentioning that the difficulties in recording sharp images of
the in-volume crack propagation resulted in the algorithm partially not being
able to clearly identify and extract the crack front. This is particular prominent
along the edges of the crack front.

236 3. Metrological assessment of crack tip detection and AE localization

237 3.1. Assessment of AE source localization

238 3.1.1. Methodology

The method of AE source localization is a widespread addition to standard 239 AE analysis. With the use of multiple AE transducers, depending of the in-240 tended dimension of observation, AE localization can provide information on 241 the origin of an AE signal. While the accurate definition of wave velocity is key 242 to the precision of traditional methods of AE source localization (e.g. (Schmidt, 243 1972; Schau and Robinson, 1987; Abel and Smith, 1987; Romhány et al., 2017; 244 Zhou et al., 2018)), recent studies focus on the development of wave velocity 245 independent AE source localization methods (e.g. (Ciampa and Meo, 2010; 246 Dehghan Niri and Salamone, 2012; Dong et al., 2019)). A review focusing on 247 sensor quantity, investigated structural geometries and method performance 248 of the different existing localization techniques is presented in Hassan et al. 249 (Hassan et al., 2021). 250

For the presented work, an inverse problem for AE source localization -251 treating wave velocity as unknown – is proposed using four AE transducers. 252 While this problem presents itself as ill-posed (Zhou et al., 2021), it can easily be 253 build for multiple sensors (here, n = 4). Based on proportional relationships of 254 distances and travel times between source and sensors, 2D source coordinates 255 can be expressed by the nonlinear governing equation, with the assumed AE 256 source location (x_s, y_s) and sensor positions (x_i, y_i) for all i from 1 to *n*. The 257 equation is taking the following form: 258

$$(x_i - x_s)^2 + (y_i - y_s)^2 - v^2(t_i - t_s)^2 = 0, \quad \forall i \in [1, n]$$
(2)

where t_i and t_s are the arrival time of the signal at each sensor and the time the signal has been released at the source, respectively. To linearize such nonlinear and coupled equation, variables x_s , y_s , t_s and v are substituted, respectively, by $x_o + dx$, $y_o + dy$, $t_o + dt$, and $v_o + dv$. These linearized contributions of Equation 2 then take the following form:

$$(x_i - x_s)^2 = (x_i - x_o)^2 + 2dx(x_i - x_o) + dx^2$$
(3)

264

$$(y_i - y_s)^2 = (y_i - y_o)^2 + 2dy(y_i - y_o) + dy^2$$
(4)

$$-v^{2}(t_{i}-t_{s})^{2} = -(v_{o}^{2}+2\mathrm{dv}v_{o}+\mathrm{dv}^{2})[(t_{i}-t_{o})^{2}+2\mathrm{dt}(t_{i}-t_{o})+\mathrm{dt}^{2}]$$
(5)

where x_o , y_o , t_o and v_o are the initial guesses with the current increments dx, dy, dt and dv.

²⁶⁸ After neglecting squared and weakly coupled terms, Equation 2 extended by

²⁶⁹ Equations 3, 4 and 5 leads to a four equation four unknown linear system.

$$L = 2 \begin{bmatrix} x_i - x_o & y_i - y_o & -v_o^2(t_i - t_o) & v_o(t_i - t_o)^2 \end{bmatrix}$$
(6)

$$b = \left[(x_i - x_o)^2 + (y_i - y_o)^2 - \nu_o^2 (t_i - t_o)^2 \right]$$
(7)

The system is eventually solved in a least squares minimization process as following:

$$L^{\mathsf{T}}L = L^{\mathsf{T}}b \tag{8}$$

272 3.1.2. Uncertainty

To evaluate the performance of the AE source detection and identify possible weak spots in the method, localization has been performed on synthetic AE signals. To mimic the localization of AE signals, time of arrivals (TOA) of the synthetic AE signals for all four sensors had to be computed. For this, the following elements were considered:

• Young's modulus (E) = 3.5 GPa

• Material density (ρ) = 1200 kg.m⁻³

• Velocity (v) =
$$\sqrt{E/\rho}$$
 = 1707.8 m.s⁻¹

• Distance to the sensors $i (d_i) = \sqrt{(x_i - x_s)^2 + (y_i - y_s)^2}$, with (x_i, y_i) and (x_s, y_s) being the sensor and source coordinates, respectively.

• Time of arrival
$$(TOA_i) = d/v$$

In the following, (a) the influence of the initial guess position on the localization uncertainty for various random source position and (b) the influence of
synthetic AE signals corrupted by expected experimental biases are investigated.

Firstly, the non-linear problem is highly sensitive to the initial guess. To highlight this sensitivity, localization error due to the initial guess has been mapped for various random source positions. For each random position of AE source, the AE localization was performed for a grid of 50x50 initial guesses. As illustration, the initial guess error map is presented in Figure 3 for four random

265

AE source positions along the expected experimental crack path. σ denotes the 293 distance between the located source position and its real location. The figure 294 reveals that for some initial guess (yellow areas), the algorithm may not only 295 poorly converge but even diverge which highlights the strong initial guess de-296 pendency. In practice, the cost function is not always convex depending on the 297 source location, so no convergence may be achieved leading to areas of 'for-298 bidden' initial guesses. Furthermore, no particular initial guess area leading to 299 good localization ($\sigma = \sim 1 \text{ mm}$) for any potential source position was detected 300 within the field of interest. Hence, an evaluation to find the most suiting initial 301 guess has to be performed before each source localization run, i.e. any new 302 sought for AE signal requires its own optimal initial guess identification. This 303 can easily be achieved a priori knowing the crack tip position from DIC and 304 using the proposed numerical twin being presented in this section. 305

Secondly, to shift the model scenario closer to a real case, main order exper-306 imental biases are introduced to the process of localization. A random normal 307 distributed error was drawn and appropriately scaled for each term of interest. 308 The target term with their standard deviation of the imposed uncertainty can 309 be found in Table 4. The potential errors for sensor placement, TOA and veloc-310 ity were determined with respect to AE transducer radii of 3.7 mm, AE temporal 311 resolution of 0.1 μ s and expected wave speeds of 1707.8 m.s⁻¹, respectively. It 312 is worthwhile mentioning that the TOA has been identified as the most critical 313 variable for a successful AE source localization. A rather large uncertainty was 314 thus introduced here (about 10 times the AE sampling) to stress-test the algo-315 rithm. Indeed, signals need on average 10 μ s to propagate through the field of 316 view presenting, on average, a signal to noise ratio of 90% on the TOA. How-317 ever, when the source goes closer to one of the sensors, since the uncertainty 318 is kept at 1 μ s, the signal to noise ratio decreases a lot with the propagation 319 time going closer to the uncertainty floor. Furthermore, identification of the 320 TOA through cross-correlating waveforms - to achieve sub-resolution accura-321 cies – was not possible with waveform characteristics changing from one sen-322 sor to the other (see Appendix C). While regular threshold crossing and float-323 ing threshold crossing are the most basic methods of TOA detection, more ad-324 vanced methods are proposed in literature. Cheng et al. (Cheng et al., 2021) 325 compared such methods in the case of I-shaped steel girder. With large dif-326 ferences in peak amplitude, the TOA was determined in the presented work 327 through a dynamic threshold and verified by the Akaike Information Criterion 328 (AIC) method (Hensman et al., 2010). The dynamic threshold was defined as 329 twice the standard deviation of the absolute volt amplitude. It was additionally 330 possible to control and potentially adapt the TOA, due to the rather manage-331 able amount of AE hits. 332

Error	Standard deviation
Sensor position	$500\mu\mathrm{m}$
ТОА	1 µs
Velocity	$5 {\rm m.s^{-1}}$

Table 4: Standard deviation (uncertainty) added to synthetic source position, time of arrival and first guess of velocity.

Various AE source locations were tested to evaluate the performance of the 333 localization algorithm with respect to different areas of the field of interest. 334 Figure 4 is showing the uncertainty (in x and y direction) of the source local-335 izations spanning a 20×20 grid. Each localization is presented as the median 336 absolute deviation (MAD) of the 200 iterations with changing copies of noise. 337 A priori identified optimal initial guesses however were kept constant for all 338 200 runs. Highest uncertainties (MAD around 20 mm) for the localization are 339 shown in yellow, while good identification of the source (MAD below 1 mm) 340 are shown in dark blue. With higher accuracies in the vicinity of the barycenter 341 of the four sensors, two main areas of weak performance can be observed be-342 low sensor one and above sensor four. Hence, with the localization accuracy 343 showing strong local variations, uncertainties have to be evaluated indepen-344 dently for each localization attempt. However, with a red rectangle indicating 345 the area of observed experimental crack paths, the activities of interest do not 346 fall into the zones of highest uncertainties. Thus, high uncertainties should be 347 avoided. 348

Ultimately, the evaluation of uncertainties shows that localization of exper-349 imental AE signals will need to consist out of the evaluation of the best suiting 350 initial guess and the area dependent localization uncertainty. The later will be 351 indicated by an error envelope (red dashed ellipse) around the detected source 352 position for any detected AE signal. In the context of this work, due to the infe-353 rior spatial localization accuracy, AE localization does not compete against DIC 354 crack tip detection, but as support to verify the link between the propagating 355 crack and the AE activity. With no a priori existing proof that AE signals are ac-356 tually emitted by the creeping crack, one needs to account for the risk of linking 357 potential noise signals to the crack. Moreover, it is worthwhile mentioning that, 358 considering through thickness variation of the crack front ($\pm 600 \mu$ m), the 2D 359 AE localization will not provide valuable information for discriminating from 360 which part of the front the AE has been emitted. However, sensibility of the 361 method to in-volume variations has still been evaluated (not presented here), 362 showing no particular additional bias on in-plane localization, other than on 363 the velocity identification. 364

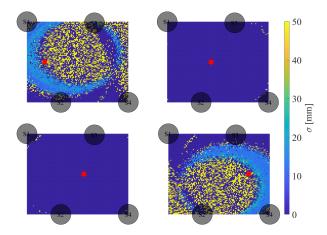


Figure 3: Map representing the sensitivity of the initial guess (50×50 grid) on the localization error for four AE source positions along the expect crack path. σ denotes the distance between the located source position and its real location (red star). Sensors are presented in scale of the real sensor base area with the area of interest being approx. 40 × 40 mm (see Figure 1)

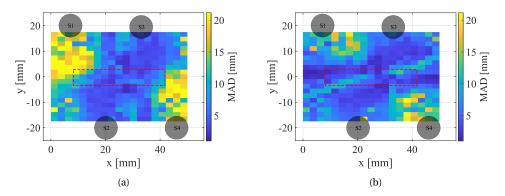


Figure 4: Median absolute deviation (MAD), i.e. mean identification uncertainty discarding outliers, on source localization depending on the source position $(20 \times 20 \text{ grid})$ for (a) x-direction and (b) y-direction. Sensors are presented in scale of the real sensor base area. The red rectangle indicates the area of observed experimental crack paths.

365 3.2. Assessment of crack tip detection from DIC

In literature, using DIC displacement fields and Williams' series expansion has become a classical method for the identification of the crack tip position (Hamam et al., 2007; Roux et al., 2009; Henninger et al., 2010; Réthoré and Estevez, 2013; Réthoré, 2015; Roux-Langlois et al., 2015). However, while a nu-

merical investigation with a curved crack front in (Réthoré et al., 2011) esti-370 mated the apparent elastic crack tip position systematically in front of its free 371 surface appearance, it has not been explored experimentally. Here, we have 372 tried to elucidate this question through in-volume recordings of transparent 373 PMMA plates with the back-face inclined camera. Thanks to temporal syn-374 chronization of the devices, each DIC frame had a corresponding in-depth 375 image visualizing the crack surface at this time. By taking the pixel to meter 376 conversion values of the two cameras into account, spatial matching was per-377 formed by taking the notch tip as common reference point. Like this, as pre-378 sented in Figure 5, detected crack tip positions were found in the in-depth vi-379 sualizations of the fracture surface. Here, the crack tip detection on the DIC 380 side and within the in-volume images are presented for the first ((a) and (c)) 381 and last ((b) and (d)) frame of experiment T13, respectively. The white rectan-382 gle in Figure 5(a) and (b) is showing the field of view (FOV) of the DIC process. 383 In Figure 5(c) and (d), the DIC face is found on the upper side of the fracture 384 surface, with the red dashed line indicating the the crack tip position detected 385 by DIC through the thickness of the sample and the crack front highlighted in 386 green retrieved by the crack front extraction algorithm (see Section 2.6). By 387 taking the constant uncertainty on the determination of the notch position in 388 the images (approx. 20 pix) and on the pixel to meter conversion ratio from the 389 FFT analysis (approx. 1.27×10^{-4}) into account, the global uncertainty on the 390 DIC crack tip detection has been found to be not more than 45 μ m (see (?) for 391 details). By taking all the above into consideration, the following points can be 392 observed: 393

• Evaluated uncertainties are lower than the in-depth crack front variations.

• Despite the in-depth crack front complexity, the crack tip is systemati-

cally detected at the position of the crack front on the DIC face.

397

Hence, DIC-based estimation of the crack tip position is suggested to be the estimation of the crack tip at the surface and not an in-depth average. The presented experiment, with a highly heterogeneous crack front made of multiple ligaments progressing and nucleating at different rates shown by bright white lines in Figure 5(c) and (d), eventually shows that DIC-based crack tip detection does not fully render such in-volume complexities.

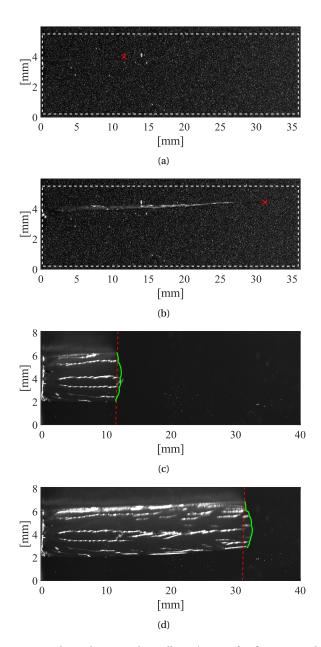


Figure 5: Accuracy in crack tip detection by Williams' series for first ((a) and (c)) and last ((b) and (d)) frame of the experiment T13. (a) and (b) shows the crack tip detection on the DIC face, with the white rectangle marking the FOV. (c) and (d) is showing the in-volume recording, where the DIC crack tip detection is vertically prolonged from the surface equivalent elastic crack tip position by the dashed red line and the crack front (obtained by the crack front extraction algorithm) is highlighted in green. The DIC face is found at the upper side of the crack surface in (c) and (d), while the maximal potential uncertainty in the equivalent crack tip detection related to the two frames is found to be approx. 40 and 45 μ m, respectively.

404 4. Results & discussion

Fracturing of TDCB shaped PMMA samples were investigated through DIC, 405 in-volume recordings, microscopy and AE. The time of interest for each exper-406 iment was 5 seconds during which, based on a common trigger (see Section 2), 407 all time-dependent devices recorded simultaneously. Microscopic images of 408 the fracture surface were obtained by a numeric microscope (Keyence) with a 409 spatial resolution of 2.53 μ m/pix. With DIC being a surface measurement tool, 410 images obtained by the inclined camera provide in-volume understandings of 411 crack front complexities to account for deviations of the crack tip location mea-412 sured on the DIC face to the crack front within the volume. Eventually, AE lo-413 calization is performed to confirm that AE signals are actually emitted within 414 the vicinity of the crack front and thereby avoid any misconceptions by po-415 tential environmental noise. DIC displacement fields and their corresponding 416 Williams' series projections are presented in Figure 6. 417

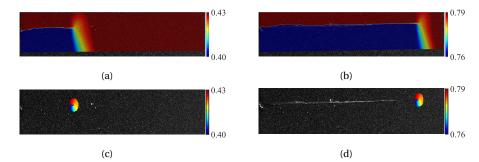


Figure 6: Vertical displacement field [mm] and corresponding Williams' series projection [mm] within the domain surrounding the crack-tip (defined by R_{min} and R_{max}) of the first and last recorded image for experiment T13. The used Williams' series parameters are listed in Table 3.

418 4.1. Distinctive macroscopic features of the cracking cases

As introduced earlier, two propagation scenarios – a reference (smooth 419 model crack propagation) and two complex cracking experiments (closer to 420 real case life cracking scenario) – have been investigated from surface kine-421 matics and acoustic emissions points of view. More precisely, a pure mode I 422 fracture experiment is denoted as reference, with T5 and T13 presenting com-423 plex fracturing experiments. Let us start from a macroscopic perspective. By 424 presenting the three experiments in the space of normalized crack length as 425 a function of experimental time (Figure 7(a)) and velocity as a function of the 426 normalized crack length (Figure 7(b)), their difference in cracking behavior is 427 highlighted. The normalization of the crack length is done with respect to the 428

maximal possible crack propagation distance of 63 mm, imposed by the sam-429 ple geometry (Figure 1). The crack propagation of the first loading stage, i.e. 430 pre-crack, is leading to slightly $(\pm 3 \text{ mm})$ different starting positions of the crack 431 length for each experiment. Apart from really tiny steps in T5 (at 2.4 s, 3.2 s and 432 4.2 s) and T13 (at 2.25 s and 3.0 s), crack propagation differences are almost un-433 recognizable in the three cracking cases by focusing on the crack length evolu-434 tion. However, by taking velocities into consideration, disturbed propagation 435 of the complex cracking cases becomes more prominent. With an imposed ex-436 tension rate of 0.07 mm.s⁻¹, mean velocities of 4.6 mm.s⁻¹, 3.9 mm.s⁻¹ and 437 4.2 mm.s⁻¹ are measured for the reference, T5 and T13, respectively. While 438 rather tiny velocity oscillations $(\pm 0.5 \text{ mm.s}^{-1})$ are found in the reference ex-439 periment, strong variations – reaching peak crack speeds of 20-30 mm.s $^{-1}$ – 440 are detected during experiments T5 (± 3.9 mm.s⁻¹) and T13 (± 3.2 mm.s⁻¹). Dif-441 ferences in crack behavior become further evident by taking the AE streaming 442 data into consideration. Figure 8 is showing the unprocessed AE streaming 443 output for all three experiments. Only limited AE activity is detected during 444 the reference case experiment, which suggests that elastic waves, potentially 445 released during this cracking, are below the experimental sensitivity of the AE 446 sensors. For the presented results, the average noise level is found to be 3.5 mV 447 (31 dB) for all experiments. However, no clear link between the AE activity 448 along the test and the velocity variations of the complex cracking is found at 449 this stage. 450

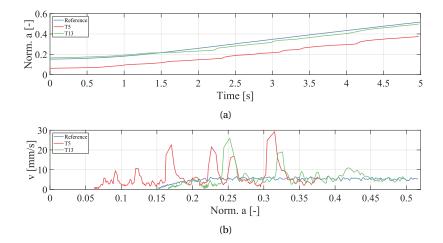


Figure 7: (a) Normalized crack length [mm] as a function of recorded time [s] and (b) velocity [mm/s] as a function of the normalized crack length [mm].

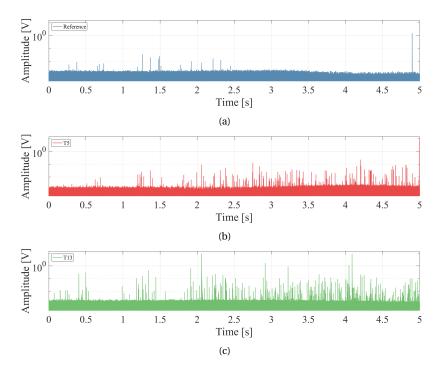


Figure 8: Raw AE streaming data (Amplitude [V] in log-scale vs. Streaming time [s]) of experiments (a) Reference, (b) T5 and (c) T13.

451 4.2. Investigation of complex cracking cases

Firstly, AE data will be investigated independently by cropping AE wave-452 forms from the streaming and the subsequent computation of AE parameters 453 from those waveforms. By solely looking at the AE streaming output of exper-454 iments T5 and T13, strongly differing signals can already be identified within 455 the set of AE responses. With peak amplitudes almost reaching 10 V (100 dB), 456 these signals present a great variation to the average peak amplitude of ap-457 prox 0.01 V (40 dB) found for all other signals. To understand and identify their 458 origin, we will focus on experiment T13, where two signals (at 2.1 s and 4.1 s) 459 with a peak amplitude of 10 V are detected. To help analyse and classify the 460 AE activity during this experiment, a Principle Component Analysis (PCA) – by 461 taking all AE descriptors into consideration except Time and Threshold - has 462 been performed on the entire set of recovered AE signals (see Appendix B for 463 detailed information on the procedure). Underlining the discrepancy, Figure 9 464 is showing both high amplitude (HA) signals in comparison with an example 465 waveform of the lower amplitude (LA) signals, and the entire set of signals be-466 ing presented in the space of the most dominant principle component axis and 467

their AE descriptor contributions. While the differences in waveform charac-468 teristics are easily visible by comparing the two HA signals to the example of a 469 LA signal, it is worthwhile mentioning that similarities comparing the two HA 470 signals are found to be rather small. This becomes further evident by compar-471 ing all signals in the space of principle component axis. Indeed, three signals 472 are found to be relatively far from the main cluster of signals that cover the 473 space from approx. -5 to 5 along PC1 and PC2. Among these these signals, the 474 two pre-defined high amplitude signal are the ones deviating the most from 475 the rest presenting a local instability, where its origin is investigated in detail 476 in the following section. However, with only a peak amplitude of 1 V, the third 477 one (appearing at approx. 4.1 s shortly before the second HA signal) deviates 478 from the majority of the lower amplitude signals, but does not compare to the 479 HA signals being associated with local instabilities. 480

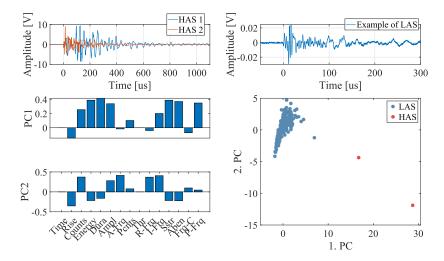


Figure 9: HA signals and an example of a LA signal, contributions to the two most dominant principle component axis (PC1 and PC2) and all AE signals presented in the space of first and second principle component.

481 4.2.1. High amplitude (HA) signals

To identify the origin of the HA signals, the position of their potential source activity needs to be spatially located on the fracture surface. As previously discussed, the time of arrival of these signals can be associated to a frame of the DIC and inclined recording due to the device synchronization. Considering a camera temporal sampling of 16 ms and wave propagation times (from sensor to any potential source location) below 30 μ s, DIC and AE timelines can be matched without any shift correction. Hence, through means of DIC crack tip

detection and in-volume recordings, the position of the crack front at the po-489 tential time of elastic wave formation can be identified. This conclusion only 490 holds true if AE signals are actually associated to the position of the DIC crack 491 tip. The crack tip is identified when any AE signal is received by the transducer 492 even in the case that the signal has not been released by the propagating crack. 493 To eliminate this question and avoid any potential misconceptions, AE source 494 localization was performed. Figure 10 shows the AE source localization of the 495 two HA signals. Black crosses indicate the current position of the crack front 496 (identified by DIC) at the time of the first AE threshold crossing. It is worthwhile 497 mentioning that the indicated crack tip position is the DIC crack tip detection 498 and therefore the position on the DIC face. Hence, no crack front complex-499 ities – potential variations of $\pm 650 \ \mu m$ – are taken into account. Green dots 500 present the results of the AE source localization. As references, positions of the 501 AE sensors (S1, S2, S3 and S4) and the field of view (FOV) covered by the DIC 502 camera are presented with black circles and a dashed rectangle, respectively. 503 The dashed red ellipse indicates the identification uncertainty for this specific 504 source location based on our numerical twin (see Section 3.1.2). With both 505 signals being located within the zone of uncertainty, it is confirmed that the AE 506 signals have been emitted from or within close vicinity of the crack tip. Thus, a 507 deeper analysis of the fracture surface in the spatial vicinity of the crack front 508 for the two considered instants can be pursued. 509

Figure 11 is showing (a) the spatial evolution of the cumulative absolute 510 energy of the AE activity and the crack front at the instant of the two HA sig-511 nals on the fracture surface, as well as (b) and (c) detail views of the fracture 512 surface. Crack propagation is from left to right with the notch tip at x = 0 mm. 513 Smooth triangular zones, visible in fracture surface zooms (Figure 11 (b) and 514 (c)), are associated to unstable dynamic crack propagation. Macroscopically 515 smoother fracture surfaces are related to cracks propagating at speeds between 516 $36-200 \text{ m.s}^{-1}$ (?). The recurrence of dynamic and quasi-static crack propaga-517 tion with their fingerprint on the fracture surface have already been observed 518 in many studies (Ravi-Chandar and Balzano, 1988; Bonamy and Ravi-Chandar, 519 2003; Hattali et al., 2012; Vasudevan, 2018), and thoroughly investigated in 520 our recent work (?). Such dynamic instabilities, i.e. cracks suddenly jumping 521 over significant distances at average speeds of approx. 100 m.s⁻¹, might be 522 induced by thermo-visco-elastic effects through rising temperatures at crack 523 tip (Vincent-Dospital et al., 2020). While large scale dynamic instabilities, un-524 der purely mode I cracking conditions, can be provoked by particular exten-525 sion rates due the existence of forbidden crack tip velocity domain for stable 526 crack propagation (see (?)), we observe that unsymmetrical through thickness 527 openings of the fracture front can lead to localized dynamic instabilities even 528

at slower extension rates (0.07 mm.s⁻¹ instead of >0.5 mm.s⁻¹ for large scale instabilities). Indeed, the particular fracture surface markings, associated with such cracking, are found in large scale and in the local scale.

As illustration, Figure 12 shows the raw streaming output with crack length 532 measurements of large scale instabilities during alternate cracking experiment 533 from our previous study (?). Here, dynamic crack propagation is defined by AE 534 signals with peak amplitudes of 10 V (100 dB) and vertical jumps in the tempo-535 ral evolution of the normalized crack length. In comparison to these previous 536 experiments where the instability stretched smoothly along the entire sample 537 thickness, our current experiments present such mechanism localized on the 538 back side facing the inclined camera. To investigate if there is a potential con-539 nection between energy released by the crack front in large scale and localized 540 dynamic instabilities, the relationship between AE absolute energy and surface 541 area spanned by the dynamic crack propagation has been analysed. In that 542 context, Figure 13 presents the AE absolute energy of dynamic bursts as a func-543 tion of the burst area in semi-log scale. Signals of the dynamic bursts observed 544 during experiment T5 and T13 are being supplemented by those recorded dur-545 ing alternate cracking experiments of our previous study (?). While cracks re-546 leased AE absolute energies between 1.5×10^7 to 2.0×10^7 aJ to overcome areas of 547 approx. 10-130 mm² during alternate cracking experiments, AE absolute ener-548 gies of approx. 6×10^{6} , 5×10^{6} and 2×10^{6} aJ for areas of 0.34, 0.24 and 0.067 mm² 549 were found for dynamic bursts during experiments T5 and T13. Figure 13 is 550 hence suggesting a linear relationship between the AE absolute energy and the 551 log of the crack propagation area. Results are presented for one sensor, while 552 no attenuation is expected due to travel small distances. However, it is worth-553 while mentioning that the established relationship does not reflect the com-554 plete fracture energy. Retrieved data solely relays on the punctual measure-555 ment of the AE transducer. Thus, AE absolute energy measurements – com-556 puted as the time integral of the squared voltage signal – bear a proportionate 557 and directional bias, while also relaying on the intrinsic transfer (potentially 558 complex) function of the sensor. 559

Furthermore, through the identification of local instabilities of the crack 560 front, crack velocity measurements can be reevaluated. For this, the crack front 561 was computed for each frame by the crack front extraction algorithm (Section 562 2.6). Before deriving the temporal evolution of the crack front to obtain the ve-563 locities, the crack front displacements were smoothed over time by a second 564 order polynomial Savitzky-Golay filter over a window of three frames. Figure 565 14 presents, as a function of the recording time, the DIC determined crack tip 566 speed, the absolute voltage signal of the AE streaming and in-volume deter-567 mined velocity map of the entire crack front. By comparing Figure 14 (a) and 568

(b), one can observe that the DIC crack speed increase (Figure 14 (a)) at 2.2 s ap-569 pears, in time, approx. 100 ms after the detection of the local instability in the 570 AE streaming (Figure 14 (b)). This can be explained by the spatial position of 571 the dynamic burst along the depth of the sample. Taking Figure 14(c) into con-572 sideration, local dynamic instabilities can be identified as crack front jumps on 573 the inclined camera face at around 16 mm and 27 mm. Hence, the first peak 574 in the DIC crack velocity can not be associated directly to the instability itself, 575 but rather to the crack front catching up belated with the strong local advance-576 ment. It is worth mentioning, that the DIC-side velocities retrieved from the 577 crack front kinematics do match the apparent crack tip speed captured by DIC. 578 However, to enhance visualization of local velocity variations, the presented 579 velocity map in Figure 14(c) limited to an upper bound of 15 mm.s⁻¹. Thus, 580 velocity peaks around the local instabilities and their secondary impact on the 581 opposite side are saturated. As reference, the peak crack tip speed appearing as 582 secondary effect on the DIC face are found to be roughly 10 mm.s⁻¹ lower than 583 directly measured through the in-volume recordings at the spatial position of 584 the instability. Nevertheless, velocities associated to the local instabilities have 585 to be taken with cautious, since sudden and strong velocity variations can not 586 be appropriately captured with the temporal resolution of the camera (16 ms 587 interframe). Hence, it has to be expected that the dynamically related velocity 588 variations are cropped in amplitude. In the vicinity of the second local instabil-589 ity (4.1 seconds), Figure 14 (b) presents a more homogeneous increase in crack 590 front velocity along the sample thickness covering up potential secondary ef-591 fects on the DIC face. However, while the first local instability (peak velocity of 592 about 34 mm.s⁻¹) was not strong enough to provoke a homogeneous increase 593 in crack tip speed along the entire sample thickness, no observable impact by 594 the second one (a peak velocity of about 22 mm.s⁻¹) can be expected on the 595 DIC face. 596

General observations of the crack front kinematics shown in Figure 14(b) 597 present a rather homogeneous crack front speed for about 2 s until the appear-598 ance of the first local instability. Thus, it seems that this local instability pro-599 duces a disturbance of the crack front behaviour resulting in global, periodic 600 accelerations and declarations of the crack front with local velocity variations. 601 Finally, Figure 15(a) presents, as a function of the recording time, both crack 602 front velocity heterogeneity (computed as the standard deviation (σ) of the ve-603 locity along the crack front at every time) and the AE streaming of experiment 604 T13. A clear correlation can be observed. Apart from some AE activity and tiny 605 velocity variations, the majority of AE activity and velocity variations are found 606 after the first dynamic instability at 2.1 seconds. Particularly around 2.1, 2.9, 607 3.5 and 4.1 seconds, good temporal agreement can be observed between the 608

increase in crack front velocity heterogeneity and the density of the AE activity. 609 Underlining this correlation, Figure 15(b) and (c) present the interframe 610 threshold crossings (counts), i.e. cummulative counts within a window of 611 16 ms, as a function of the mean and standard deviation of the velocity along 612 the crack front, respectively. The colorbar presents the experimental time. 613 Both figures highlight the crack front disturbance introduced by the first dy-614 namic instability. Figure 15(b) clearly shows a separation of the homogeneous 615 crack front phase with low AE activity (i.e. small number of interframe counts) 616 from the heterogeneous crack front phase with high AE activity (i.e. high num-617 ber of interframe counts). However, the separation of these phases is not only 618 found in time with the appearance of the local instability as disruption of the 619 balance crack front propagation, but also by a crack front mean velocity (\bar{v}) 620 threshold of about 4 mm.s⁻¹. With the interframe count as a function of the 621 crack front variations ($\sigma(v)$), Figure 15(c) is presenting a different angle on the 622 correlation defined in Figure 15(a). A more heterogeneous crack front propa-623 gation results in a higher density of AE activity. Again, taking the experimental 624 time into consideration, the first dynamic instability is found in the transition 625 between the two phases. 626

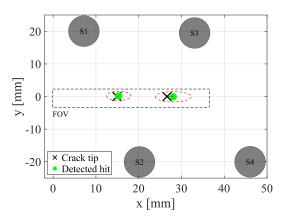


Figure 10: AE localization of the HA signals of experiment T13.

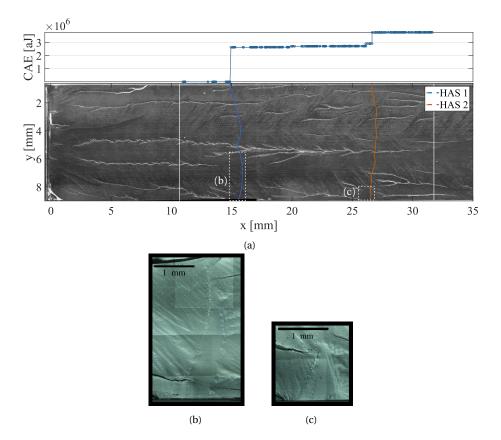


Figure 11: (a) Cumulative absolute energy (CAE) [aJ] of AE signals as a function of the crack tip position on the fracture surface with the crack front complexity for the two signals related to the dynamic bursts. (b) and (c) show a detailed view of the particular fracture surface markings associated to dynamic crack propagation.

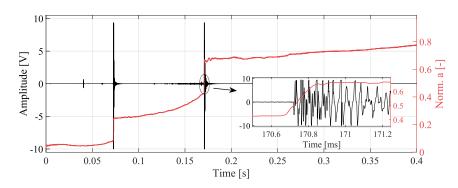


Figure 12: Normalized crack length [-] and amplitude [V] as a function of the recording time for an alternate cracking experiment.

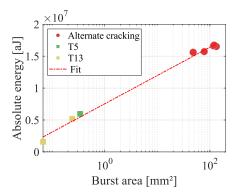


Figure 13: The AE absolute energy [aJ] as a function of the burst area (log-scale) for dynamic propagating cracks. Results are extended with data from alternate cracking experiments investigated in (?).

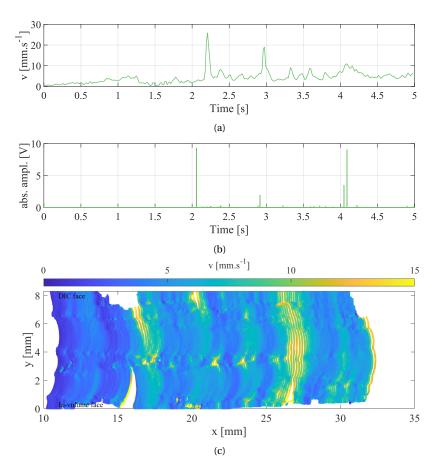


Figure 14: For experiment T13, (a) and (b) present, as a function of the recording time [s], DIC determined crack tip speed $[mm.s^{-1}]$ and the absolute voltage signal of the AE streaming, respectively, while crack front velocities $[mm.s^{-1}]$ along the sample thickness are shown in (c). Notice, white areas at the borders of the velocity map stem from the algorithm not being able to properly detect the edge of the crack front within the volume.

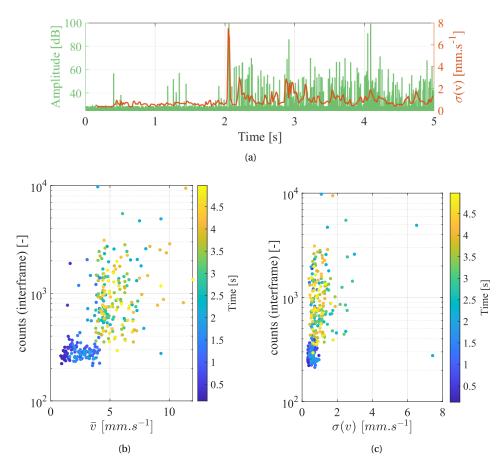


Figure 15: (a) AE streaming [dB] and the standard deviation (σ) of the velocity map [mm.s⁻¹] as a function of the recording time [s] for experiment T13. (b) and (c) present the interframe (16 ms) threshold (26 dB) crossings (counts) as a function of the mean (\bar{v}) and standard deviation ($\sigma(v)$) of the crack front velocity [mm.s⁻¹].

627 4.2.2. Lower amplitude (LA) signals

After discussing the origin of apparent crack tip speed variations, HA sig-628 nals evident relation to the localized dynamic instabilities, as well as clear con-629 nection between crack front velocity heterogeneity and the density/amplitude 630 of AE signals, we will focus on the remaining lower amplitude (LA) signals. First 631 of all, it is worthwhile mentioning that conclusions might differ with respect to 632 the AE sensor used for performing the analysis. Even when the theoretical ap-633 plication of the AE method seems rather trivial, waves propagating at different 634 velocities, while being reflected, dispersed and refracted, increases the diffi-635 culty of adequate interpretation of the recorded AE activity. Particularly in the 636

case of LA signals, the impact of each individual sensor, directionality of elastic 637 waves due to crack front complexities or the attenuation of signals from differ-638 ent wave traveling distances result in the variation of waveform characteristics 639 of the same AE signal for different sensors. This has similarly been pointed out 640 by (Maillet et al., 2015) for the classification of damage modes in composite 641 materials. To underline this, a LA example signal is presented in the Appendix 642 C (Figure C.26) with their computed AE parameters (Table C.6) for all four sen-643 sors. With extensive literature existing on the investigation and classification of 644 AE activity, the objective here is not to provide an exhaustive analysis of LA sig-645 nals but underline, complementary to the previous part, intrinsic difficulties in 646 properly associating AE responses to source mechanisms and their fingerprint 647 on the fracture surface. Contrary to HA signals, where a straightforward link 648 between apparent crack velocity variations, AE responses and fracture surface 649 features can be established, LA signals are more numerous (somehow simi-650 larly spread along the entire recording), while potentially being associated to 651 various and subtle fracture surface features. This section proposes to use the 652 developed experiment and analysis tools to discuss this complex relationship. 653 Firstly, the fracture surface of the reference and complex cracking case will 654 be compared by taking their AE activity into consideration. For this, a mi-655 croscopic image of the post-mortem fracture surface of the two fracture cases 656 are presented in Figure 16. On the one hand, with almost no AE activity (see 657 Figure 8(a)), purely mode I cracking experiments in PMMA produce a surface 658 with symmetric, wave like ligaments (see also (Hattali et al., 2012; Vasudevan, 659 2018)). These waves are found almost parallel to the crack propagation direc-660 tion with a tendency to the boundaries, while showing topographical varia-661 tions of approx. $\pm 70 \ \mu$ m. In addition, tiny regularly spaced waves (every ~ 50 -662 100 μ m), perpendicular to the crack propagation, are observed. Theses waves 663 may potentially be associated to small crack advances. On the other hand, 664 deep and unstructured scratches on a rather flat fracture surface are observed 665 during complex cracking cases, where strong AE activity is detected (see Figure 666 8(b) and (c)). At this stage, it seems reasonable to say that the change in AE ac-667 tivity is mainly due to the discrepancy observed at macro-scale, i.e. scratching 668 marks. 669

For the classification of AE signals and their characteristics, plenty of analytical methods are proposed in literature (e.g. waveform cross-correlation (Deschanel et al., 2017), parametric clustering (Guo et al., 2017, 2022), wavelet analysis (Sung et al., 2000), b-value analysis (Sagar et al., 2012), moment tensor inversion (Grosse and Ohtsu, 2008)). For this study, the more specific method of multiplet identification through waveform cross-correlation (Deschanel et al., 2017) will be pursued. As the foundation of AE analysis, the

method relies on the assumption that similar waveforms are most likely related 677 to the same source mechanism. The identification of multiplets directly com-678 pares signal characteristics by cross-correlating normalized waveforms to de-679 fine highly correlated groups of signals, i.e. multiplets (nearly identical wave-680 forms as signature of a unique source (Deschanel et al., 2017)). In the following, 681 LA signals will be investigated by waveform cross-correlation with the aim of 682 identifying AE signals, as in the case of HA signals, being linked to particular 683 fracture surface markings. To present multiplets in the AE descriptor Princi-684 pal Component (PC) space, signals were firstly normalized in this case. Indeed 685 since multiplets are based on normalized waveforms, while e.g. amplitudes 686 and energies may vary from one signal to another within a particular multi-687 plet, direct comparison between AE feature and multiplet classification would 688 be meaningless without an identical normalization in both techniques. 689

The identification of multiplets was performed only over the impulsive part, i.e. the duration of a signal free of rebounding waves. Thus, only primary waves will lead to the multiplet classification of signals. In the present case, the impulsive part was defined to be 40 μ s starting from a 5 μ s pre-trig preceding the detected time of arrival (TOA) of each waveform. A correlation coefficient above 0.75 was defined for the collection of AE multiplets.

Figure 17(a) is showing the signals associated to two multiplets in the space 696 of the first and second principle component axis of the normalized AE param-697 eters, with the contributions to the two principle components shown in Figure 698 17(b) and Figure 17(c), respectively. In the present case, due to normalization, 699 some meaningless features have been removed from the analysis: Time and 700 Threshold (as in the previous analysis of HA signals in Section 4.2.1), as well as 701 Energy, Signal Strength and R-frequency (see Appendix B for feature details). 702 When looking at Figure 17(a), clear multiplet separation is mainly observed 703 along the first principal axis. Hence, taking Figure 17(b) into consideration, 704 differentiation between AE signals associated to the two multiplets is driven by 705 rise time, count and duration. However, it is worth mentioning that a classifi-706 cation, similar to multiplet, could not be achieved using neither k-means nor 707 DBSCAN unsupervised classification methods. Different explanation could be 708 proposed for such observation: (1) Multiplets are obtained from the impulsive 709 part (40 μ s), while the AE descriptor are computed using the entire waveform. 710 Hence, the coda of the waveform makes the standard AE descriptor classifi-711 cation less straightforward. (2) Figure 17(a) shows that the entire set of lower 712 amplitude signals are closely packed within the AE descriptor principal com-713 ponent space. Thus, no clear separation can be observed in between multiplets 714 indicating that all signals share common features. 715 Furthermore, by identifying rise time, counts and duration as influential 716

waveform descriptors, one can define the RA-value (i.e. rise rime over ampli-717 tude) and relate it to the average frequency (counts over duration). Figure 18 718 is presenting all AE hits and the multiplets in the space of these two variables. 719 For granular materials, the separation of AE hits in the space of average fre-720 quency and RA-value has been correlated to tensile and shear fracture modes 721 (Aggelis, 2011; Noorsuhada et al., 2017). However, with limited information on 722 the source activity in the case of PMMA, Figure 18 allows solely for highlighting 723 the presence of two categories of AE signals, where the two multiplets are only 724 represented in one. 725

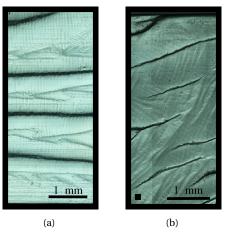


Figure 16: Microscopic image of fracture surface for (a) reference and (b) complex (T5) cracking case. Crack propagation is from left to right.

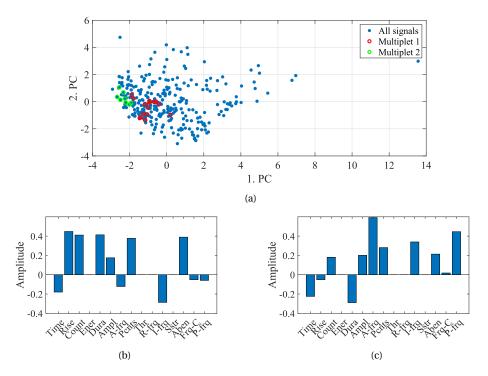


Figure 17: (a) Multiplet are presented in the space of first and second principle component axis of parameters computed from normalized AE signals, while (b) and (c) show the parametric contributions to the first and second principle component axis, respectively.

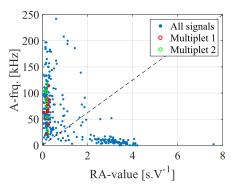


Figure 18: Average frequency [kHz] as a function of the RA-value (Rise Time over Amplitude) $[{\rm s.V^{-1}}].$

726 4.2.3. Multiplets vs fracture surface fingerprints

The normalized waveforms of the two multiplets are presented next to the 727 histogram of their correlation coefficients in Figure 19, while AE localization 728 results are presented in Figure 20 to confirm the link between AE signals and 729 crack tip activity. Indeed, waveforms associated to the two multiplets show 730 to be highly similar over the duration of the defined impulsive part (40 μ s). 731 With an average correlation coefficient of 0.48 among all captured AE signals, 732 average (and lowest) correlation coefficient of 0.88 (and 0.77) and 0.92 (and 733 0.83) were found among AE waveforms associated to Multiplet 1 and 2, respec-734 tively. Furthermore, information on the non-normalized waveforms presented 735 in Figure 19 are presented in Table 5. The position of the multiplets on the frac-736 ture surface are shown in Figure 21. Notice that three signals (3-5) of Multiplet 737 1 appear within the same time frame and are thus linked to the same crack 738 front. Hence, while 15 waveforms are collected in Multiplet 1, only 13 crack 739 front lines are shown in Figure 21. Considering the high level of correlation 740 between signals of a multiplet, one would expect to observe fingerprints of a 741 similar source mechanisms during the fracture surface investigation. However, 742 after inspecting the fracture surface in the vicinity of the expected source activ-743 ity, no particular reoccurring surface mark is observed. For both multiplets, no 744 repeating event can be unambiguously identified that is solely linked to their 745 expected position of waveform formation. In an attempt to understand such 746 observation, i.e. no clear macroscopic systematic fingerprint is observed at 747 each crack front position associated to multiplet emissions, an extrapolation 748 of Figure 12(b) is proposed. Indeed, following the observed linear relationship 749 between AE absolute energies and the log of the growth fractured area in the 750 case of dynamic instabilities (HA signals either macro or localized) and assum-751 ing similar mechanisms but at much smaller scale, an expected crack surface 752 growth associated to multiplet signals can be estimated. With a difference in 753 the dimension of millions between the AE absolute energy of LA signals (below 754 235 aJ, see Table 5) and HA signals (above 2×10^6 aJ), propagation areas below 755 \sim 22.7 \times 10³ μ m² will be associated to LA signals. In the case of a homogeneously 756 propagating crack front, this would result in crack advances of approx. 2.8 μ m 757 over the sample thickness of 8 mm for the strongest LA signal. If expressed as 758 a square with ~151 μ m sides, the sought for area is presented in Figure 16(b) 759 in the left bottom corner as reference. This underlines the difficulty to unam-760 biguously identify systematic similar fracture surface fingerprints for LA sig-761 nals with the naked eye. However, while more advance image analysis tools 762 may help, no obvious solution has been found in this work. 763

Nevertheless, Figure 15 has shown that link between AE and crack front

may be more connected to the actual kinematic of the crack front than on its 765 post-mortem characteristics. To take advantage of the observations in Figure 766 15 for the correlation of AE activity with crack front velocity heterogeneity, Fig-767 ure 22 is proposing an identification of potential locations of the AE signal ori-768 gin on the fracture surface based on crack front velocity heterogeneity. For this, 769 22(a) shows, as reference, a fracture surface extraction of the crack propagation 770 area during which the synchronized devices were active and 22(b) the velocity 771 heterogeneity of the crack front for each frame of the inclined camera record-772 ing. The figure is supplemented with the AE hits positioned for HA signals at 773 both, (1) the right time (i.e. within the crack front associated to this particular 774 time) and (2) the velocity peak along the crack front and for LA signals just at (1) 775 the right time (i.e. within the crack front associated to this particular time). No-776 tice, while positioning HA signals onto the peak velocity along the crack front 777 results in perfect identification of the source activity within the volume, one 778 can not assume the same for LA signals, since the multiplet signal does not 779 necessarily present the highest recorded AE signals associated to this frame. 780

Nevertheless, let us first focus only on the relation between the fracture sur-781 face and the crack front kinematics. Interestingly, no particular difference in 782 terms of crack surface features can be identified with respect to the two phases 783 of homogeneous (10-15 mm) and heterogeneous (15-32 mm) crack front prop-784 agation. However, velocity heterogeneity's – although different in scale – can 785 be seen in both phases in the vicinity of the artifacts (white marks) on the frac-786 ture surface. Especially notable are the two local crack front jumps between 787 two consecutive frames at approx. 15.5 mm and 27 mm that are associated 788 to the first and second local dynamic instability, respectively. Extending the 789 discussion by the AE waveforms, the two dynamic instabilities - being already 790 well understood and localized during the previous discussion - are well iden-791 tified (asterisk markers colored in magenta in Figure 22(b)) at the spatial posi-792 tion of the dynamic instability along the thickness of the sample. Noteworthy, 793 the location of the dynamic instabilities has only been identified on the DIC 794 face up to this point. Its correct fracture surface location was detected through 795 pre-existing knowledge on fracture surface patterns associated to dynamic in-796 stabilities. However, by taking the above into consideration, before made as-797 sumptions have been evidenced. 798

With respect to AE signals being related to the multiplets, one can observe that all signals appear during the more 'responsive' section of the streaming (Figure 15) after the first dynamic instability. While the crucial information provided by the through thickness crack front growth rate heterogeneity seems to correlate the signals to local perturbations (scratches/artifacts) observed on the surface, it did not provide an unambiguous explanation for the natural 805 multiplet classification.

This section, while presenting a side discussion, is a perfect example of 806 potential miss interpretation when dealing with partial AE data. Indeed, it is 807 shown that a large amount of highly similar signals - coming from the crack 808 tip - can not be systematically attributed, at least from post-mortem fracture 809 surface features, to a particular mechanism or behavior. While discriminat-810 ing fracture phenomena on signal levels has been found to be straightforward, 811 classifying within signals of similar amplitudes have been found potentially 812 misleading. 813

Table 5: Information on non-normalized waveforms associated to the multiplets.

Multiplet	Peak amplitude range	Absolute Energy range (mean)				
1	8.9 mV (39 dB) to 50 mV (54 dB)	7 aJ to 235 aJ (63 aJ)				
2	7.9 mV (38 dB) to 25 mV (48 dB)	4 aJ to 50 aJ (28 aJ)				

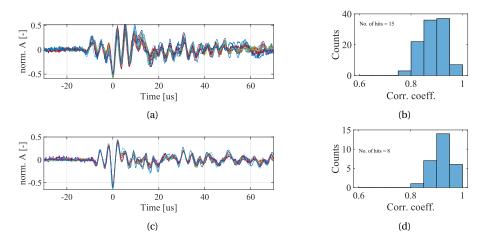


Figure 19: Normalized waveforms associated to (a) multiplet 1 and (c) multiplet 2, with their corresponding histogram of correlation coefficients ((b) and (d)).

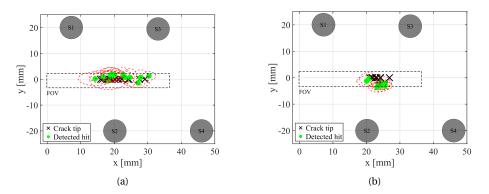


Figure 20: AE localization of (a) Multiplet 1 and (b) Multiplets 2.

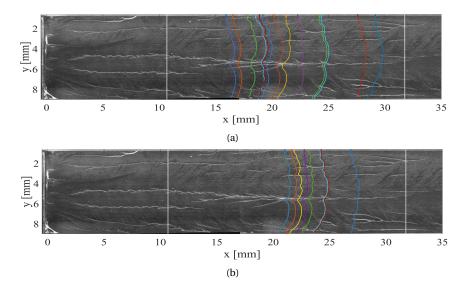


Figure 21: Crack front complexities related to waveforms associated with (a) Multiplet 1 and (b) Multiplet 2.

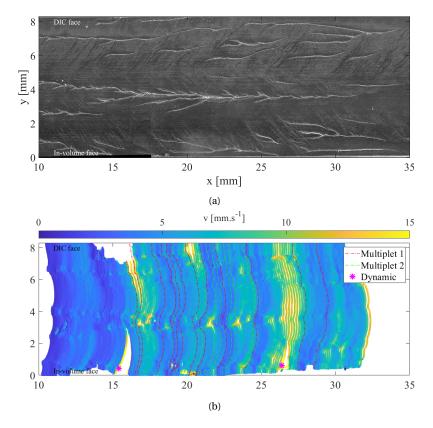


Figure 22: (a) Fracture surface crop over which the crack propagated during the experimental time and (b) corresponding crack front velocities $[mm.s^{-1}]$ presented on the extracted crack fronts from the inclined images.

5. Conclusion and perspectives

A model lab experiment under mode I dominating opening mode – with 815 slight front/back opening asymmetry leading to complex cracking behavior 816 and high AE activity - has been designed and studied through a multiple point 817 view perspective. With the aim of linking source mechanisms of AE signals 818 to post-mortem fracture surface characteristics, the combination of devices 819 allowed for a holistic investigation of the fracturing process. DIC, in-volume 820 recordings and the combination of multiple AE sensor was used for crack tip 821 detection, identification of crack front complexities/kinematics and AE source 822 localization, respectively. The analysis relies on both, automatic crack tip de-823 tection using DIC and Williams series expansion, as well as AE source localiza-824 tion. 825

The present work provides (1) a methodological/numerical and (2) physical contribution that are summarized in the following:

- 1. On the methodological side, it has been shown that:
- 829

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 The ill-posed problem of AE localization, without a priori knowl-830 edge on the wave speed, using multiple AE sensor is highly sensitive 831 to the initial guess when solving it with classical Newton-Raphson 832 algorithms. This issue can be partly overcome by designing an op-833 timization procedure for the initial guess. It has been done finding 834 for each crack tip position the best initial guess parameters for con-835 vergence using a simple numerical twin. Eventually, for the sensor 836 position considered in this work (not optimized), a localization un-837 certainty lower than 2 mm can be achieved for most of the crack 838 propagation. 839 · An image analysis procedure has been proposed to capture the po-840 sition and the kinematics of complex crack front using in-volume 841 842

- recording in the case of a transparent material. It allows for capturing local variation of the crack front kinematics, which has been found highly valuable for connecting macroscopic AE activity and crack front behavior.
- The combination of in-volume observations and apparent crack tip position from LEFM theory and DIC, it has been shown that the apparent crack tip position is closely related to the surface crack front position and does not reflect crack front complexity by a through thickness homogenization process. This point remained unclear in the literature associated to crack tip detection using William's series expansion and DIC.

2. On the physical interpretation side, the following points have been ob-served:

• A systematic connection between AE activity and crack front position has been demonstrated using both apparent crack tip detection, through DIC/Williams' series expansion, and AE localization.

 Combining AE streaming and in-volume crack front kinematics data, a strong correlation between amount and intensity of acoustic emission and heterogeneity of the crack front kinematics has been observed. Indeed, while homogeneous crack front velocity does not

862	produce signals, at least high enough to leave noise floor, once the
863	crack front kinematics become heterogeneous, strong AE activity
864	occurred. It explains the difference in term of AE activity observed
865	between pure mode I and perturbed mode I experiments in PMMA.
866	This observation is highly valuable since it demonstrates that post-
867	mortem analysis could be misleading in term of AE source mech-
868	anism analysis, since it does not necessarily reflects the transient
869	kinematics of the front.
870	• Different families of AE signals have been observed: High ampli-
871	tude (HA), a dominant class of lower amplitude (LA) signals and
872	among them two multiplets, i.e. set of signals having highly cor-
873	related impulsive waveform parts.
874	• A connection between dynamic instabilities of intermittent stick-
875	slip phenomenon produced macroscopically in PMMA when crack
876	growth rates reach the forbidden velocity domain (see (?)) and of
877	the front/back asymmetric experiments during dominant mode I
878	loading was presented. Both produce significantly higher AE sig-
879	nals compared to any other crack front relared AE activity, while
880	their particular fracture surface pattern evidenced local velocities
881	around $30-200 \text{ m.s}^{-1}$ (see (?)).
882	• A linear relationship between AE absolute energy of HA signals
883	and the log of the fracture growth area has been found considering
884	both: the present localized dynamic instabilities and macroscopic
885	stick-slip phenomenon investigated in the previous work (see (?)).
886	An attempt of extrapolation, from this relationship to LA signals,
887	has been done leading to potential fracture growth area of about
888	$150 \times 150 \mu$ m. It may evidence that LA emission are rather induced
889	by localized small crack growth than macroscopic crack advance.
890	• Two important multiplets have been observed composed of 15 and
891	8 successive AE signals with highly correlated impulsive waveform
892	parts. While their impulsive parts clearly characterize them, it has
893	been found difficult to find a similar classification using standard
894	procedures such as k-means or DBSCAN clustering algorithms of
895	the waveforms in the dominand PC space of the AE descriptors. In-
896	deed most of the LA signals share close characteristics, and consid-
897	ering the entire wave form instead of only the impulsive part makes
898	classification difficult.
899	• No clear relationship between post-mortem fracture surface fea-
900	tures, transient crack front kinematics and multiplets, or system-
	· · · ·

901atical identification of source mechanisms has been found, which902reflects the complexity of classifying (especially in a blind NDT ap-903proach) AE signals sharing similar AE amplitudes. A proposition904has been done, linking AE to localized crack front accelerations905in line with the HA signal analysis and AE/velocity heterogeneity906observations done macroscopically. However, conclusions remain907vague.

This paper has demonstrated that combining different investigation tools 908 - surface and in-volume imagine, AE and post-mortem analysis - AE sources 909 and the crack front can be undoubtedly connected for AE signals with extreme 910 characteristics such as dynamic instabilities. However, classification of LA sig-911 nals, dominant during quasi-static crack propagation, remains highly difficult 912 to connect unambiguously to a particular source mechanism even for highly 913 correlated wavesforms successively reappearing along 15 mm of crack propa-914 gation. We do believe that such lab experiment may help the design of NDT 915 algorithm discriminating in-real time different AE sources. Nevertheless, to 916 completely shed light on all blind-spots in the process of AE source identifica-917 tion, one would need to account for the visualization of elastic waves traveling 918 from their source to the transducer. Here, the presented experimental cam-919 paign would need to be extended by an ultra-high speed imaging device with 920 potential high spatial resolution (Vinel et al., 2021). However, with expected 921 strain levels induced by the energy released during small crack propagation, 922 this remains a significant experimental challenge. 923

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927 Declarations

- 928 Conflict of interest:
- ⁹²⁹ No conflict of interest is declared by the authors.

930 Appendix A. Fracture parameters by DIC

The foundation for retrieving the sought-after fracture mechanics variables is found in DIC by providing fulfield displacement measurements from sequential images. By following the principle of conservation of brightness between a reference (f) and a deformed image (g), i.e. the equation of optical ⁹³⁵ flow, DIC presents an ill-posed non-linear inverse problem:

$$f(\underline{X}) = g(\underline{X} + \underline{u}(\underline{X})) \tag{A.1}$$

with u(X) being the sought displacement field. To bypass this ill-posed prob-936 lem, the pixel displacement has to be parameterized using shape functions. 937 Here, FE discretization has been used (Besnard et al., 2006). Eventually, the 938 problem can be linearized and solved iteratively in a least-squares sense. A 939 median regularization is used to mitigate detrimental impact of noise and 940 smaller elements. By post-treating the displacement field, variables relevant 941 for fracture mechanics analysis (e.g. SIFs and crack tip positions) were derived 942 through Williams' series expansion. Traditionally, in the case of a semi infinite 943 linear elastic isotropic media, stress and displacement fields around the crack 944 tip depend on SIF, the distance to the crack tip (r) and the angle (θ) in a polar 945 reference system attached to the crack tip (Williams, 1957). Thus, by knowing 946 the displacement field through DIC and projecting it onto the analytical solu-947 tion, different fracture mechanics parameters can be derived through a non-948 linear inverse problem (Roux and Hild, 2006; Réthoré, 2015; Roux-Langlois 949 et al., 2015). The displacement field around the crack tip is written as following: 950

$$u(r,\theta) = \sum_{i=I,II} \sum_{n=-\infty}^{\infty} A_i^n r^{n/2} g_i^n(\theta)$$
(A.2)

with the distance to the crack tip r, the angle θ in a polar reference system attached to the crack tip, Williams' coefficients A and base function g. The base function $g_i^n(\theta)$ has the following form:

$$g_{I}^{n}(\theta) = \frac{1}{2\mu} \begin{bmatrix} (\kappa + n/2 + (-1)^{n}) \cos[(n/2)\theta] - (n/2)\cos[(n/2 - 2)\theta] \\ (\kappa - n/2 - (-1)^{n})\sin[(n/2)\theta] + (n/2)\sin[(n/2 - 2)\theta] \end{bmatrix}_{(e_{t}, e_{n})}$$
(A.3)

$$g_{II}^{n}(\theta) = \frac{1}{2\mu} \begin{bmatrix} -(\kappa + n/2 - (-1)^{n}) \sin[(n/2)\theta] + (n/2)\sin[(n/2 - 2)\theta] \\ (\kappa - n/2 - (-1)^{n}) \cos[(n/2)\theta] + (n/2)\cos[(n/2 - 2)\theta] \end{bmatrix}_{(e_{1}, e_{n})}$$
(A.4)

with μ and κ being the shear modulus and the Kolossov's constant, respectively. Kolossov's constant under plane stress is $\kappa = (3 - \nu)/(1 + \nu)$ with ν being the Poisson's ratio.

Equation A.2 states, that displacements can be computed for an infinite sum of modes. However, limiting the solution to $n_{min} = -3$ and $n_{max} = 7$ is sufficient to retain the relevant crack features. For quasi-brittle medium, good agreement of the mechanical fields can be established outside the process zone of the crack for the following Williams' series coefficient (A_i^n) solutions: n = 0, in-plane rigid body translations

n = 1, asymptotic terms K_I and K_{II}

n = 2, T-stress and in-plane body rotations

Notice that the projection zone (Figure 6) is defined by R_{min} and R_{max} . On 965 the one hand, the asymptotic behaviour near the crack tip of the fields com-966 puted by the super-singular terms (n < 0) do not provide any physical meaning 967 and are therefore classically neglected. However, when the crack tip position is 968 sought, these super-singular functions appear in the required basis (n=-1 be-969 ing, up to a scaling factor, the derivative of n=1 with respect to the assumed 970 crack tip position). To not induce biases due to truncation, terms for *n* down 971 to -3 are considered. Hence, data at a distance to the crack tip smaller than 972 R_{min} are discarded to maintain reasonable conditioning of the least-squares 973 problem. On the other hand, R_{max} – defining the projection zone size exter-974 nally – has to be small enough to avoid influences of the free boundary, but 975 large enough to still include a sufficient amount of mesh points in the domain. 976 The right size of projection zone, i.e. defining R_{min} and R_{max} (see Table 3), 977 has been identified through a parametric study. Furthermore, by using a pre-978 defined crack path, the super-singular term n = -1 is used to estimate the po-979 sition to the equivalent elastic crack tip along this path (Réthoré et al., 2011). 980

981 Appendix B. Principle component analysis

In AE analysis, 16 AE waveform parameters are computed by the AE system.
They are used as waveform descriptors to define the characteristics of each AE
hit. The descriptors are defined as following:

- Amplitude highest voltage in the AE waveform, expressed on the dB AE
 amplitude scale.
- Energy time integral of the absolute signal voltage. The reported mag nitude, depends on the value selected for Energy Reference Gain. Pro portional to Signal Strength.
- Counts number of times the signal crosses the detection threshold.
- Duration time from first to last threshold crossing (µs).
- RMS root mean square voltage during a period of time based on a soft ware programmable time constant, referred to the input to the signal
 processing board.

995 996	• ASL - RMS, converted to the dB AE scale (0dB AE = 1μ V at the sensor, before any amplification).
997	• Threshold - detection threshold, on the dB AE scale.
998 999	- Rise Time - time from first threshold crossing to highest voltage point on the waveform (μ s).
1000 1001	• Counts to Peak - number of threshold crossings from first to highest volt- age point on the waveform.
1002 1003 1004	• Average Frequency - Counts divided by Duration, divided by 1000 (thus, kHz). Note that this is not a spectral domain calculation, but a calculation from time domain features.
1005 1006	• Reverberation Frequency - (Counts - Counts to Peak) divided by (Dura- tion - Risetime)
1007	• Initiation Frequency - Counts to Peak divided by Risetime.
1008 1009 1010	• Signal Strength - time integral of the absolute signal voltage, expressed in pVs (picovolt-seconds) referenced to the sensor, before any amplification. Proportional to Energy.
1011 1012 1013	• Absolute Energy - time integral of the square of the signal voltage at the sensor before any amplification, divided by a $10k\Omega$ impedance and expressed in aJ (attojoules).
1014	• Frequency centroid - the center of mass of the power spectrum graph.
1015	• Peak frequency - the point where the power spectrum is greatest.
1016 1017	These descriptors are being used to identify similarities among different AE re- sponses and thereby help linking them to physical, chemical and/or mechani-
1018	cal source mechanisms. In literature and industry, different methods are being
1019	used to distinguish among sets of AE responses. Here, the Mistras group soft-
1020 1021	ware Noesis has been taken as reference and replicated in Matlab. The follow- ing methodology has then been pursued, presented on example data:
1022	1. Correlation matrix of waveform descriptors
1023	Here, a Pearson (Freedman, David et al., 2007) pairwise linear correla-

Here, a Pearson (Freedman, David et al., 2007) pairwise linear correlation between each pair of columns, i.e. waveform descriptors, has been

¹⁰²⁵ performed as followed:

$$\rho(a,b) = \frac{\sum_{i=1}^{n} (X_{a,i} - \overline{X_a})(X_{b,i} - \overline{X_b})}{[\sum_{i=1}^{n} (X_{a,i} - \overline{X_a})^2 \sum_{j=1}^{n} (X_{b,j} - \overline{X_b})^2]^{1/2}},$$
(B.1)

1026 with

$$\overline{X_a} = \frac{\sum_{i=1}^{n} X_{a,i}}{n}$$
(B.2)

and

1027

$$\overline{X_b} = \frac{\sum_{j=1}^n X_{b,j}}{n},$$
(B.3)

where X_a and X_b are columns in the parametric matrix, while n is the length of the column.

1030 2. Dendrogram plot of correlation matrix

The degree of correlation between the features of the data set has then 1031 been displayed in the form of a dendrogram. With the most correlated 1032 features joined together at the top, the degree of correlation decreases 1033 towards the bottom of the graph. This has been done to narrow down 1034 the amount of descriptors to be used for clustering and hence neglect 1035 descriptors with similar tendencies. The dendrogram plot is presented in 1036 Figure B.23. Descriptors that have high coefficients of correlation (again, 1037 1.0 being the maximum) are linked at their value of correlation and can 1038 thereby be identified. 1039

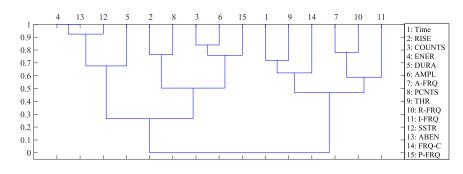


Figure B.23: Correlation matrix of waveform descriptors presented as dendrogram.

In this example, very strong correlation is found between Energy and
 Absolute Energy, which would allow the user to neglect one of them to
 reduce complexity without loosing information. Remaining parameters
 are then used for the continuation of the analysis.

1044 3. Principle components analysis

1045The principle component analysis (Karamizadeh et al., 2013) has been1046applied to increase understanding of the AE observation. In a first step,1047the most relevant principle components have to be identified.

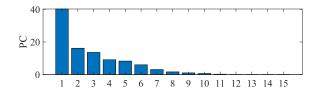


Figure B.24: Evaluation of most influential principle component axes.

1048	Based on the example case of a typical PCA of waveform descriptors pre-
1049	sented in Figure B.24, the first and second principle components con-
1050	tribute the most to the differentiation of the waveforms. Thus, investi-
1051	gated data would best be visualized in the space of the two axis. Their
1052	contribution by each AE parameter is presented in Figure B.25.

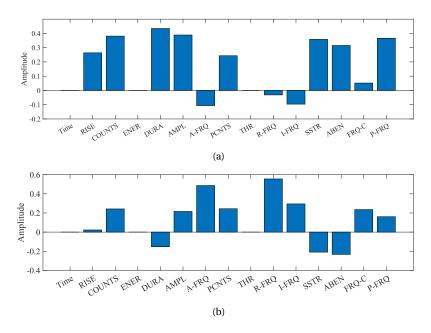


Figure B.25: Feature contributions to the (a) first and (b) second principle component axis.

1053 Appendix C. Sensor comparison

This appendix presents a particular AE signal – extracted from a multiplet - received at all four sensors. Figure C.26 shows the same signal detected at all four sensors for (a) 300 μ s and (b) 40 μ s (impulsive) of the entire signal duration. The threshold is indicated by the red dashed lines. AE parameters of the signal computed for all four sensors are presented in Figure C.6. Figure C.26(b) corresponds to a signal being presented in the core of paper in Figure 19 associated to Multiplet 1.

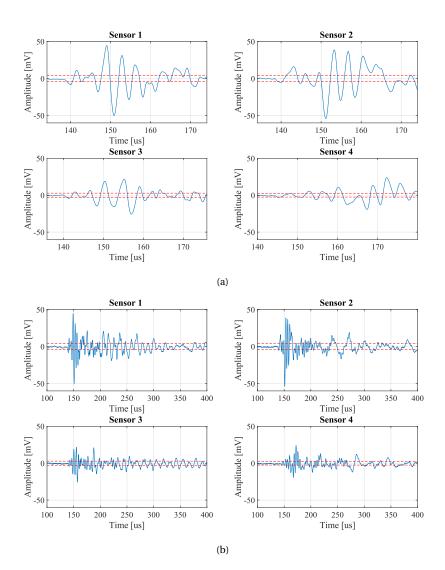


Figure C.26: Same signal detected at all four sensors for (a) 300 μ s and (b) 40 μ s (coda) of the signal. The threshold is indicated by the red dashed lines.

Table C.6: AE parameters computed for the signal in Figure C.26 in chronological order of the sensor number.

Т	ime	RISE	COUN	ENER	DURA	AMP	A-FRQ	PCNTS	THR	R-FRQ	I-FRQ	SIG STR	ABS-ENER	FRQ-C	P-FRQ
2	.4769143	12	27	3	975	53	28	3	31	25	250	2606.29	19.72	1904	106
2	.4769145	12	31	2	975	52	32	3	31	29	250	2169.2	17.21	1449	41
2	.4769161	17	32	2	973	47	33	4	31	29	235	1773.92	8.07	1276	93
2	.4769203	28	27	2	969	48	28	6	31	22	214	1795.97	7.3	1667	1

As precised in the core of the text, we can observe that the same source 1061 event can produce a significantly different signal on each sensors. While all 1062 the analysis in the paper has been done on Sensor 2, it shows that performing 1063 the analysis on different sensor may lead to slightly different results in term of 1064 classification and multiplet detection. In the present case, Sensor 1 and Sen-1065 sor 2 are systematically behind the crack front, while Sensor 3 and Sensor 4 are 1066 in front. We observe that the main difference, in terms of impulsive response 1067 (see Figure C.26(b)), is observed between signals in front or behind the source, 1068 which potentially evidences a clear directionality of the wave propagating. It 1069 underlines the complexity of analysis and classifying, in a bulk, crack propa-1070 gating, branching, turning with respect to the sensors. 1071

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