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19 Investigation of fracture source mechanisms through
20 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 in-laboratory 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 failure 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

24 **1. Introduction**

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

37 One commonly used technique is the method of Acoustic Emissions (AE).
38 With the material being subjected to external loads, sudden stress redistribu-
39 tion take place in the material due to permanent or irreversible damage phe-
40 nomena. This causes the release of elastic strain energy in the form of dissi-
41 pated heat and elastic waves. The transient elastic waves, as surface motion,
42 are captured by a transducer translating the mechanical to electrical energy
43 through the process of piezoelectricity (Arnau and Soares, 2008). After pre-
44 amplification, electrical signals are interpreted and used for the investigation
45 of source activities. Globally, AE analysis can be subdivided into three branches
46 of application: localization, lifetime prediction and damage analysis. The aim
47 of this work is however solely related to AE as a technique for damage analy-
48 sis, where AE signals have shown to be highly dependent on the type of source
49 mechanism. Different physical or chemical phenomena – material degrada-
50 tion (e.g. cracking (Kong et al., 2020)), reversible processes (e.g. melting or so-
51 lidification (Wadley and Mehrabian, 1984)), fabrication processes (e.g. grind-
52 ing (Jayakumar et al., 2005)), leak and flow (e.g. gas evolution (Cao et al., 1998))
53 – have been identified in literature as potential AE source mechanisms. The
54 appearance of these source activities are generally identified – supported by
55 methods like machine learning (Almeida et al., 2023; Ciaburro and Iannace,
56 2022), parameter clustering analysis (Li et al., 2014) or waveform processing
57 analysis (Arumugam et al., 2011) – through the identification of similar wave-
58 form characteristics of repetitive signals. However, the complexity around ac-
59 curate interpretation of the AE activity by the user prevails in each considered
60 method. Hence, to support the process of interpretation of AE signals, it seems
61 useful to approach AE analysis through the scope of reverse engineering. Due
62 to direct visible access to the fingerprint of the source activity on the fracture

63 surface, cracking phenomena seem to present a suitable activity of interest for
64 such investigation. The complete picture of the link between AE activities, state
65 variables, fracture mechanisms and fingerprints on the post-mortem fracture
66 surface might provide valuable information for the design of robust and reli-
67 able NDT algorithms.

68 To achieve a holistic understanding of source mechanisms during fracture
69 experiments of classical quasi-fragile material, this work proposes a multi-
70 modal experimental setup combining different NDT tools. With the purpose
71 of AE localization, crack tip detection and determination of crack front com-
72 plexities, combined time resolved AE, DIC and in-volume measurements with
73 post-mortem fracture surface analysis are applied on cracking experiments, re-
74 spectively. Each technique was considered to bypass the need of blind inter-
75 pretation, while allowing to tie AE signals to fracture surface patterns, i.e. en-
76 abling traceability of any captured AE signal to the spatial position of the elas-
77 tic waveform formation on the fracture surface. Model experiments on PMMA
78 are performed under predominant mode I loading conditions leading to stable
79 crack propagation, where heterogeneous crack fronts generate high density of
80 AE emissions with localized dynamic instabilities, that are leading to high am-
81 plitude AE responses. Compared with proper pure mode I experiments as a
82 baseline and unstable alternate (stick-slip) cracking (previously investigated in
83 (Heinzmann et al., 2023), the paper discusses the complexity around the abil-
84 ity of correlating AE to local fracture regimes. Such experiments may help the
85 chain of understanding the connection of fracture mechanisms and their AE
86 signature.

87 The presented work is structured as following: at first, the experimental
88 setup is described by giving detailed information on the applied NDT methods
89 DIC, AE and crack front extraction. Thereupon, a metrological assessment of
90 AE source localization and DIC crack tip detection is presented to verify the
91 applicability of the established inverse problem and detection of the equiv-
92 alent elastic crack tip position w.r.t. complex crack fronts, respectively. The
93 presented work is then concluded by a discussion on the PMMA fracturing
94 through the multi-point view setup.

95 **2. Experimental program**

96 *2.1. Material, sample geometry and AE sensor placement*

97 TDCB-shaped samples were obtained from 8 mm thick molded PMMA
98 plates (Plexiglas®) through laser cutting (Class-4 laser system). To make in-
99 tended in-volume recordings possible, only transparent PMMA plates were
100 considered. The sample geometry, as well as AE sensor positions are shown

101 in Figure 1. The coordinates $(x; y)$ of the sensor positions, with the notch tip
102 as origin, are marked in red.

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

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

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

113 With the objective of this work being the investigation of AE and crack growths
114 relationship, the second case has been considered to be a good candidate with
115 the pure mode I crack propagation case serving as reference. In the contin-
116 uation of the work, this type of cracking will be referred to as complex, while
117 referring to the reference case as smooth. For discussion, the presented data
118 is combined with AE measurements from previous experiments (Heinzmann
119 et al., 2023), where unstable crack propagation where analysed though the eye
120 of linear elastic fracture mechanics (LEFM) theory, without presenting the AE
121 measurements.

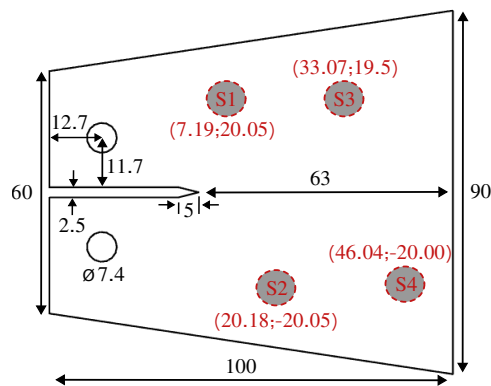


Figure 1: Sample geometry with the AE sensor positions and their coordinates (red) with respect to the notch tip [mm]. Radius of the notch tip is defined by the laser beam diameter of approximately $200 \mu\text{m}$.

Table 1: List of experiments.

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

122 *2.2. Loading and test configuration*

123 Experiments were conducted with an ElectroPuls E10 000 Instron device
 124 with a load cell of 1 kN maximum loading capacity. The room temperature
 125 was controlled at 21°C. With a two staged loading procedure (Heinzmann et al.,
 126 2023), influences of the notch tip on the cracking process were avoided. Extension
 127 rates of 0.01 mm.s⁻¹ were applied during the first loading stage initiating
 128 an approx. 1 cm pre-crack, while subsequent cracking was driven by extension
 129 rates of 0.07 mm.s⁻¹.

130 *2.3. Experimental setup and methods*

131 The investigated crack propagation was simultaneously monitored by an
 132 AE system (MISTRAS Express-8) and a camera system with two high-resolution
 133 cameras (Viework VP-50MX-M/C 30). Each of the cameras, having different
 134 purposes, faced one side of the sample. One camera was used to perform DIC,
 135 while the other was used for in-volume fracture surface recordings of the prop-
 136 agating crack. This was achieved by placing the camera with an inclination to-
 137 wards the sample surface. Notice that in-place alignment has been checked to
 138 make face-to-face image registration straightforward. Lightning for the cam-
 139 eras was provided by multiple EFFI-Sharp PWR FF (Effilux) LED projectors.
 140 The sample surface facing the camera intended for DIC measurements was
 141 coated with a speckle pattern. A form was designed and attached to the surface
 142 before coating the surface with regular spray paint, in order to ensure the best
 143 AE sensor to surface coupling by protecting the intended sensor positions from
 144 paint. Furthermore, consistent sensor placement from one test to the other
 145 was eventually achieved. Four AE sensors, positioned as visualized in Figure
 146 1, were used to capture AE activities. To improve AE localization, sensors were
 147 placed with horizontal offsets. Synchronous triggering of the systems was per-
 148 formed with a trigger box (R&D vision) being activated by the stage change of
 149 the Instron device. Like this, temporal accordance of the devices was achieved
 150 to simplify data comparison in the wake. A sketch of the experimental setup
 151 with a picture of a mounted sample is presented in Figure 2, while camera hard-
 152 ware parameters are given in Table 2.

Table 2: Camera hardware parameters

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	

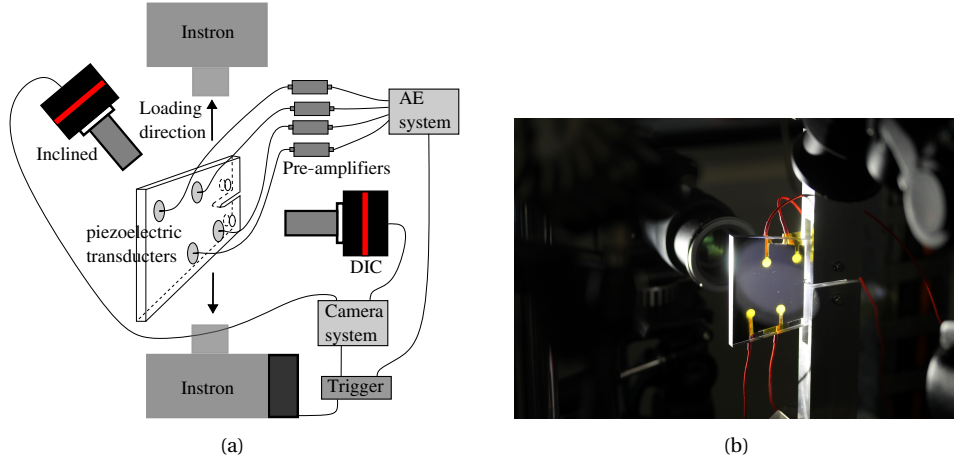


Figure 2: (a) Sketch of the experimental setup and (b) picture of an unbroken sample mounted in the mechanical device.

153 **2.4. Digital image correlation (DIC)**

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

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

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

160 using FE-based quadrilateral elements and bi-linear shape functions. Further-
 161 more, with the displacement field obtained through DIC and a post-projection
 162 of the displacement field onto the Williams' series expansion, fracture param-
 163 eter can be derived (Roux and Hild, 2006; Réthoré, 2015). Among others, the
 164 method allows for the detection of the crack tip position with a sub-pixel accu-
 165 racy. For more details on the extraction of fracture mechanics parameters, the
 166 authors refer to the Appendix A presenting an extraction from (Heinzmann
 167 et al., 2023). DIC and Williams' series projection has been performed by us-
 168 ing the library of the open-source software UFreckles (Réthoré, 2018), while
 169 required variables are listed in Table 3. Notice that in the context of this work
 170 only crack tip position will be analysed, with the projection zone (R_{min} and
 171 R_{max}) being defined by a parametric study. Furthermore, with DIC techniques
 172 working in pixels, a conversion variable is needed to find the corresponding
 173 metric/imperial data. Taking an image of a ruler placed on the sample surface
 174 and using an FFT analysis, the pixel to meter conversion value is systemati-
 175 cally obtained with a sub-pixel precision. Finally, a Savitzky-Golay filter (Poly-
 176 nomial), with a rolling windows of 50 ms, i.e. 3 frames, is applied on projected
 177 data.

Table 3: DIC & Williams' series parameters

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

178 2.5. Acoustic emission(AE)

179 AE analysis was performed with four resonant piezoelectric sensors
 180 (Medium Frequency resonant Miniature sensors Nano30 by MISTRAS). They
 181 have been mounted with conductive scotch and super glue. AE data was ob-

182 tained by the AEwin streaming option to improve optimal recovery of AE ac-
183 tivity by taking advantage of the short experiment duration (5 s). Hence, signal
184 descriptors and waveforms were computed, through in-house Matlab scripts
185 during post-processing. The AE responses were enhanced by a pre-amplifier
186 with a gain of 40 dB, while background noise filtering through an imposed
187 threshold was unnecessary since AE data was retrieved by streaming. The
188 system was calibrated and tested for appropriate coupling before each test
189 through the pencil lead break procedure (Scruby, 1987).

190 2.6. Crack front identification

191 Collecting information from within the volume, one would need CT scan
192 techniques (Crandall et al., 2017) for the investigation of opaque materials.
193 However, with PMMA existing as transparent material, capturing crack front
194 kinematics is feasible with standard image techniques. To do so, the cam-
195 era system has to be placed with an inclination to the sample surface causing
196 experimental challenges in providing sufficient light and sharpness over the
197 full sample length and thickness. Thus, lens and light settings were defined
198 on a test sample, in which the crack propagated to about half of the sample
199 length. However, already tiny deviations from the crack path of this example
200 case led to strong local variations and losses in sharpness and light with respect
201 to each newly propagating crack. Hence, a compromised lens setting and light
202 positions had to be used to facilitate the recovery of the crack front kinemat-
203 ics for any possible crack path. For post-processing, a crack front extraction
204 algorithm was built along the following steps:

- 205 1. *Normalization*: To begin with, images were normalized to correct for
206 light variations between frames.
- 207 2. *ZOI*: A zone of interest (ZOI) around the crack front was defined, within
208 which the extraction was performed.
- 209 3. *Revealing advancement*: To reveal the advance of the crack front, preced-
210 ing images were subtracted from the current one. To increase robustness,
211 not only one preceding image, but the average of a pre-defined number
212 of preceding images was taken into consideration.
- 213 4. *Binarization*: A pixel threshold, based on the mean and standard devia-
214 tion (std) of the newly created image (step 3), was defined. This threshold
215 was used to binarize the image.
- 216 5. *Erosion and dilation*: The binary image was eroded (to remove unwanted
217 pixels) and dilated (to recover continuous objects).

- 218 6. *Boundary*: Tracing the boundaries of each object to define their pixel co-
219 ordinates by the MATLAB function `bwboundaries`, which is based on the
220 Moore-Neighbor tracing algorithm modified by Jacob's stopping criteria
221 (Gonzalez et al., 2004).
- 222 7. *Exclusion*: Excluding tiny objects with a minimum amount associated
223 pixels.
- 224 8. *Reconstruction*: Rebuilding the crack front mask based on the different
225 objects.
- 226 9. *Finishing*: Recovering a clean crack front by only considering the most
227 advanced position of the rough crack front mask.
- 228 10. *Smoothing*: Applying a moving median filter to reduce periodic trends
229 from outliers along the crack front.

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

234 **3. Metrological assessment of crack tip detection and AE localization**

235 *3.1. Assessment of AE source localization*

236 *3.1.1. Methodology*

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

249 For the presented work, an inverse problem for AE source localization –
250 treating wave velocity as unknown – is proposed using four AE transducers.
251 While this problem presents itself as ill-posed (Zhou et al., 2021), it can easily be

252 build for multiple sensors (here, $n = 4$). Based on proportional relationships of
 253 distances and travel times between source and sensors, 2D source coordinates
 254 can be expressed by the nonlinear governing equation, with the assumed AE
 255 source location (x_s, y_s) and sensor positions (x_i, y_i) for all i from 1 to n . The
 256 equation is taking the following form:

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

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

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

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

$$-v^2(t_i - t_s)^2 = -(v_o^2 + 2dvv_o + dv^2)[(t_i - t_o)^2 + 2dt(t_i - t_o) + dt^2] \quad (5)$$

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

266 After neglecting squared and weakly coupled terms, Equation 2 extended by
 267 Equations 3, 4 and 5 leads to a four equation four unknown linear system.

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

$$b = [(x_i - x_o)^2 + (y_i - y_o)^2 - v_o^2(t_i - t_o)^2] \quad (7)$$

268 The system is eventually solved in a least squares minimization process as fol-
 269 lowing:

$$L^\top L = L^\top b \quad (8)$$

270 3.1.2. Uncertainty

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

- 276 • Young's modulus (E) = 3.5 GPa
- 277 • Material density (ρ) = 1200 kg.m⁻³

- 278 • Velocity (v) = $\sqrt{E/\rho} = 1707.8 \text{ m.s}^{-1}$
- 279 • Distance to the sensors i (d_i) = $\sqrt{(x_i - x_s)^2 + (y_i - y_s)^2}$, with (x_i, y_i) and
280 (x_s, y_s) being the sensor and source coordinates, respectively.
- 281 • Time of arrival (TOA_i) = d/v

282 In the following, (a) the influence of the initial guess position on the localiza-
283 tion uncertainty for various random source position and (b) the influence of
284 synthetic AE signals corrupted by expected experimental biases are investi-
285 gated.

286 Firstly, the non-linear problem is highly sensitive to the initial guess. To
287 highlight this sensitivity, localization error due to the initial guess has been
288 mapped for various random source positions. For each random position of
289 AE source, the AE localization was performed for a grid of 50x50 initial guesses.
290 As illustration, the initial guess error map is presented in Figure 3 for four ran-
291 dom AE source positions. σ denotes the distance between the located source
292 position and its real location. The figure reveals that for some initial guess (yel-
293 low areas), the algorithm may not only poorly converge but even diverge which
294 highlights the strong initial guess dependency. In practice, the cost function is
295 not always convex depending on the source location, so no convergence may
296 be achieved leading to areas of 'forbidden' initial guesses. Furthermore, no
297 particular initial guess area leading to good localization ($\sigma \approx 1 \text{ mm}$) for any
298 potential source position was detected within the field of interest. Hence, an
299 evaluation to find the most suiting initial guess has to be performed before each
300 source localization run, i.e. any new sought for AE signal requires its own op-
301 timal initial guess identification. This can easily be achieved a priori knowing
302 the crack tip position from DIC and using the proposed numerical twin being
303 presented in this section.

304 Secondly, to shift the model scenario closer to a real case, main order exper-
305 imental biases are introduced to the process of localization. A random normal
306 distributed error was drawn and appropriately scaled for each term of interest.
307 The target term with their standard deviation of the imposed uncertainty can
308 be found in Table 4. The potential errors for sensor placement, TOA and veloc-
309 ity were determined with respect to AE transducer radii of 3.7 mm, AE temporal
310 resolution of $0.1 \mu\text{s}$ and expected wave speeds of 1707.8 m.s^{-1} , respectively. It
311 is worthwhile mentioning that the TOA has been identified as the most critical
312 variable for a successful AE source localization. A rather large uncertainty was
313 thus introduced here (about 10 times the AE sampling) to stress-test the algo-
314 rithm. Indeed, signals need on average $10 \mu\text{s}$ to propagate through the field of

315 view presenting, on average, a signal to noise ratio of 90% on the TOA. How-
 316 ever, when the source goes closer to one of the sensors, since the uncertainty
 317 is kept at $1 \mu s$, the signal to noise ratio decreases a lot with the propagation
 318 time going closer to the uncertainty floor. Furthermore, identification of the
 319 TOA through cross-correlating waveforms – to achieve sub-resolution accura-
 320 cies – was not possible with waveform characteristics changing from one sen-
 321 sor to the other (see Appendix C). While regular threshold crossing and float-
 322 ing threshold crossing are the most basic methods of TOA detection, more ad-
 323 vanced methods are proposed in literature. Cheng et al. (Cheng et al., 2021)
 324 compared such methods in the case of I-shaped steel girder. With large dif-
 325 ferences in peak amplitude, the TOA was determined in the presented work
 326 through a dynamic threshold and verified by the Akaike Information Criterion
 327 (AIC) method (Hensman et al., 2010). The dynamic threshold was defined as
 328 twice the standard deviation of the absolute volt amplitude. It was additionally
 329 possible to control and potentially adapt the TOA, due to the rather manage-
 330 able amount of AE hits.

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

Error	Standard deviation
Sensor position	$500 \mu m$
TOA	$1 \mu s$
Velocity	$5 m.s^{-1}$

331 Various AE source locations were tested to evaluate the performance of the
 332 localization algorithm with respect to different areas of the field of interest.
 333 Figure 4 is showing the uncertainty (in x and y direction) of the source local-
 334 izations spanning a 20×20 grid. Each localization is presented as the median
 335 absolute deviation (MAD) of the 200 iterations with changing copies of noise.
 336 A priori identified optimal initial guesses however were kept constant for all
 337 200 runs. Highest uncertainties (MAD around 20 mm) for the localization are
 338 shown in yellow, while good identification of the source (MAD below 1 mm)
 339 are shown in dark blue. With higher accuracies in the vicinity of the barycenter
 340 of the four sensors, two main areas of weak performance can be observed be-
 341 low sensor one and above sensor four. Hence, with the localization accuracy
 342 showing strong local variations, uncertainties have to be evaluated indepen-
 343 dently for each localization attempt.

344 Ultimately, the evaluation of uncertainties shows that localization of exper-
 345 imental AE signals will need to consist out of the evaluation of the best suiting

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

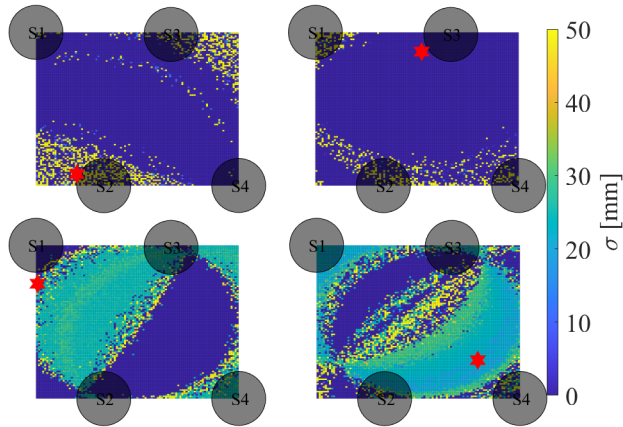


Figure 3: Map representing the sensitivity of the initial guess (50×50 grid) on the localization error for four random of AE source positions. σ denotes the distance between the located source position and its real location (red star). Sensors are presented in scale of the real sensor base area with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

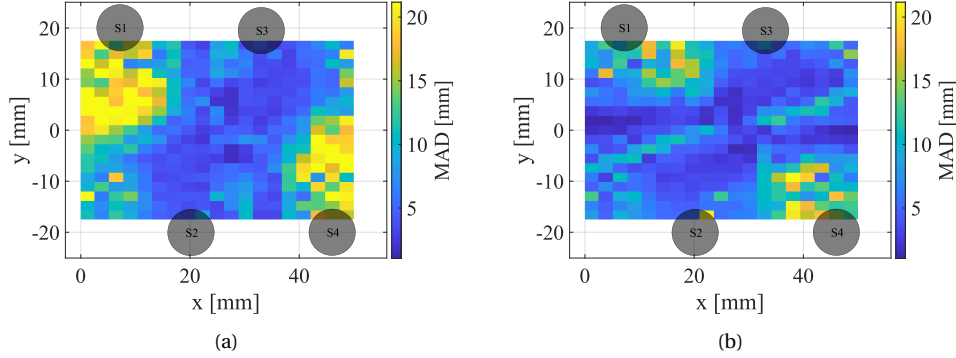


Figure 4: Median absolute deviation (MAD), i.e. mean identification uncertainty discarding outliers, on source localization depending on the source position (20×20 grid) for (a) x-direction and (b) y-direction. Sensors are presented in scale of the real sensor base area.

3.2. Assessment of crack tip detection from DIC

360 In literature, using DIC displacement fields and Williams' series expansion
 361 has become a classical method for the identification of the crack tip position
 362 (Hamam et al., 2007; Roux et al., 2009; Henninger et al., 2010; Réthoré and Es-
 363 tevez, 2013; Réthoré, 2015; Roux-Langlois et al., 2015). However, while a nu-
 364 merical investigation with a curved crack front in (Réthoré et al., 2011) esti-
 365 mated the apparent elastic crack tip position systematically in front of its free
 366 surface appearance, it has not been explored experimentally. Here, we have
 367 tried to elucidate this question through in-volume recordings of transparent
 368 PMMA plates with the back-face inclined camera. Thanks to temporal syn-
 369 chronization of the devices, each DIC frame had a corresponding in-depth
 370 image visualizing the crack surface at this time. By taking the pixel to meter
 371 conversion values of the two cameras into account, spatial matching was per-
 372 formed by taking the notch tip as common reference point. Like this, as pre-
 373 sented in Figure 5, detected crack tip positions were found in the in-depth vi-
 374 sualizations of the fracture surface. Here, the crack tip detection on the DIC
 375 side and within the in-volume images are presented for the first ((a) and (c))
 376 and last ((b) and (d)) frame of experiment T13, respectively. The white rectan-
 377 gle in Figure 5(a) and (b) is showing the field of view (FOV) of the DIC process.
 378 In Figure 5(c) and (d), the DIC face is found on the upper side of the fracture
 379 surface, with the red dashed line indicating the the crack tip position detected
 380 by DIC through the thickness of the sample and the crack front highlighted in
 381 green retrieved by the crack front extraction algorithm (see Section 2.6). By
 382 taking the constant uncertainty on the determination of the notch position in
 383 the images (approx. 20 pix) and on the pixel to meter conversion ratio from the
 384

385 FFT analysis (approx. 1.27×10^{-4}) into account, the global uncertainty on the
386 DIC crack tip detection has been found to be not more than $45 \mu\text{m}$ (see (Heinz-
387 mann et al., 2023) for details). By taking all the above into consideration, the
388 following points can be observed:

- 389 • Evaluated uncertainties are lower than the in-depth crack front varia-
390 tions.
- 391 • Despite the in-depth crack front complexity, the crack tip is systemati-
392 cally detected at the position of the crack front on the DIC face.

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

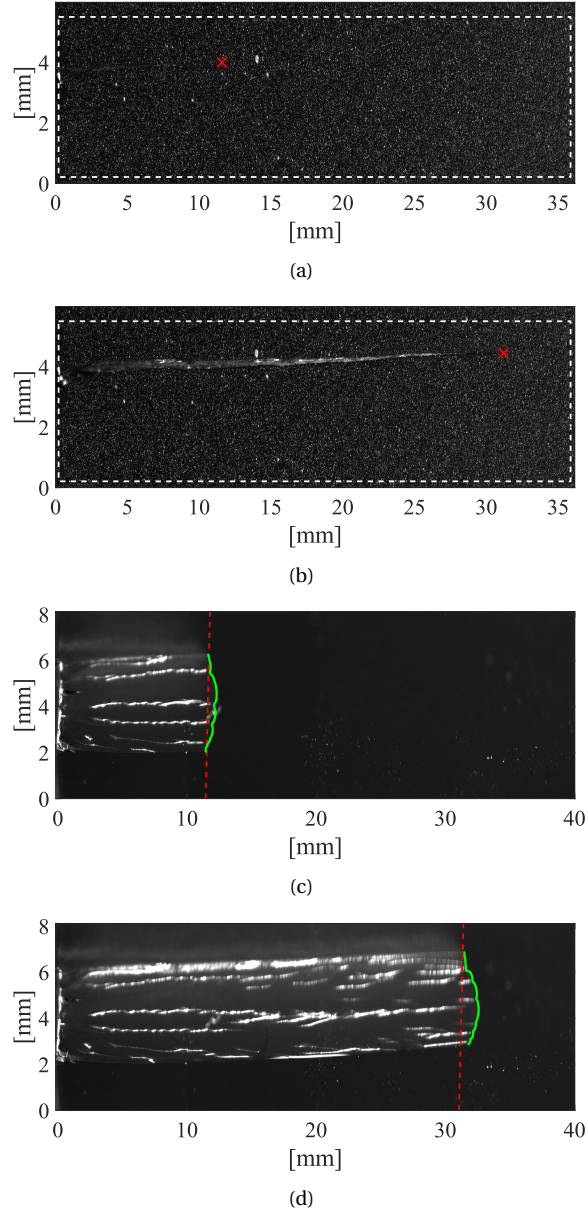


Figure 5: Accuracy in crack tip detection by Williams' series for first ((a) and (c)) and last ((b) and (d)) frame of the experiment T13. (a) and (b) shows the crack tip detection on the DIC face, with the white rectangle marking the FOV. (c) and (d) is showing the in-volume recording, where the DIC 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 μm , respectively.

399 **4. Results**

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

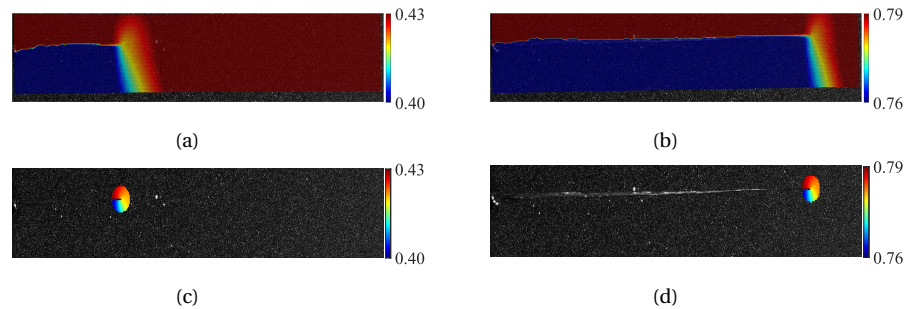


Figure 6: Vertical displacement field [mm] and corresponding Williams' series projection [mm] within the domain surrounding the crack-tip (defined by R_{min} and R_{max}) of the first and last recorded image for experiment T13. The used Williams' series parameters are listed in Table 3.

413 *4.1. Distinctive macroscopic features of the cracking cases*

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

424 maximal possible crack propagation distance of 63 mm, imposed by the sam-
 425 ple geometry (Figure 1). The crack propagation of the first loading stage, i.e.
 426 pre-crack, is leading to slightly (± 3 mm) different starting positions of the crack
 427 length for each experiment. Apart from really tiny steps in T5 (at 2.4 s, 3.2 s and
 428 4.2 s) and T13 (at 2.25 s and 3.0 s), crack propagation differences are almost un-
 429 recognizable in the three cracking cases by focusing on the crack length evolu-
 430 tion. However, by taking velocities into consideration, disturbed propagation
 431 of the complex cracking cases becomes more prominent. With an imposed ex-
 432 tension rate of $0.07 \text{ mm}\cdot\text{s}^{-1}$, mean velocities of $4.6 \text{ mm}\cdot\text{s}^{-1}$, $3.9 \text{ mm}\cdot\text{s}^{-1}$ and
 433 $4.2 \text{ mm}\cdot\text{s}^{-1}$ are measured for the reference, T5 and T13, respectively. While
 434 rather tiny velocity oscillations ($\pm 0.5 \text{ mm}\cdot\text{s}^{-1}$) are found in the reference ex-
 435 periment, strong variations – reaching peak crack speeds of $20\text{-}30 \text{ mm}\cdot\text{s}^{-1}$ –
 436 are detected during experiments T5 ($\pm 3.9 \text{ mm}\cdot\text{s}^{-1}$) and T13 ($\pm 3.2 \text{ mm}\cdot\text{s}^{-1}$). Dif-
 437 ferences in crack behavior become further evident by taking the AE streaming
 438 data into consideration. Figure 8 is showing the unprocessed AE streaming
 439 output for all three experiments. Only limited AE activity is detected during
 440 the reference case experiment, which suggests that elastic waves, potentially
 441 released during this cracking, are below the experimental sensitivity of the AE
 442 sensors. For the presented results, the average noise level is found to be 3.5 mV
 443 (31 dB) for all experiments. However, no clear link between the AE activity
 444 along the test and the velocity variations of the complex cracking is found at
 445 this stage.

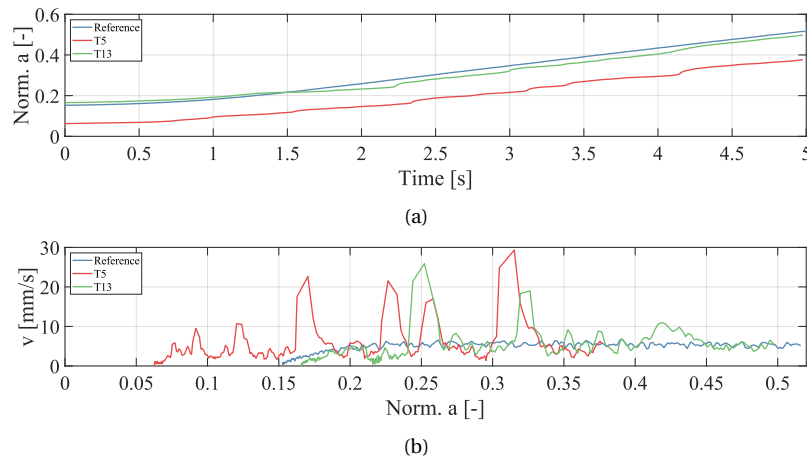


Figure 7: (a) Normalized crack length [mm] as a function of recorded time [s] and (b) velocity [mm/s] as a function of the normalized crack length [mm].

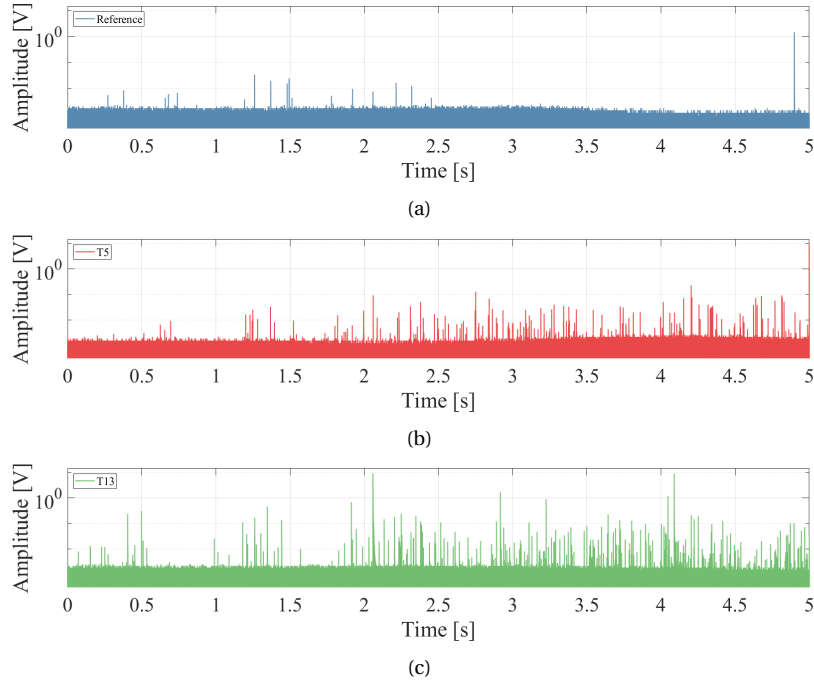


Figure 8: Raw AE streaming data (Amplitude [V] in log-scale vs. Streaming time [s]) of experiments (a) Reference, (b) T5 and (c) T13.

446 *4.2. Investigation of complex cracking cases*

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

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

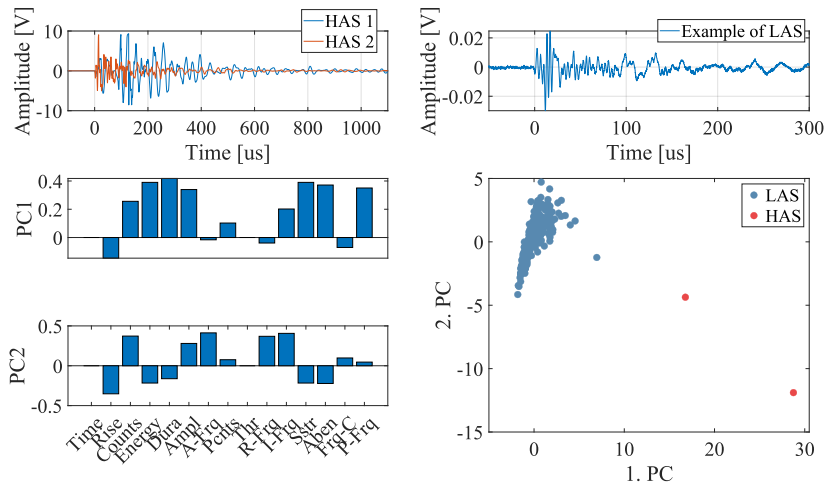


Figure 9: HA signals and an example of a LA signal, contributions to the two most dominant principle component axis (PC1 and PC2) and all AE signals presented in the space of first and second principle component.

4.2.1. High amplitude (HA) signals

476 To identify the origin of the HA signals, the position of their potential source
 477 activity needs to be spatially located on the fracture surface. As previously dis-
 478 cussed, the time of arrival of these signals can be associated to a frame of the
 479 DIC and inclined recording due to the device synchronization. Considering a
 480 camera temporal sampling of 16 ms and wave propagation times (from sensor to
 481 any potential source location) below $30 \mu\text{s}$, DIC and AE timelines can be
 482 matched without any shift correction. Hence, through means of DIC crack tip
 483

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

505 Figure 11 is showing (a) the spatial evolution of the cumulative absolute
506 energy of the AE activity and the crack front at the instant of the two HA sig-
507 nals on the fracture surface, as well as (b) and (c) detail views of the frac-
508 ture surface. Crack propagation is from left to right with the notch tip at $x =$
509 0 mm . Smooth triangular zones, visible in fracture surface zooms (Figure 11 (b)
510 and (c)), are associated to unstable dynamic crack propagation. Macroscop-
511 ically smoother fracture surfaces are related to cracks propagating at speeds
512 between $36\text{-}200 \text{ m}\cdot\text{s}^{-1}$ (Heinzmann et al., 2023). The recurrence of dynamic
513 and quasi-static crack propagation with their fingerprint on the fracture sur-
514 face have already been observed in many studies (Ravi-Chandar and Balzano,
515 1988; Bonamy and Ravi-Chandar, 2003; Hattali et al., 2012; Vasudevan, 2018),
516 and thoroughly investigated in our recent work (Heinzmann et al., 2023). Such
517 dynamic instabilities, i.e. cracks suddenly jumping over significant distances
518 at average speeds of approx. $100 \text{ m}\cdot\text{s}^{-1}$, might be induced by thermo-visco-
519 elastic effects through rising temperatures at crack tip (Vincent-Dospital et al.,
520 2020). While large scale dynamic instabilities, under purely mode I cracking
521 conditions, can be provoked by particular extension rates due the existence of
522 forbidden crack tip velocity domain for stable crack propagation (see (Heinz-
523 mann et al., 2023)), we observe that unsymmetrical through thickness open-

524 ings of the fracture front can lead to localized dynamic instabilities even at
525 slower extension rates (0.07 mm.s^{-1} instead of $>0.5 \text{ mm.s}^{-1}$ for large scale in-
526 stabilities). Indeed, the particular fracture surface markings, associated with
527 such cracking, are found in large scale and in the local scale.

528 As illustration, Figure 12 shows the raw streaming output with crack length
529 measurements of large scale instabilities during alternate cracking experi-
530 ment from our previous study (Heinzmann et al., 2023). Here, dynamic crack
531 propagation is defined by AE signals with peak amplitudes of 10 V (100 dB)
532 and vertical jumps in the temporal evolution of the normalized crack length.
533 In comparison to these previous experiments where the instability stretched
534 smoothly along the entire sample thickness, our current experiments present
535 such mechanism localized on the back side facing the inclined camera. To
536 investigate if there is a potential connection between energy released by the
537 crack front in large scale and localized dynamic instabilities, the relationship
538 between AE absolute energy and surface area spanned by the dynamic crack
539 propagation has been analysed. In that context, Figure 13 presents the AE ab-
540 solute energy of dynamic bursts as a function of the burst area in semi-log scale.
541 Signals of the dynamic bursts observed during experiment T5 and T13 are be-
542 ing supplemented by those recorded during alternate cracking experiments of
543 our previous study (Heinzmann et al., 2023). While cracks released AE abso-
544 lute energies between 1.5×10^7 to 2.0×10^7 aJ to overcome areas of approx. 10-
545 130 mm^2 during alternate cracking experiments, AE absolute energies of ap-
546 prox. 6×10^6 , 5×10^6 and 2×10^6 aJ for areas of 0.34, 0.24 and 0.067 mm^2 were
547 found for dynamic bursts during experiments T5 and T13. Figure 13 is hence
548 suggesting a linear relationship between the AE absolute energy and the log
549 of the crack propagation area. Results are presented for one sensor, while no
550 attenuation is expected due to travel small distances. However, it is worth-
551 while mentioning that the established relationship does not reflect the com-
552 plete fracture energy. Retrieved data solely relies on the punctual measure-
553 ment of the AE transducer. Thus, AE absolute energy measurements – com-
554 puted as the time integral of the squared voltage signal – bear a proportionate
555 and directional bias, while also relying on the intrinsic transfer (potentially
556 complex) function of the sensor.

557 Furthermore, through the identification of local instabilities of the crack
558 front, crack velocity measurements can be reevaluated. For this, the crack front
559 was computed for each frame by the crack front extraction algorithm (Section
560 2.6). Before deriving the temporal evolution of the crack front to obtain the ve-
561 locities, the crack front displacements were smoothed over time by a second
562 order polynomial Savitzky-Golay filter over a window of three frames. Figure
563 14 presents, as a function of the recording time, the DIC determined crack tip

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

594 General observations of the crack front kinematics shown in Figure 14(b)
595 present a rather homogeneous crack front speed for about 2 s until the appear-
596 ance of the first local instability. Thus, it seems that this local instability pro-
597 duces a disturbance of the crack front behaviour resulting in global, periodic
598 accelerations and decelerations of the crack front with local velocity variations.

599 Finally, Figure 15(a) presents, as a function of the recording time, both crack
600 front velocity heterogeneity (computed as the standard deviation (σ) of the ve-
601 locity along the crack front at every time) and the AE streaming of experiment
602 T13. A clear correlation can be observed. Apart from some AE activity and tiny
603 velocity variations, the majority of AE activity and velocity variations are found

604 after the first dynamic instability at 2.1 seconds. Particularly around 2.1, 2.9,
 605 3.5 and 4.1 seconds, good temporal agreement can be observed between the
 606 increase in crack front velocity heterogeneity and the density of the AE activity.
 607 Underlining this correlation, Figure 15(b) and (c) present the interframe
 608 threshold crossings (counts), i.e. cumulative counts within a window of
 609 16 ms, as a function of the mean and standard deviation of the velocity along
 610 the crack front, respectively. The colorbar presents the experimental time.
 611 Both figures highlight the crack front disturbance introduced by the first dy-
 612 namic instability. Figure 15(b) clearly shows a separation of the homogeneous
 613 crack front phase with low AE activity (i.e. small number of interframe counts)
 614 from the heterogeneous crack front phase with high AE activity (i.e. high num-
 615 ber of interframe counts). However, the separation of these phases is not only
 616 found in time with the appearance of the local instability as disruption of the
 617 balance crack front propagation, but also by a crack front mean velocity (\bar{v})
 618 threshold of about $4 \text{ mm}\cdot\text{s}^{-1}$. With the interframe count as a function of the
 619 crack front variations ($\sigma(v)$), Figure 15(c) is presenting a different angle on the
 620 correlation defined in Figure 15(a). A more heterogeneous crack front propa-
 621 gation results in a higher density of AE activity. Again, taking the experimental
 622 time into consideration, the first dynamic instability is found in the transition
 623 between the two phases.

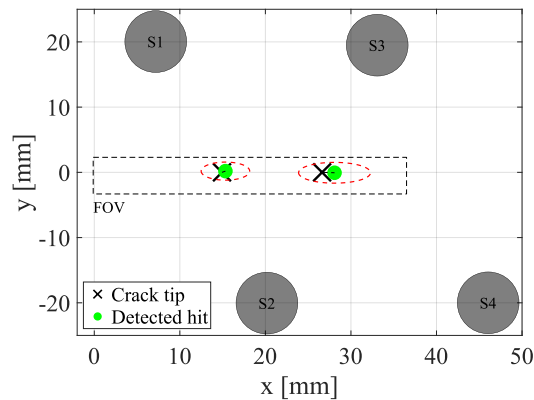
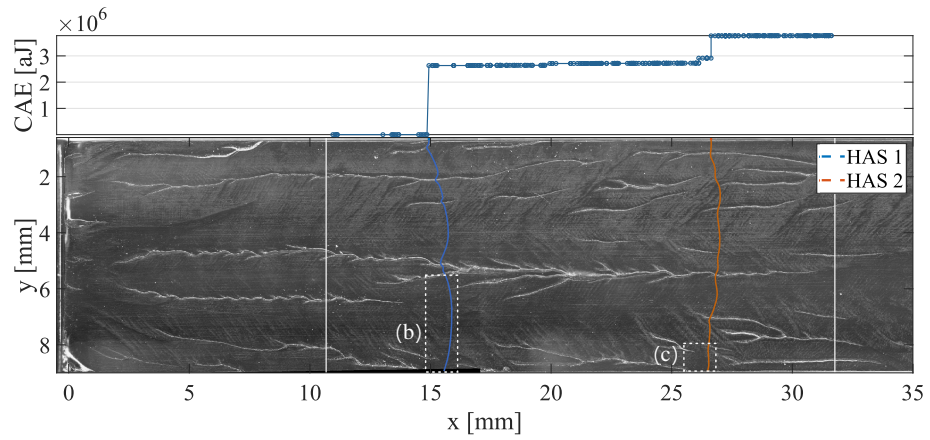
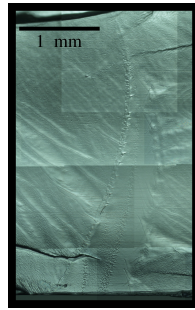


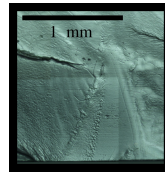
Figure 10: AE localization of the HA signals of experiment T13.



(a)



(b)



(c)

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.

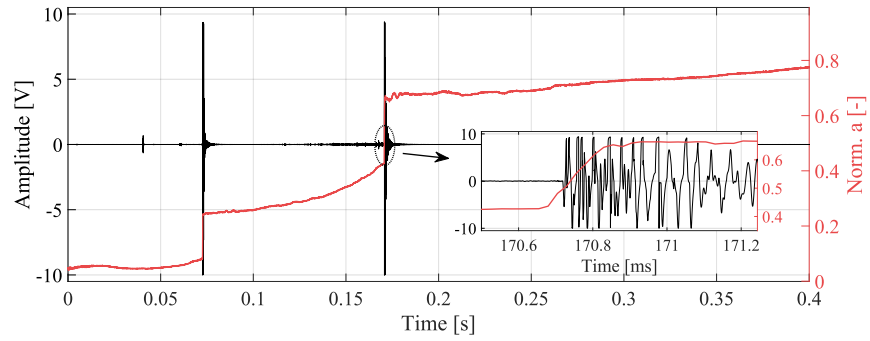


Figure 12: Normalized crack length [-] and amplitude [V] as a function of the recording time for an alternate cracking experiment.

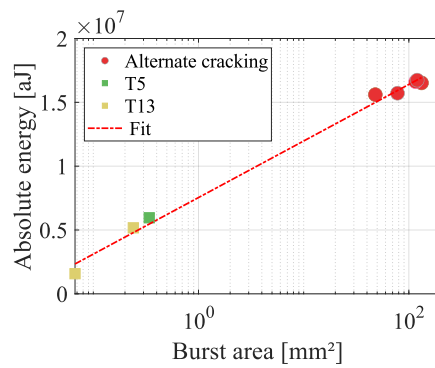


Figure 13: The AE absolute energy [aJ] as a function of the burst area (log-scale) for dynamic propagating cracks. Results are extended with data from alternate cracking experiments investigated in (Heinzmann et al., 2023).

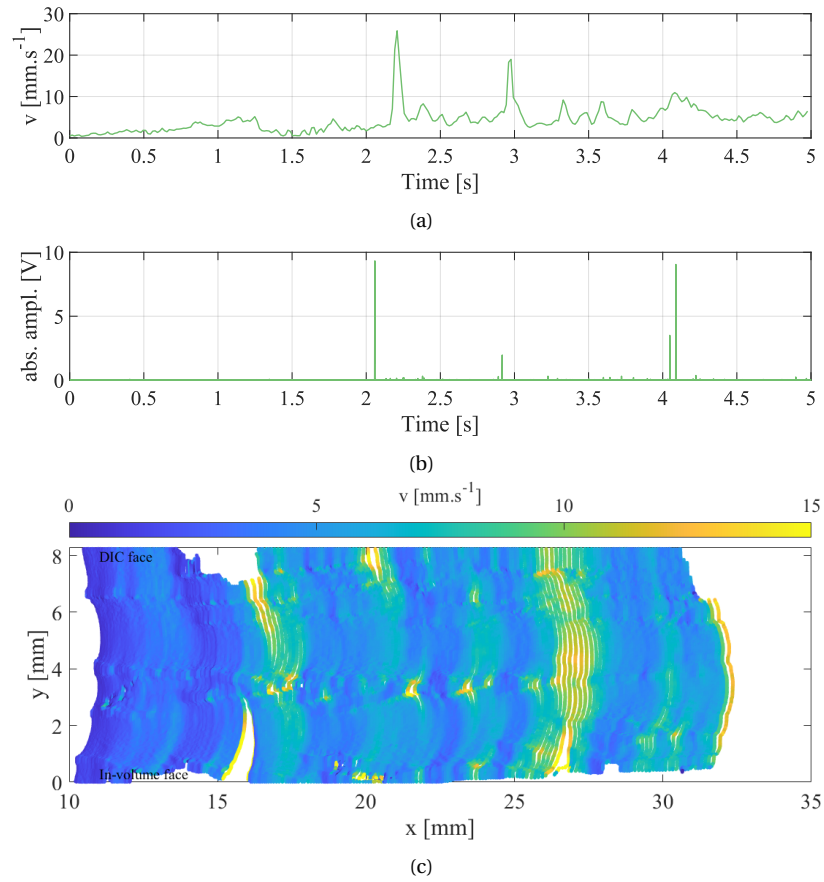


Figure 14: For experiment T13, (a) and (b) present, as a function of the recording time [s], DIC determined crack tip speed [mm.s^{-1}] and the absolute voltage signal of the AE streaming, respectively, while crack front velocities [mm.s^{-1}] along the sample thickness are shown in (c). Notice, white 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.

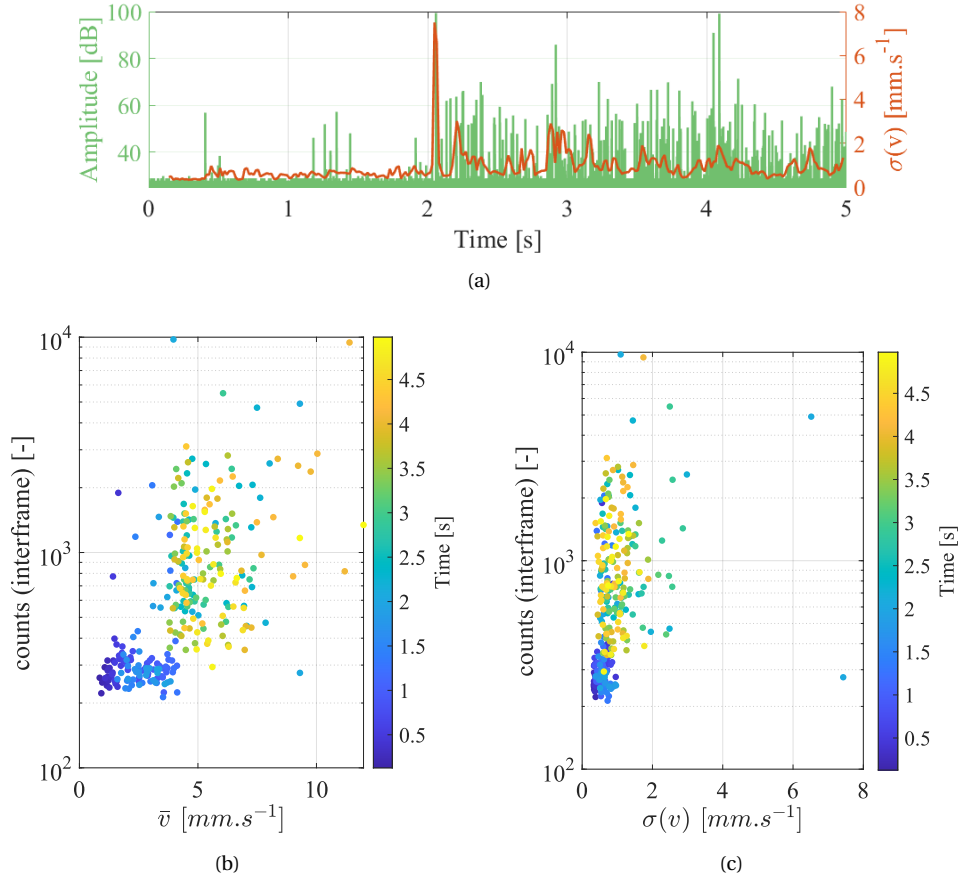


Figure 15: (a) AE streaming [dB] and the standard deviation (σ) of the velocity map [mm.s⁻¹] as a function of the recording time [s] for experiment T13. (b) and (c) present the interframe (16 ms) threshold (26 dB) crossings (counts) as a function of the mean (\bar{v}) and standard deviation ($\sigma(v)$)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

624 4.2.2. Lower amplitude (LA) signals

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

634 case of LA signals, the impact of each individual sensor, directionality of elastic
635 waves due to crack front complexities or the attenuation of signals from differ-
636 ent wave traveling distances result in the variation of waveform characteristics
637 of the same AE signal for different sensors. This has similarly been pointed out
638 by (Maillet et al., 2015) for the classification of damage modes in composite
639 materials. To underline this, a LA example signal is presented in the Appendix
640 C (Figure C.26) with their computed AE parameters (Table C.6) for all four sen-
641 sors. With extensive literature existing on the investigation and classification of
642 AE activity, the objective here is not to provide an exhaustive analysis of LA sig-
643 nals but underline, complementary to the previous part, intrinsic difficulties in
644 properly associating AE responses to source mechanisms and their fingerprint
645 on the fracture surface. Contrary to HA signals, where a straightforward link
646 between apparent crack velocity variations, AE responses and fracture surface
647 features can be established, LA signals are more numerous (somehow simi-
648 larly spread along the entire recording), while potentially being associated to
649 various and subtle fracture surface features. This section proposes to use the
650 developed experiment and analysis tools to discuss this complex relationship.

651 Firstly, the fracture surface of the reference and complex cracking case will
652 be compared by taking their AE activity into consideration. For this, a mi-
653 croscopic image of the post-mortem fracture surface of the two fracture cases
654 are presented in Figure 16. On the one hand, with almost no AE activity (see
655 Figure 8(a)), purely mode I cracking experiments in PMMA produce a surface
656 with symmetric, wave like ligaments (see also (Hattali et al., 2012; Vasudevan,
657 2018)). These waves are found almost parallel to the crack propagation direc-
658 tion with a tendency to the boundaries, while showing topographical varia-
659 tions of approx. $\pm 70 \mu\text{m}$. In addition, tiny regularly spaced waves (every ~ 50 -
660 $100 \mu\text{m}$), perpendicular to the crack propagation, are observed. These waves
661 may potentially be associated to small crack advances. On the other hand,
662 deep and unstructured scratches on a rather flat fracture surface are observed
663 during complex cracking cases, where strong AE activity is detected (see Figure
664 8(b) and (c)). At this stage, it seems reasonable to say that the change in AE ac-
665 tivity is mainly due to the discrepancy observed at macro-scale, i.e. scratching
666 marks.

667 For the classification of AE signals and their characteristics, plenty of an-
668 alytical methods are proposed in literature (e.g. waveform cross-correlation
669 (Deschanel et al., 2017), parametric clustering (Guo et al., 2017, 2022), wavelet
670 analysis (Sung et al., 2000), b-value analysis (Sagar et al., 2012), moment ten-
671 sor inversion (Grosse and Ohtsu, 2008)). For this study, the more specific
672 method of multiplet identification through waveform cross-correlation (De-
673 schanel et al., 2017) will be pursued. As the foundation of AE analysis, the

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

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

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

713 Furthermore, by identifying rise time, counts and duration as influential

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

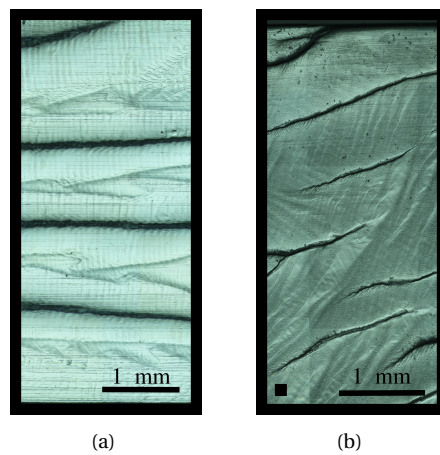


Figure 16: Microscopic image of fracture surface for (a) reference and (b) complex (T5) cracking case. Crack propagation is from left to right.

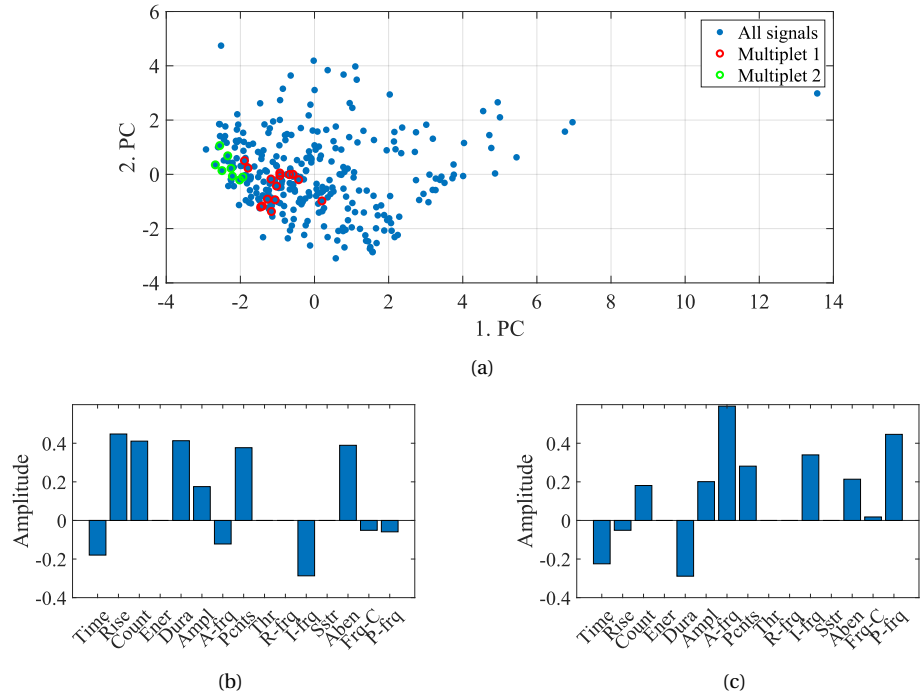


Figure 17: (a) Multiplet are presented in the space of first and second principle component axis of parameters computed from normalized AE signals, while (b) and (c) show the parametric contributions to the first and second principle component axis, respectively.

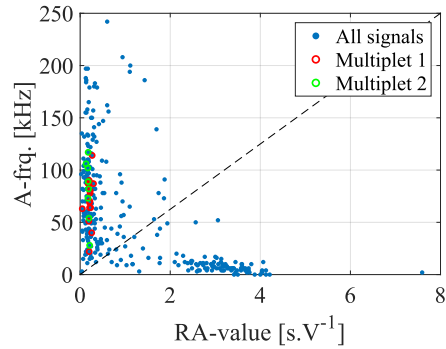


Figure 18: Average frequency [kHz] as a function of the RA-value (Rise Time over Amplitude) [s.V⁻¹].

723 4.2.3. *Multiplets vs fracture surface fingerprints*

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

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

762 may be more connected to the actual kinematic of the crack front than on its
763 post-mortem characteristics. To take advantage of the observations in Figure
764 15 for the correlation of AE activity with crack front velocity heterogeneity, Fig-
765 ure 22 is proposing an identification of potential locations of the AE signal ori-
766 gin on the fracture surface based on crack front velocity heterogeneity. For this,
767 22(a) shows, as reference, a fracture surface extraction of the crack propagation
768 area during which the synchronized devices were active and 22(b) the velocity
769 heterogeneity of the crack front for each frame of the inclined camera record-
770 ing. The figure is supplemented with the AE hits positioned for HA signals at
771 both, (1) the right time (i.e. within the crack front associated to this particular
772 time) and (2) the velocity peak along the crack front and for LA signals just at (1)
773 the right time (i.e. within the crack front associated to this particular time). No-
774 tice, while positioning HA signals onto the peak velocity along the crack front
775 results in perfect identification of the source activity within the volume, one
776 can not assume the same for LA signals, since the multiplet signal does not
777 necessarily present the highest recorded AE signals associated to this frame.

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

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

802 multiplet classification.

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

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)

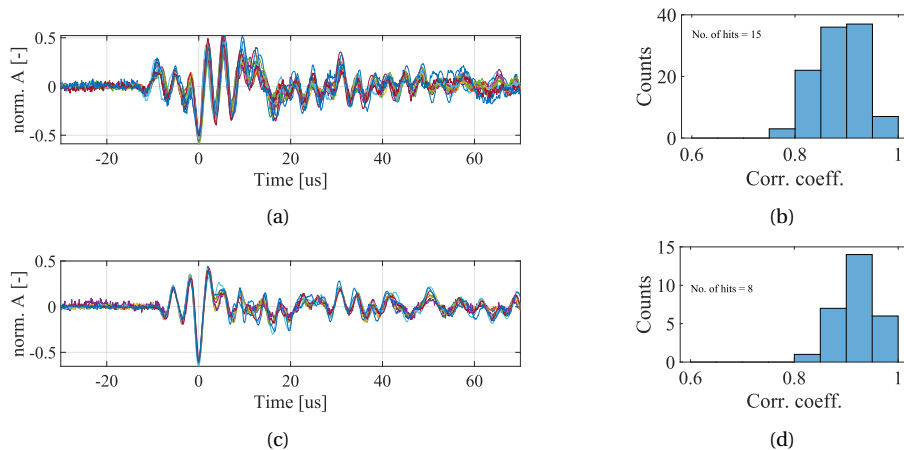


Figure 19: Normalized waveforms associated to (a) multiplet 1 and (c) multiplet 2, with their corresponding histogram of correlation coefficients ((b) and (d)).

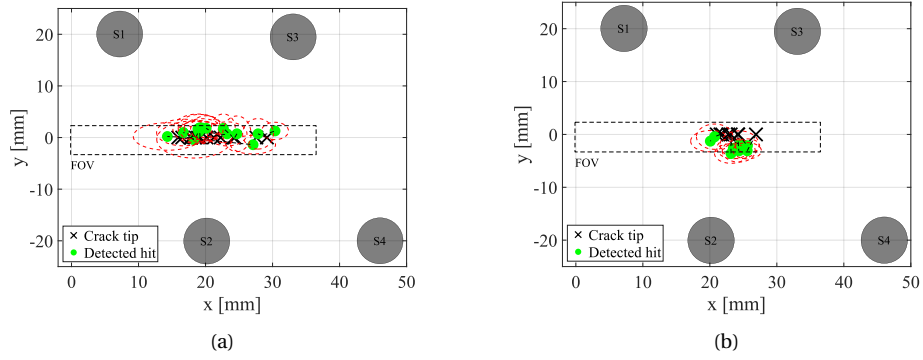


Figure 20: AE localization of (a) Multiplet 1 and (b) Multiplets 2.

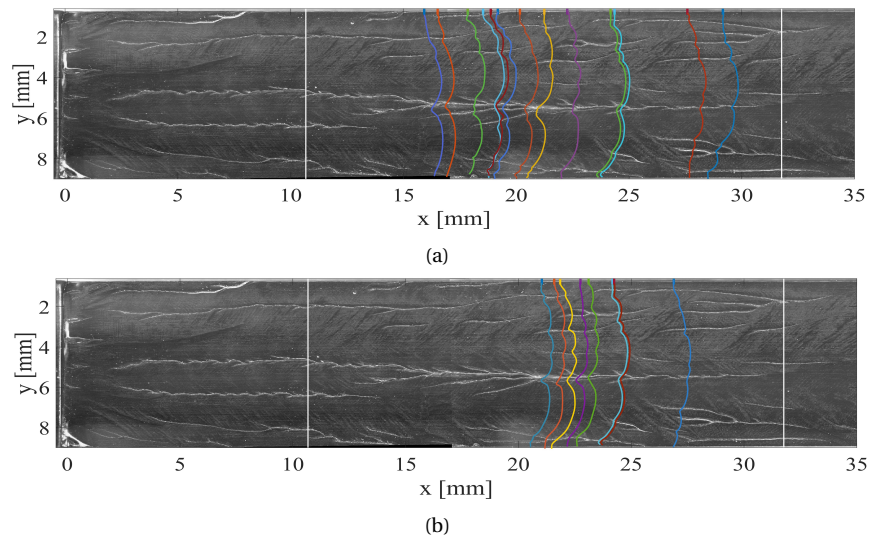


Figure 21: Crack front complexities related to waveforms associated with (a) Multiplet 1 and (b) Multiplet 2.

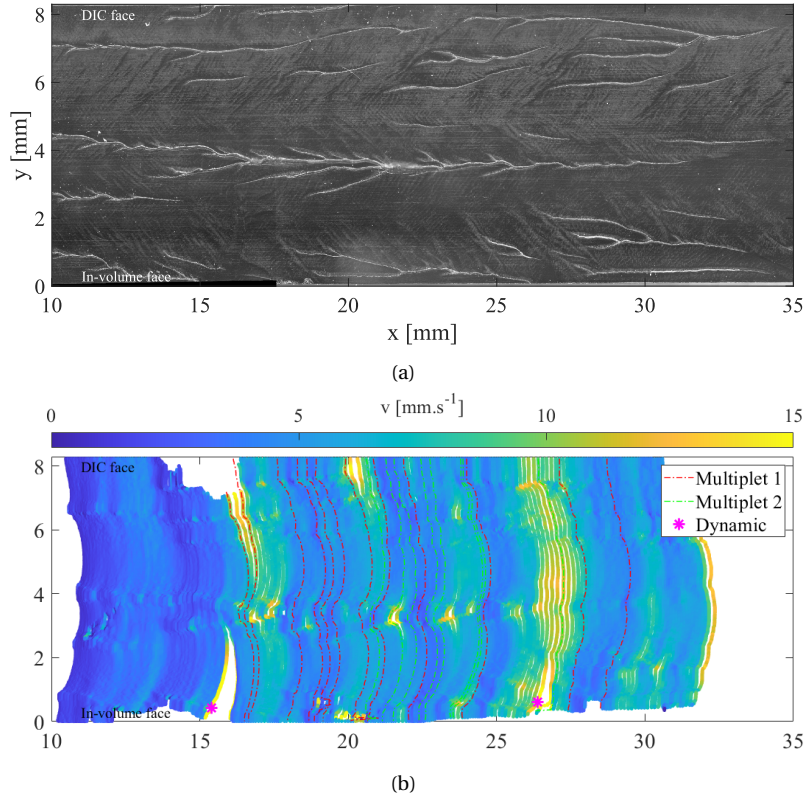


Figure 22: (a) Fracture surface crop over which the crack propagated during the experimental time and (b) corresponding crack front velocities [$\text{mm}\cdot\text{s}^{-1}$] presented on the extracted crack fronts from the inclined images.

811 5. Conclusion and perspectives

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

823 The present work provides (1) a methodological/numerical and (2) physi-
824 cal contribution that are summarized in the following:

825 1. On the methodological side, it has been shown that:
826

- 827 • The ill-posed problem of AE localization, without a priori knowl-
828 edge on the wave speed, using multiple AE sensor is highly sensitive
829 to the initial guess when solving it with classical Newton-Raphson
830 algorithms. This issue can be partly overcome by designing an op-
831 timization procedure for the initial guess. It has been done finding
832 for each crack tip position the best initial guess parameters for con-
833 vergence using a simple numerical twin. Eventually, for the sensor
834 position considered in this work (not optimized), a localization un-
835 certainty lower than 2 mm can be achieved for most of the crack
836 propagation.
- 837 • An image analysis procedure has been proposed to capture the po-
838 sition and the kinematics of complex crack front using in-volume
839 recording in the case of a transparent material. It allows for cap-
840 turing local variation of the crack front kinematics, which has been
841 found highly valuable for connecting macroscopic AE activity and
842 crack front behavior.
- 843 • The combination of in-volume observations and apparent crack tip
844 position from LEFM theory and DIC, it has been shown that the ap-
845 parent crack tip position is closely related to the surface crack front
846 position and does not reflect crack front complexity by a through
847 thickness homogenization process. This point remained unclear in
848 the literature associated to crack tip detection using William's series
849 expansion and DIC.

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

- 852 • A systematic connection between AE activity and crack front posi-
853 tion has been demonstrated using both apparent crack tip detec-
854 tion, through DIC/Williams' series expansion, and AE localization.
- 855 • Combining AE streaming and in-volume crack front kinematics
856 data, a strong correlation between amount and intensity of acoustic
857 emission and heterogeneity of the crack front kinematics has been
858 observed. Indeed, while homogeneous crack front velocity does not

859 produce signals, at least high enough to leave noise floor, once the
860 crack front kinematics become heterogeneous, strong AE activity
861 occurred. It explains the difference in term of AE activity observed
862 between pure mode I and perturbed mode I experiments in PMMA.
863 This observation is highly valuable since it demonstrates that post-
864 mortem analysis could be misleading in term of AE source mech-
865 anism analysis, since it does not necessarily reflects the transient
866 kinematics of the front.

- 867 • Different families of AE signals have been observed: High ampli-
868 tude (HA), a dominant class of lower amplitude (LA) signals and
869 among them two multiplets, i.e. set of signals having highly cor-
870 related impulsive waveform parts.
- 871 • A connection between dynamic instabilities of intermittent stick-
872 slip phenomenon produced macroscopically in PMMA when crack
873 growth rates reach the forbidden velocity domain (see (Heinzmann
874 et al., 2023)) and of the front/back asymmetric experiments dur-
875 ing dominant mode I loading was presented. Both produce signifi-
876 cantly higher AE signals compared to any other crack front related
877 AE activity, while their particular fracture surface pattern evidenced
878 local velocities around $30\text{-}200\text{ m}\cdot\text{s}^{-1}$ (see (Heinzmann et al., 2023)).
- 879 • A linear relationship between AE absolute energy of HA signals and
880 the log of the fracture growth area has been found considering both:
881 the present localized dynamic instabilities and macroscopic stick-
882 slip phenomenon investigated in the previous work (see (Heinz-
883 mann et al., 2023)). An attempt of extrapolation, from this rela-
884 tionship to LA signals, has been done leading to potential fracture
885 growth area of about $150 \times 150\ \mu\text{m}$. It may evidence that LA emis-
886 sion are rather induced by localized small crack growth than macro-
887 scopic crack advance.
- 888 • Two important multiplets have been observed composed of 15 and
889 8 successive AE signals with highly correlated impulsive waveform
890 parts. While their impulsive parts clearly characterize them, it has
891 been found difficult to find a similar classification using standard
892 procedures such as k-means or DBSCAN clustering algorithms of
893 the waveforms in the dominant PC space of the AE descriptors. In-
894 deed most of the LA signals share close characteristics, and consid-
895 ering the entire wave form instead of only the impulsive part makes
896 classification difficult.

897 • No clear relationship between post-mortem fracture surface fea-
898 tures, transient crack front kinematics and multiplets, or system-
899 atical identification of source mechanisms has been found, which
900 reflects the complexity of classifying (especially in a blind NDT ap-
901 proach) AE signals sharing similar AE amplitudes. A proposition
902 has been done, linking AE to localized crack front accelerations
903 in line with the HA signal analysis and AE/velocity heterogeneity
904 observations done macroscopically. However, conclusions remain
905 vague.

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

922 **Acknowledgement**

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924 la Recherche (ANR) through grant ANR-19-CE42-0012.

925 **Declarations**

926 *Conflict of interest:*

927 No conflict of interest is declared by the authors.

928 **Appendix A. Fracture parameters by DIC**

929 The foundation for retrieving the sought-after fracture mechanics variables
 930 is found in DIC by providing fullfield displacement measurements from se-
 931 quential images. By following the principle of conservation of brightness be-
 932 tween a reference (f) and a deformed image (g), i.e. the equation of optical
 933 flow, DIC presents an ill-posed non-linear inverse problem:

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

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

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

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

$$g_I^n(\theta) = \frac{1}{2\mu} \left[\begin{aligned} &(\kappa + n/2 + (-1)^n) \cos[(n/2)\theta] - (n/2) \cos[(n/2 - 2)\theta] \\ &(\kappa - n/2 - (-1)^n) \sin[(n/2)\theta] + (n/2) \sin[(n/2 - 2)\theta] \end{aligned} \right]_{(e_t, e_n)} \quad (\text{A.3})$$

$$g_{II}^n(\theta) = \frac{1}{2\mu} \left[\begin{aligned} &-(\kappa + n/2 - (-1)^n) \sin[(n/2)\theta] + (n/2) \sin[(n/2 - 2)\theta] \\ &(\kappa - n/2 - (-1)^n) \cos[(n/2)\theta] + (n/2) \cos[(n/2 - 2)\theta] \end{aligned} \right]_{(e_t, e_n)} \quad (\text{A.4})$$

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

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

960 $n = 0$, in-plane rigid body translations

961 $n = 1$, asymptotic terms K_I and K_{II}

962 $n = 2$, T-stress and in-plane body rotations

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

979 **Appendix B. Principle component analysis**

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

- 983 • Amplitude - highest voltage in the AE waveform, expressed on the dB AE
984 amplitude scale.
- 985 • Energy - time integral of the absolute signal voltage. The reported mag-
986 nitude, depends on the value selected for Energy Reference Gain. Pro-
987 portional to Signal Strength.

- 988 • Counts - number of times the signal crosses the detection threshold.
- 989 • Duration - time from first to last threshold crossing (μs).
- 990 • RMS - root mean square voltage during a period of time based on a soft-
991 ware programmable time constant, referred to the input to the signal
992 processing board.
- 993 • ASL - RMS, converted to the dB AE scale ($0\text{dB AE} = 1\mu\text{V}$ at the sensor,
994 before any amplification).
- 995 • Threshold - detection threshold, on the dB AE scale.
- 996 • Rise Time - time from first threshold crossing to highest voltage point on
997 the waveform (μs).
- 998 • Counts to Peak - number of threshold crossings from first to highest volt-
999 age point on the waveform.
- 1000 • Average Frequency - Counts divided by Duration, divided by 1000 (thus,
1001 kHz). Note that this is not a spectral domain calculation, but a calcula-
1002 tion from time domain features.
- 1003 • Reverberation Frequency - (Counts - Counts to Peak) divided by (Dura-
1004 tion - Risetime). .
- 1005 • Initiation Frequency - Counts to Peak divided by Risetime.
- 1006 • Signal Strength - time integral of the absolute signal voltage, expressed
1007 in pVs (picovolt-seconds) referenced to the sensor, before any amplifica-
1008 tion. Proportional to Energy.
- 1009 • Absolute Energy - time integral of the square of the signal voltage at the
1010 sensor before any amplification, divided by a $10k\Omega$ impedance and ex-
1011 pressed in aJ (attojoules).
- 1012 • Frequency centroid - the center of mass of the power spectrum graph.
- 1013 • Peak frequency - the point where the power spectrum is greatest.

1014 These descriptors are being used to identify similarities among different AE re-
1015 sponses and thereby help linking them to physical, chemical and/or mechani-
1016 cal source mechanisms. In literature and industry, different methods are being
1017 used to distinguish among sets of AE responses. Here, the Mistras group soft-
1018 ware Noesis has been taken as reference and replicated in Matlab. The follow-
1019 ing methodology has then been pursued, presented on example data:

1020 1. *Correlation matrix of waveform descriptors*
 1021 Here, a Pearson (Freedman, David et al., 2007) pairwise linear correla-
 1022 tion between each pair of columns, i.e. waveform descriptors, has been
 1023 performed as followed:

$$\rho(a, b) = \frac{\sum_{i=1}^n (X_{a,i} - \bar{X}_a)(X_{b,i} - \bar{X}_b)}{[\sum_{i=1}^n (X_{a,i} - \bar{X}_a)^2 \sum_{j=1}^n (X_{b,j} - \bar{X}_b)^2]^{1/2}}, \quad (\text{B.1})$$

1024 with

$$\bar{X}_a = \frac{\sum_{i=1}^n X_{a,i}}{n} \quad (\text{B.2})$$

1025 and

$$\bar{X}_b = \frac{\sum_{j=1}^n X_{b,j}}{n}, \quad (\text{B.3})$$

1026 where X_a and X_b are columns in the parametric matrix, while n is the
 1027 length of the column.

1028 2. *Dendrogram plot of correlation matrix*

1029 The degree of correlation between the features of the data set has then
 1030 been displayed in the form of a dendrogram. With the most correlated
 1031 features joined together at the top, the degree of correlation decreases
 1032 towards the bottom of the graph. This has been done to narrow down
 1033 the amount of descriptors to be used for clustering and hence neglect
 1034 descriptors with similar tendencies. The dendrogram plot is presented in
 1035 Figure B.23. Descriptors that have high coefficients of correlation (again,
 1036 1.0 being the maximum) are linked at their value of correlation and can
 1037 thereby be identified.

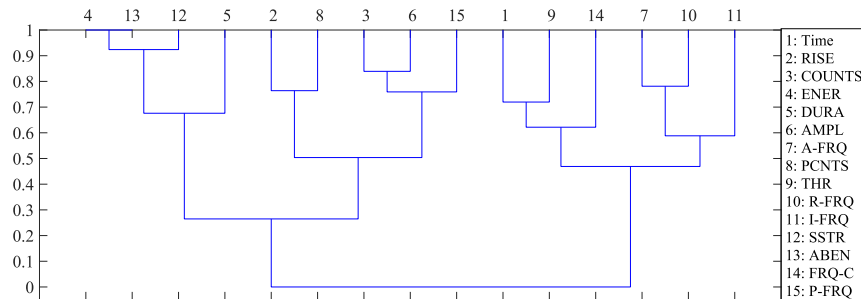


Figure B.23: Correlation matrix of waveform descriptors presented as dendrogram.

1038 In this example, very strong correlation is found between Energy and
 1039 Absolute Energy, which would allow the user to neglect one of them to
 1040 reduce complexity without losing information. Remaining parameters
 1041 are then used for the continuation of the analysis.

1042 3. Principle components analysis

1043 The principle component analysis (Karamizadeh et al., 2013) has been
 1044 applied to increase understanding of the AE observation. In a first step,
 1045 the most relevant principle components have to be identified.

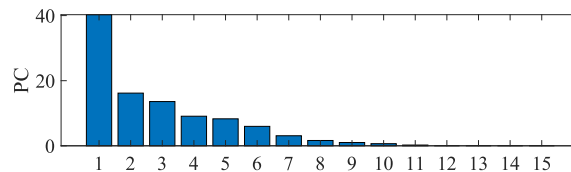


Figure B.24: Evaluation of most influential principle component axes.

1046 Based on the example case of a typical PCA of waveform descriptors pre-
 1047 sented in Figure B.24, the first and second principle components con-
 1048 tribute the most to the differentiation of the waveforms. Thus, investi-
 1049 gated data would best be visualized in the space of the two axis. Their
 1050 contribution by each AE parameter is presented in Figure B.25.

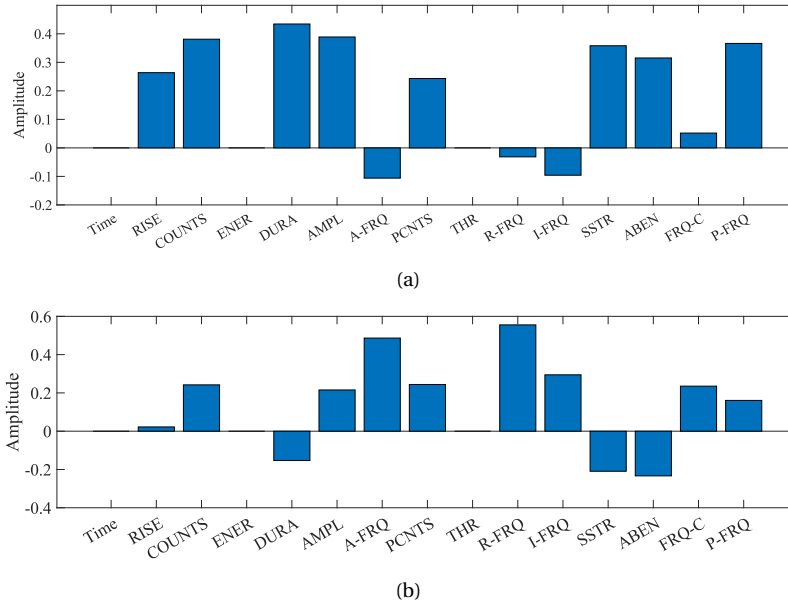
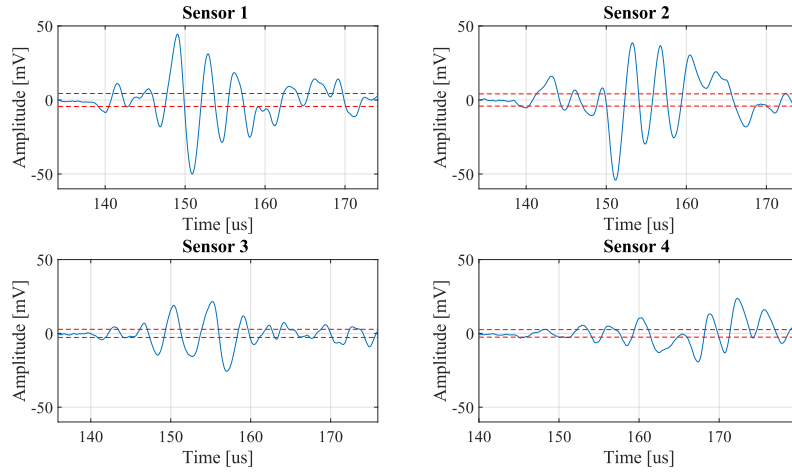


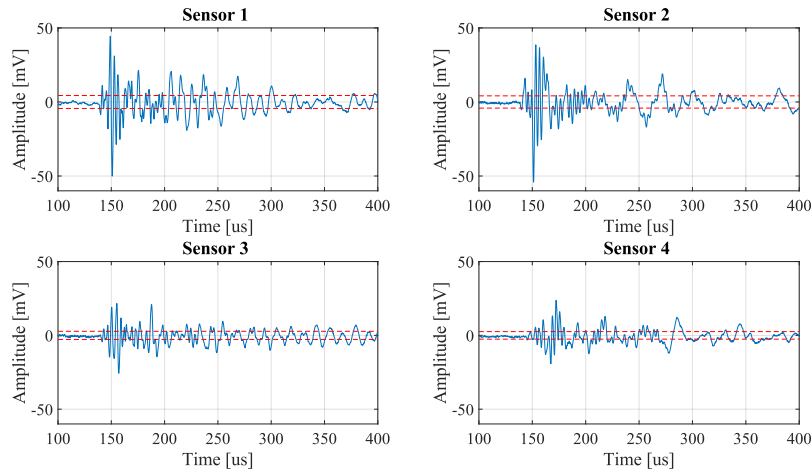
Figure B.25: Feature contributions to the (a) first and (b) second principle component axis.

1051 **Appendix C. Sensor comparison**

1052 This appendix presents a particular AE signal – extracted from a multiplet
 1053 – received at all four sensors. Figure C.26 shows the same signal detected at all
 1054 four sensors for (a) $300 \mu\text{s}$ and (b) $40 \mu\text{s}$ (impulsive) of the entire signal dura-
 1055 tion. The threshold is indicated by the red dashed lines. AE parameters of the
 1056 signal computed for all four sensors are presented in Figure C.6. Figure C.26(b)
 1057 corresponds to a signal being presented in the core of paper in Figure 19 asso-
 1058 ciated to Multiplet 1.



(a)



(b)

Figure C.26: Same signal detected at all four sensors for (a) 300 μs and (b) 40 μs (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.

Time	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

1059 As precised in the core of the text, we can observe that the same source
1060 event can produce a significantly different signal on each sensors. While all
1061 the analysis in the paper has been done on Sensor 2, it shows that performing
1062 the analysis on different sensor may lead to slightly different results in term of
1063 classification and multiplet detection. In the present case, Sensor 1 and Sen-
1064 sor 2 are systematically behind the crack front, while Sensor 3 and Sensor 4 are
1065 in front. We observe that the main difference, in terms of impulsive response
1066 (see Figure C.26(b)), is observed between signals in front or behind the source,
1067 which potentially evidences a clear directionality of the wave propagating. It
1068 underlines the complexity of analysis and classifying, in a bulk, crack propa-
1069 gating, branching, turning with respect to the sensors.

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