

Interprétation des émissions acoustiques

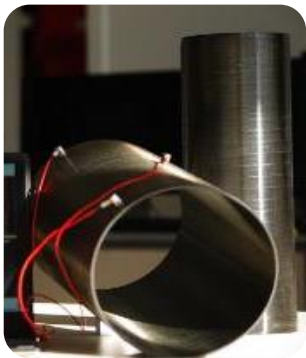
Initiative open-source

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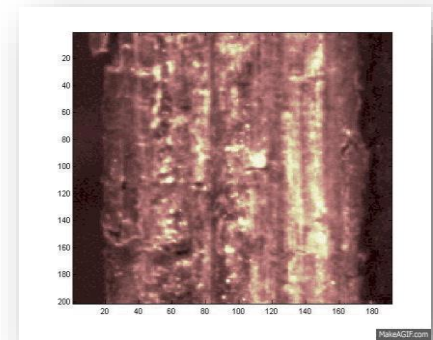
<https://github.com/emmanuelramasso>

Aidé par plusieurs étudiants et CDD : Xavier Gabrion, Mohamed Kharrat, Pablo Juesas, Thomas Jeannin, Pauline Butaud, David Renault, Benoit Verdin, Quentin Lefevre and Neha Chandarana, Fausto Simeone...
et collègues : Vincent Placet, Lamine Boubakar, Gaël Chevallier, Sébastien Thibaud, Thierry Denoex, Fabrizio Sarasini, Nathalie Godin, Matthieu Gresil...



ENSMM / FEMTO-ST / Besançon
Département Mécanique Appliquée

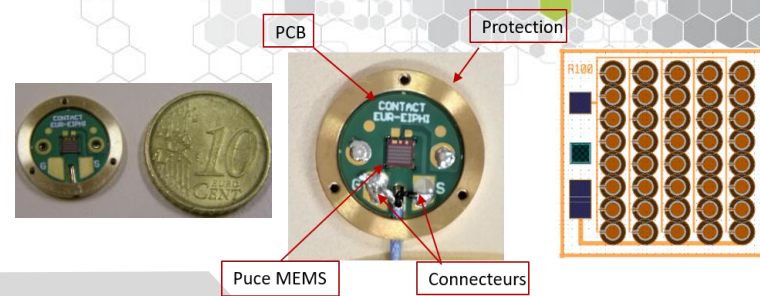
SHM-France, 6 juillet 2021



Research directions on SHM since 2011

Integrated / multidisciplinary

COLLECT



MODELING OF AE
SOURCE AND
PROPAGATION

Physics based
models

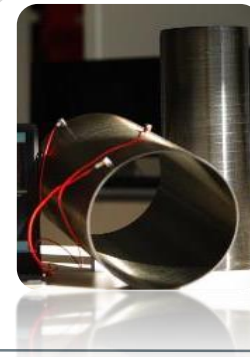
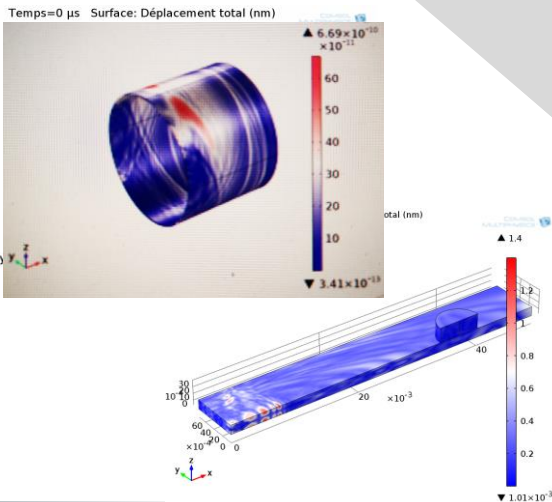
Damage detection
(transducers)

Data driven
models

SURVEILLANCE
ALGORITHMS

Demonstrators
(lab, semi or full
structural scales)

DEMONSTRATION



Three new methods and a benchmark

BENCHMARK ORION-AE

MODELE
PARAMETRIQUE SUR
LES INSTANTS DE
DECLENCHEMENT et
CINETIQUE

SIGNAUX BRUTS / RAW
SIGNALS

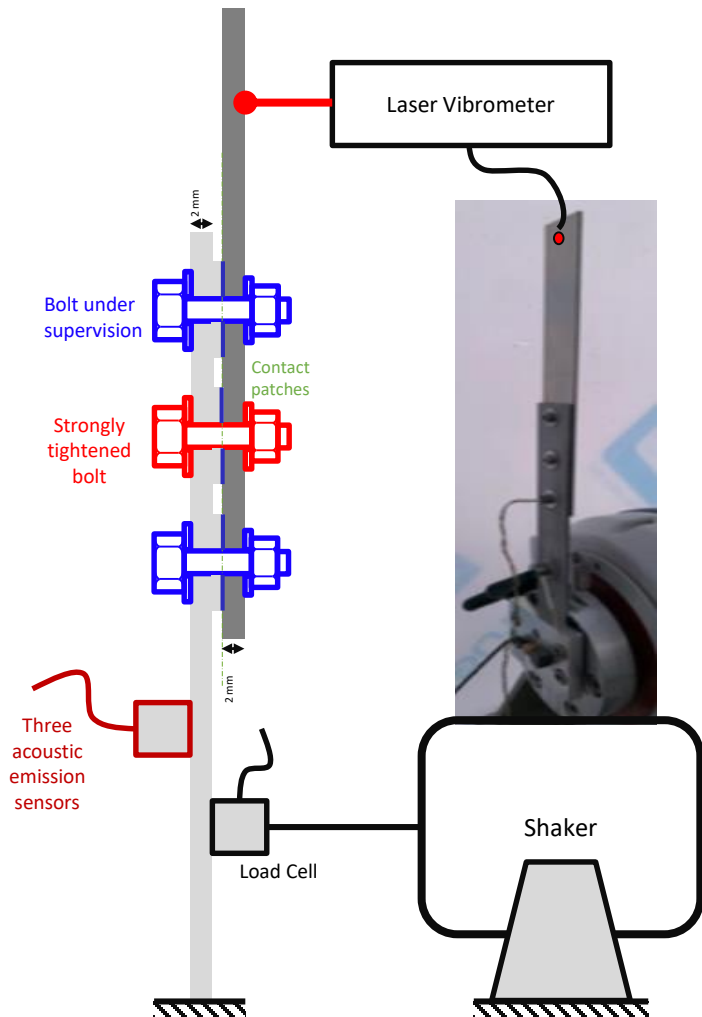
CONSENSUS
CLUSTERING

ORION-AE datasets



A common benchmark for AE clustering with ground truth.

The datasets can also be used for signal processing and (semi-)supervised (deep) learning.



- One bolt strongly tightened, one untightened manually
- **Seven** different levels considered: Can serve as « ground truth » for clustering validation.
- Harmonic sollicitation during periods of 10s at each level
- **Three different AE sensors + 1 vibrometry** data (used for controlling the displacement mainly but can be used to help in settings the signal processing step).
- Full AE data streams (5 MHz).
- Sources of AE signals: shocks between plates, tribological phenomenon (stick-slip + debris in contact), ...



Discover the level of tightening from AE data stream.

The **Dataverse** Project

MATLAB

GitHub

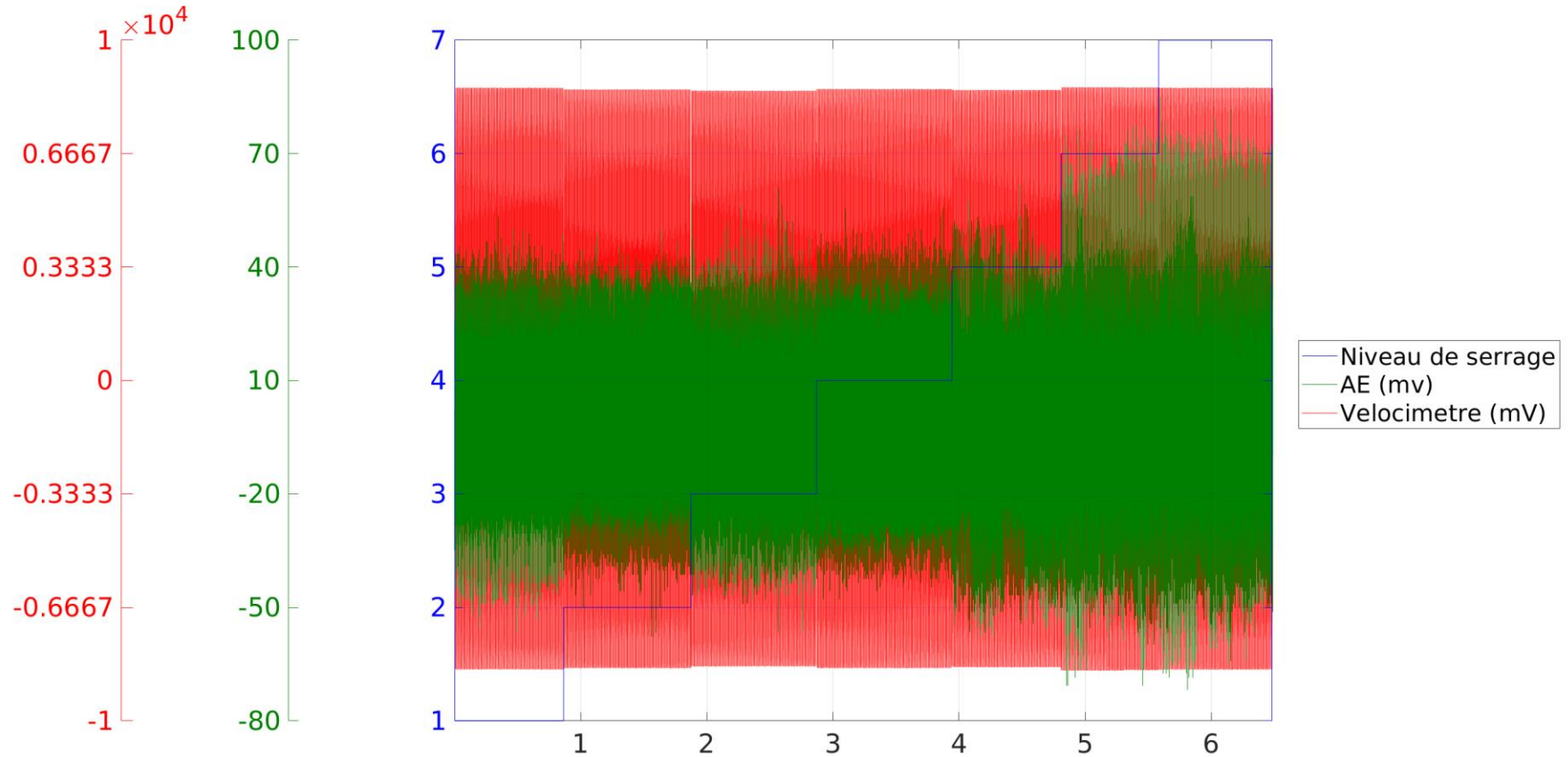
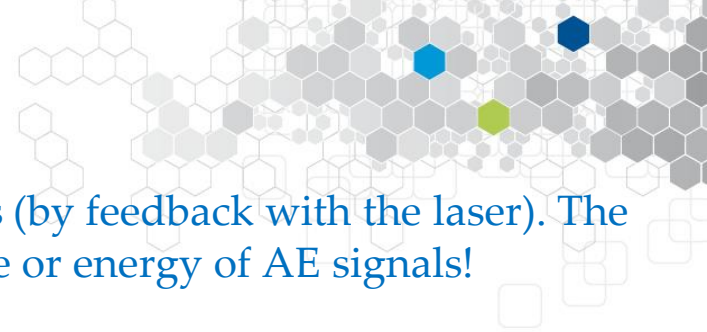
Data shared on Dataverse. MATLAB codes shared on GITHUB for loading it.



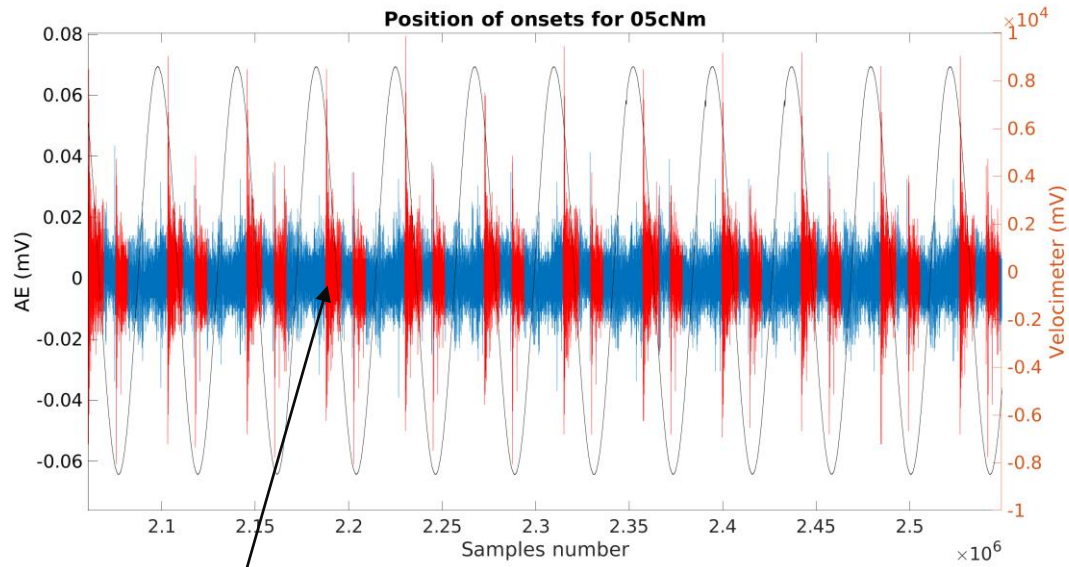
IFR **m2p**
ANR

Example of AE data stream

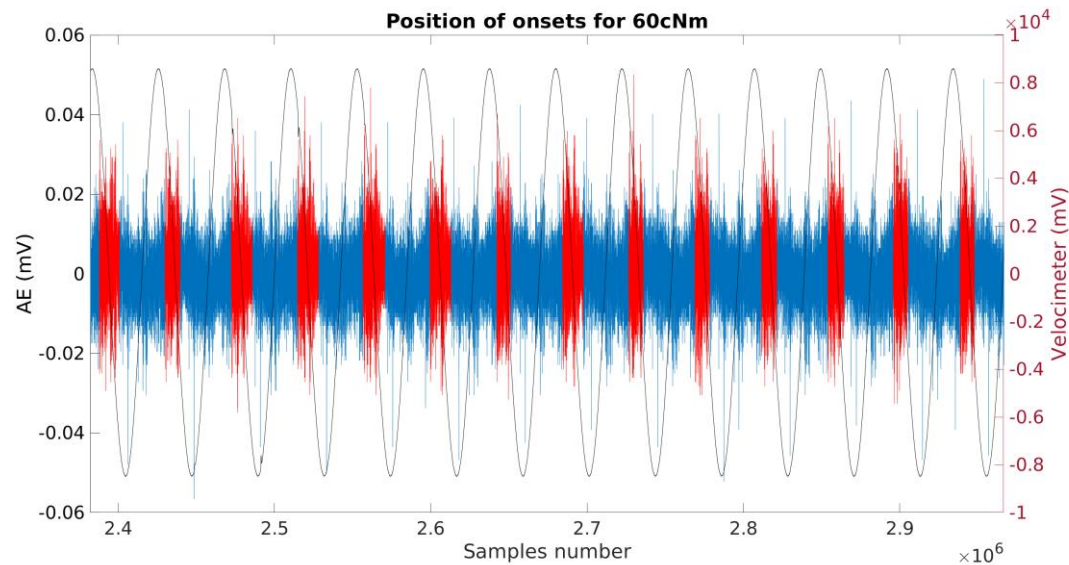
The displacement of the beam is about the same for all levels (by feedback with the laser). The levels can not be discriminated precisely by the amplitude or energy of AE signals!



Close up view for two levels, with hit detection

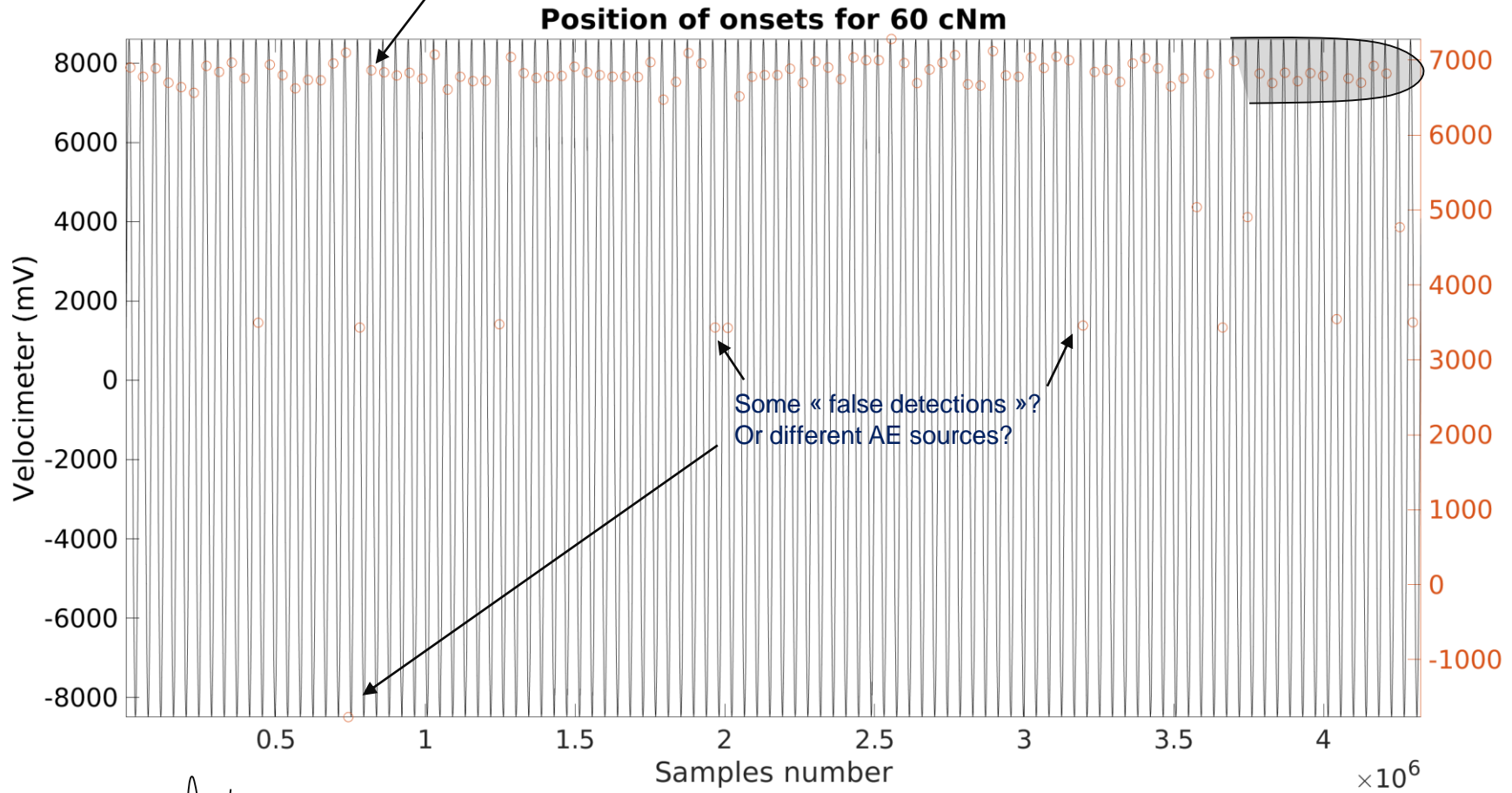


Next slide: position of onsets of AE signals detected by [3] superimposed onto velocimeter data



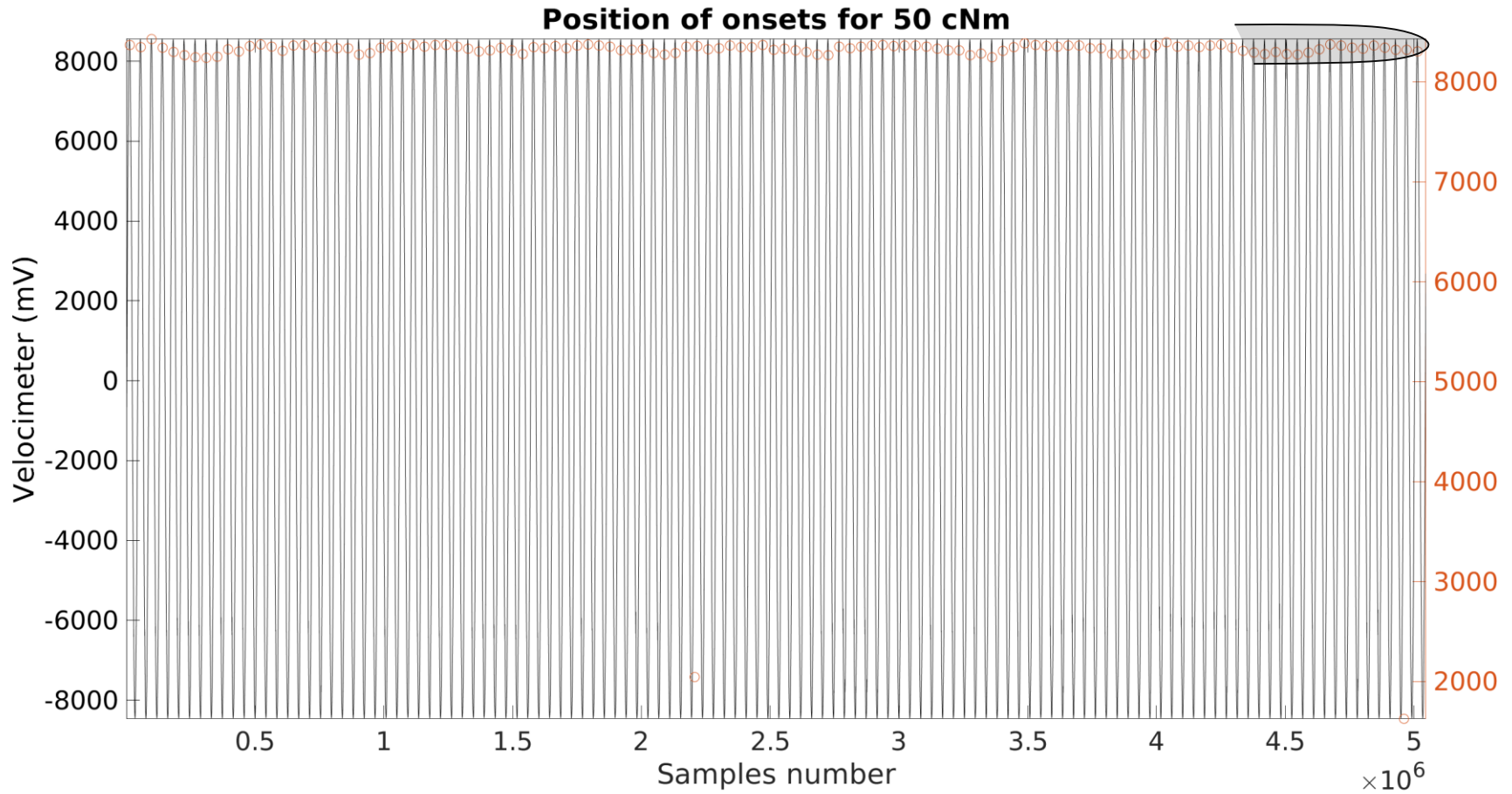
[3] Hit detection and feature extraction in AE streaming. Modified version of <https://doi.org/10.1016/j.ymsp.2015.08.028>.

Position of AE signals onset after hit detection



 Measurement of the displacement by laser vibrometry

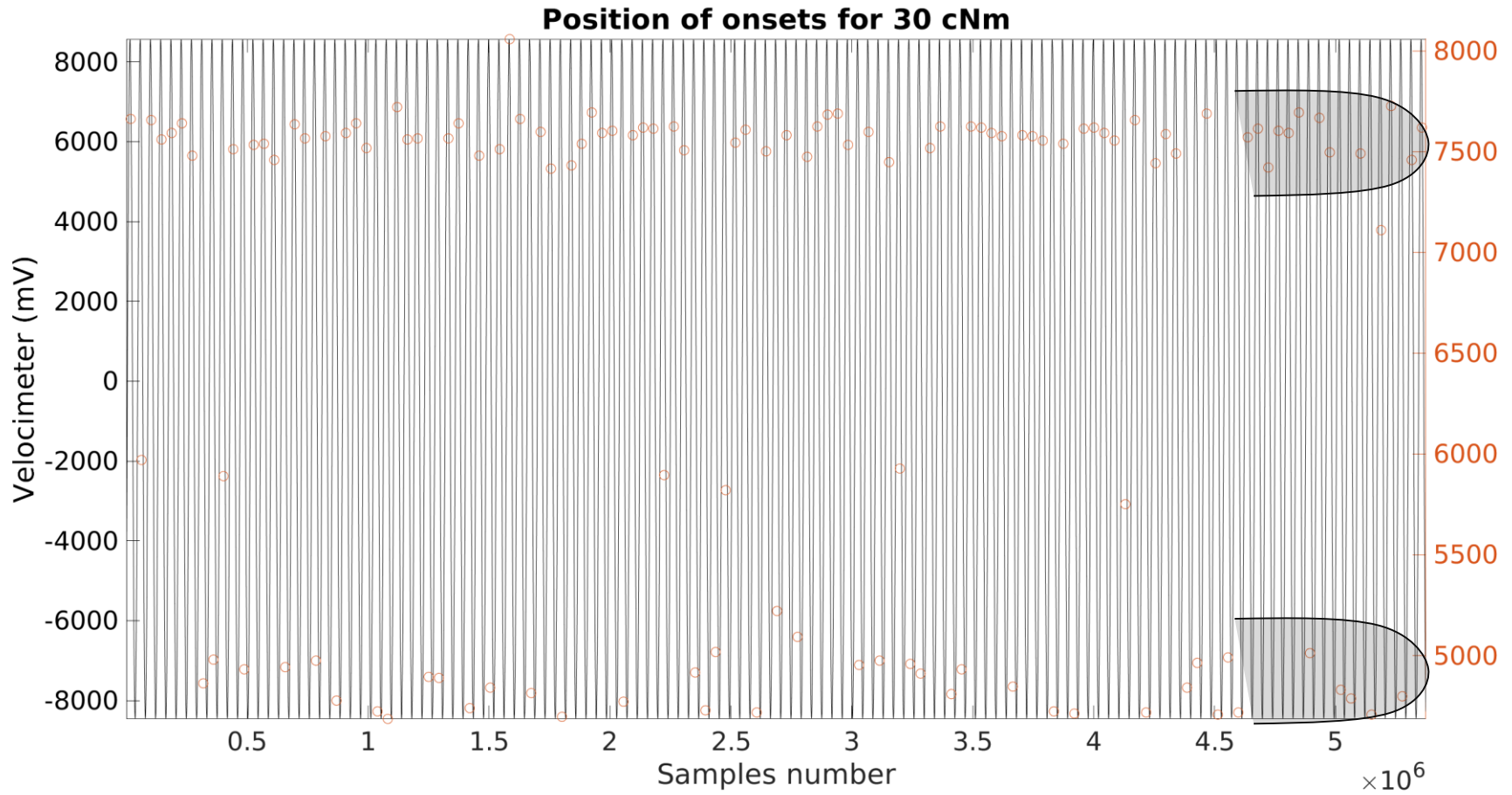
Position of AE signals onset after hit detection



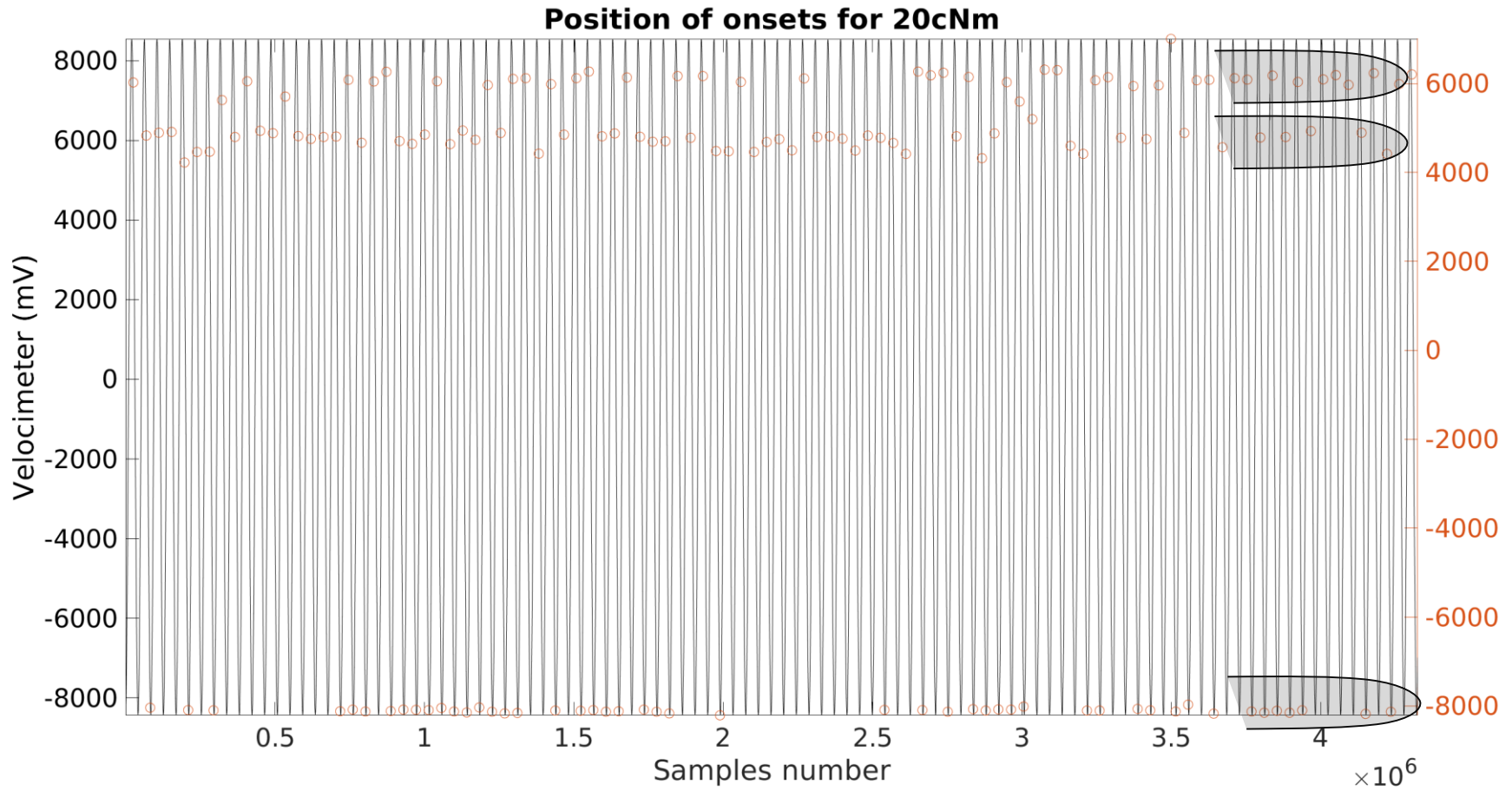
Position of AE signals onset after hit detection



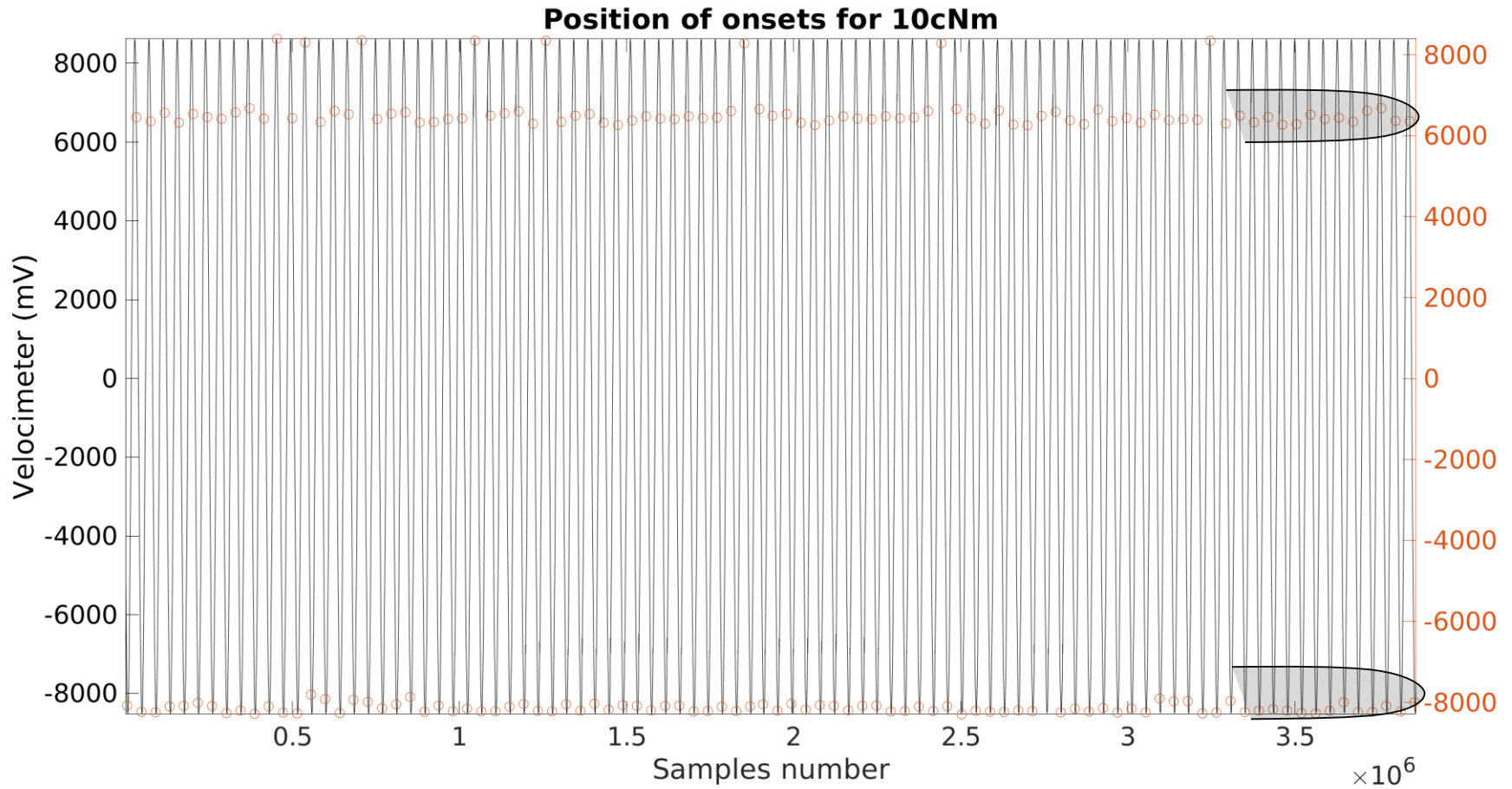
Position of AE signals onset after hit detection



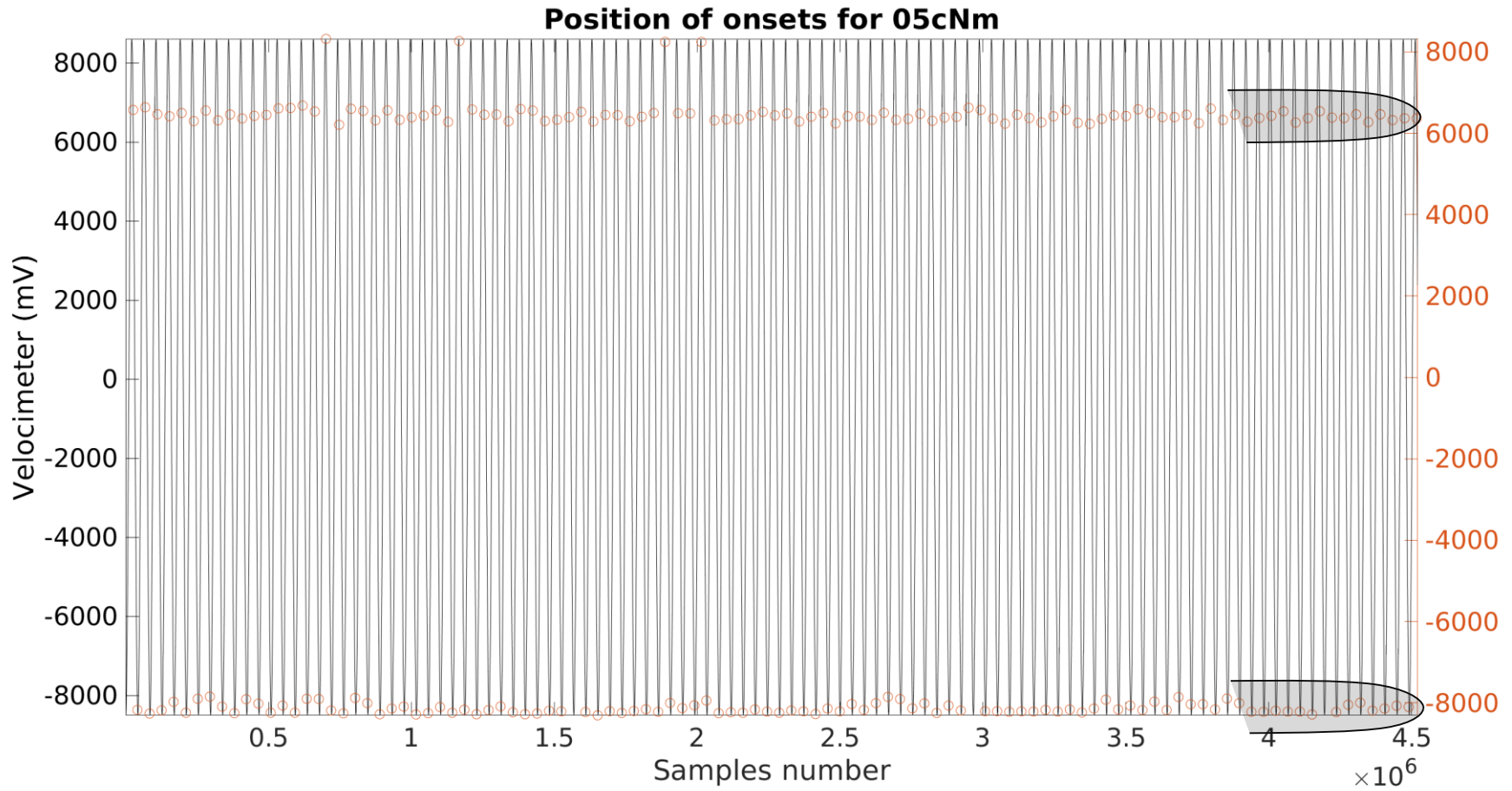
Position of AE signals onset after hit detection



Position of AE signals onset after hit detection



Position of AE signals onset after hit detection



Three new methods and a benchmark

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CONSENSUS CLUSTERING

Combination / fusion of multifarious subsets and parameterizations and focus on the timeline of clusters

First idea of consensus clustering proposed in A. Fred and A. Jain, *Combining multiple clusterings using evidence accumulation*, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 27, no. 6, pp. 835–850, Jun 2005.

Adapted for AE (clusters fusion specific to AE data)

[4] Ramasso, E., Placet, V., & Boubakar, M. L. (2015). *Unsupervised consensus clustering of acoustic emission time-series for robust damage sequence estimation in composites*. IEEE Transactions on Instrumentation and Measurement, 64(12), 3297-3307. <https://doi.org/10.1109/TIM.2015.2450354>

Evolution of the criterion proposed in collaboration with University of Manchester

[5] Neha Chandarana, PhD thesis, Manchester University, 2019.



The University of Manchester

And La Sapienza and INSA Lyon

[6] *Learning the representation of raw acoustic emission signals by direct generative modelling and its use in chronology-based clusters identification*, E Ramasso, P Butaud, T Jeannin, F Sarasini, V Placet, N Godin, J Tirillo, F Sarasini, X Gabrion, Engineering Applications of Artificial Intelligence 90, doi.org/10.1016/j.engappai.2020.103478.



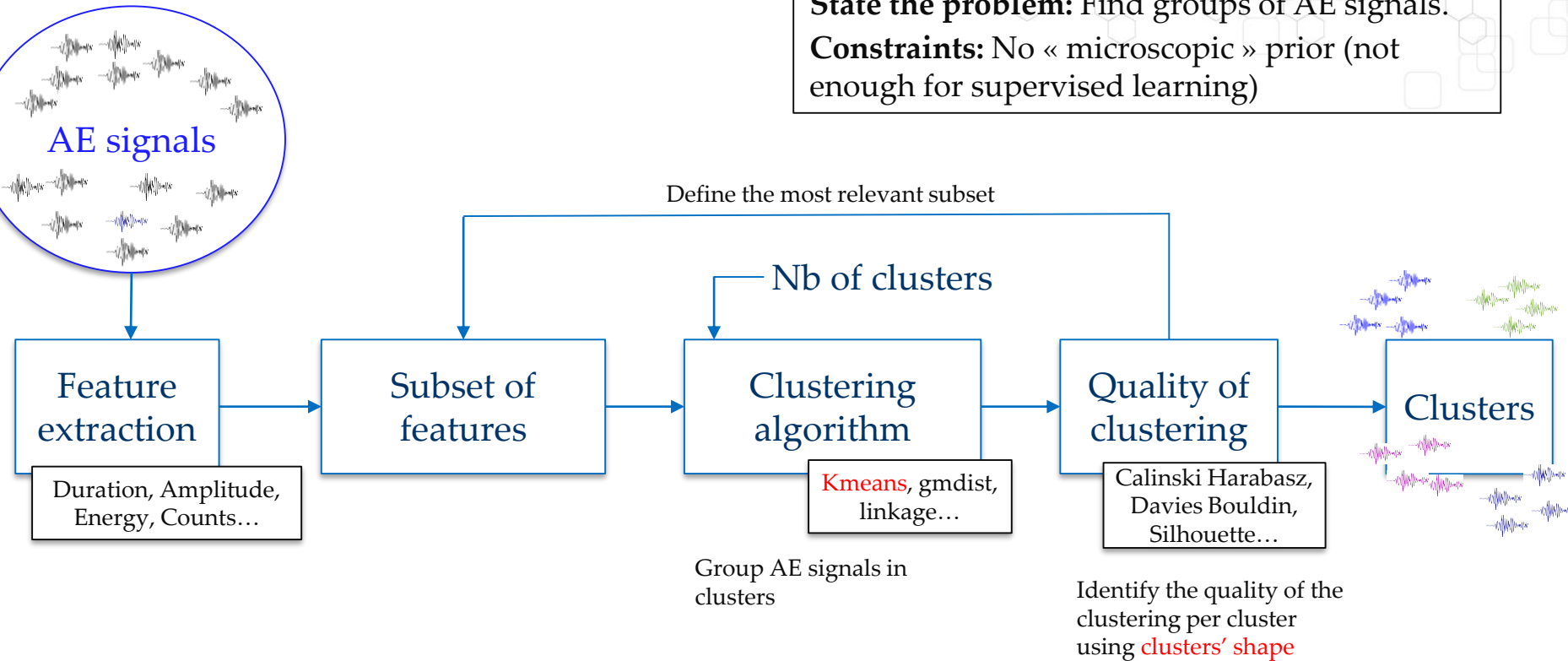
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We want to build a damage scenario

Standard approach

State the problem: Find groups of AE signals.

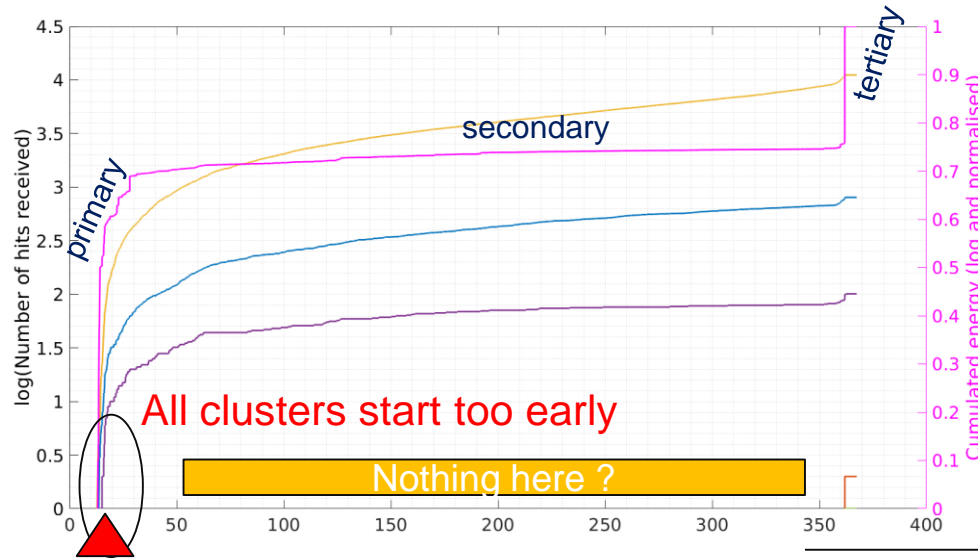
Constraints: No « microscopic » prior (not enough for supervised learning)



- Feature extraction represents each signal by a set of characteristics called **features**.
- The process to find the « groups of features », called **clusters**, is called **clustering**.
- The set of clusters for all data points is called **partition**.
- Clusters are expected to be related to **AE sources** within the materials.
- Clustering **quality** indices are the criteria used to evaluate the quality of clusters.

Illustrations on biocomposites

with inserted MEMS sensors

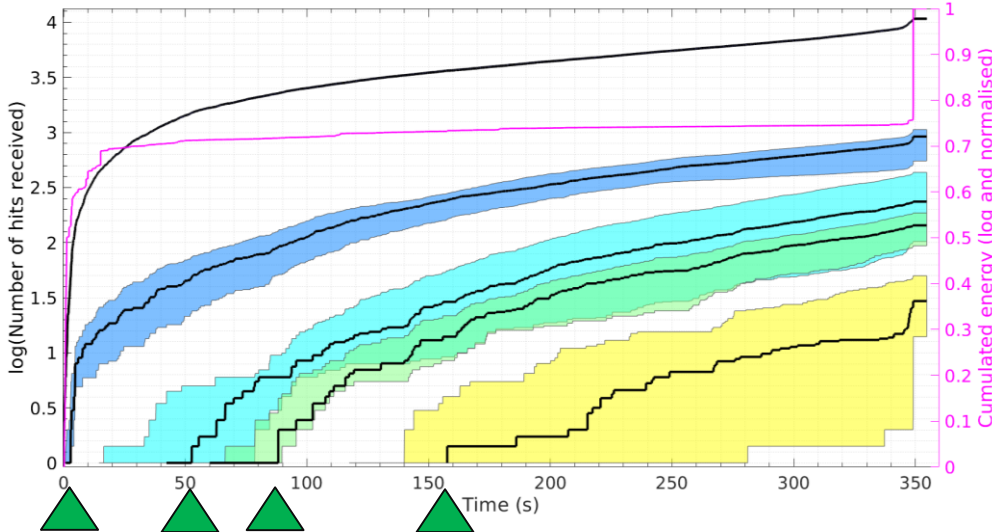


Gold standard (voting scheme):

For all subsets of features
Perform clustering
Give a note using validity indices
(e.g. Calinski, Davies-Bouldin, ...)

Select the subset with the highest note

Finally, plot the clusters: Take the cumulated number of hits per cluster. Superimpose the energy (here normalised).



Clusters onsets are spread onto the horizontal axis

Consensus clustering + timeline [4,5,6] :

For all subsets of features
Perform clustering
Evaluate onsets for each cluster

Sort the subsets according to how the onsets are spread onto the horizontal axis (time, load...)

« Fuse » the clusters, get a « consensus » partition and the uncertainty around clusters

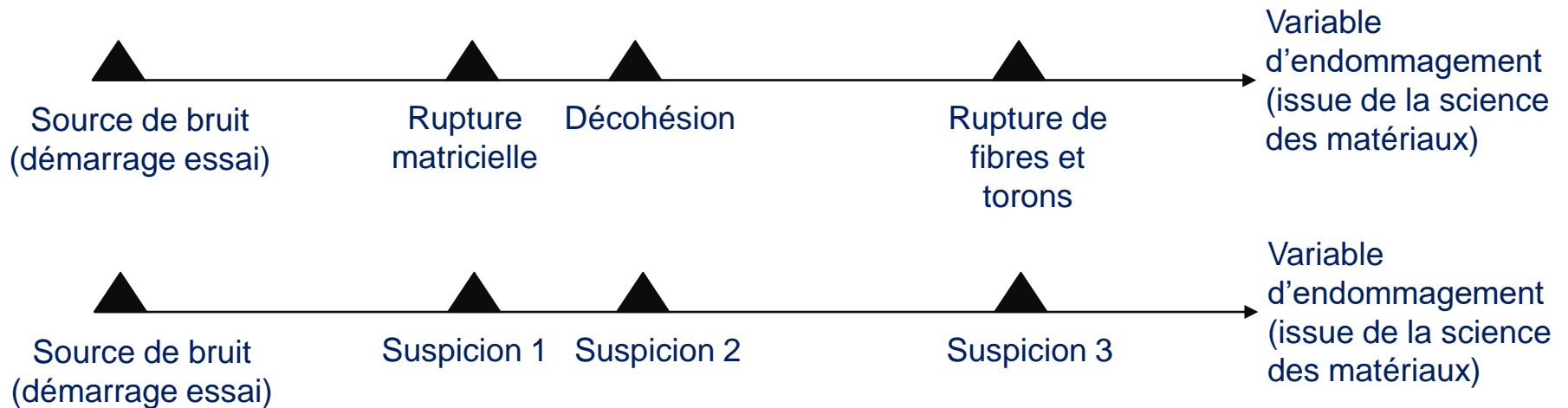
What is a good clustering?

If clusters are well spread on the horizontal axis



The one leading to useful information for monitoring

- Determine damage scenarios
- Set the "horizontal axis of clustering": Calculate a damage variable ; if not possible, use strain measurements or the time attached to transients (test machine sync with AE)
- Estimate partitions by varying hyperparameters
- Calculate the number of cumulative hits per cluster (cumulated clusters plot)
- Determine the onsets: for example the first occurrence of each cluster
- Compare these onsets to a "reference"



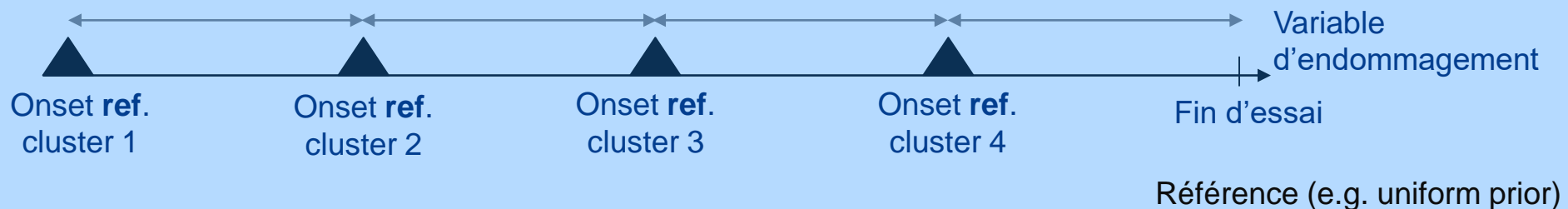
Focus on the timeline during unsupervised learning

Without prior scenario: principle of maximum entropy

Method of reasoning ensuring that no unconscious arbitrary assumptions are introduced in a predictive model [Jaynes, 1957]

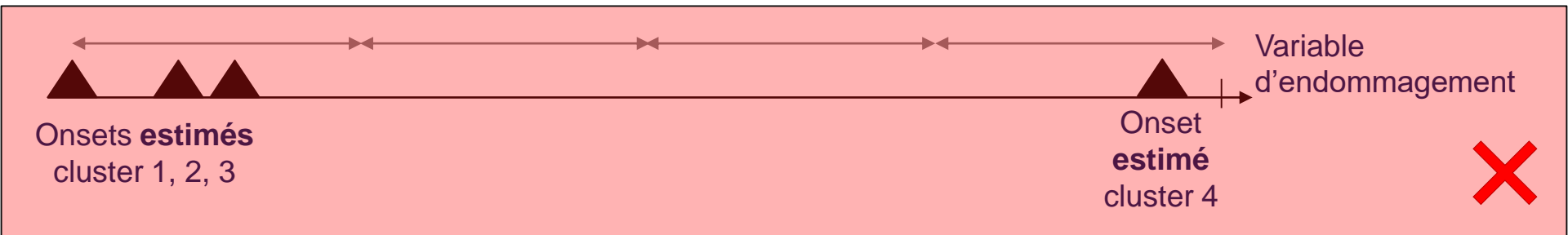
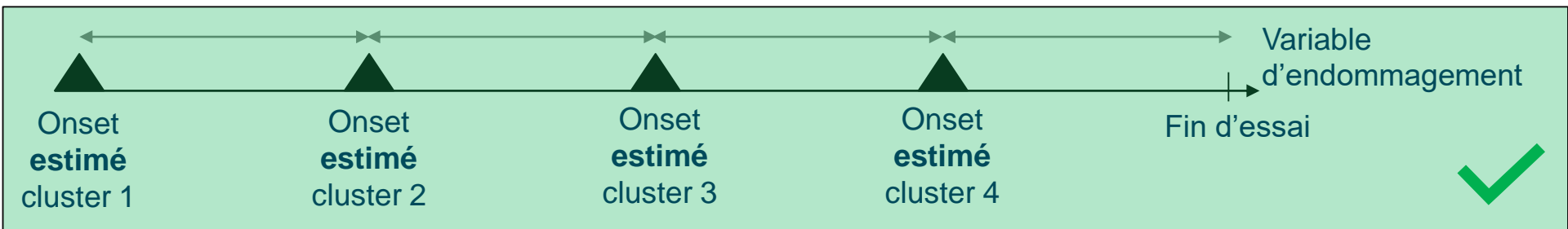
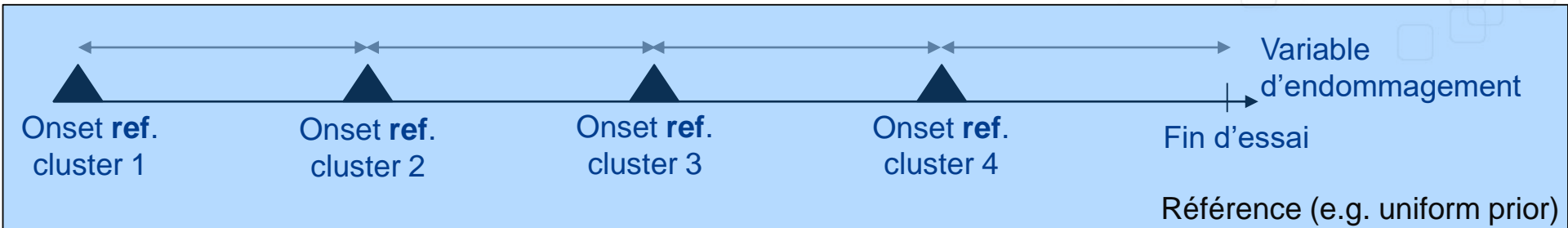
One should avoid introducing biases other than those that are already present in the data, as they would be unwarranted and discretionary [De Martino et al, 2018].

Principe d'entropie maximale pour représenter une connaissance imparfaite : 1) identifier les contraintes auxquelles la distribution doit répondre (moyenne, etc) ; 2) choisir de toutes les distributions répondant à ces contraintes celle ayant la plus grande entropie au sens de Shannon. C'est alors la moins arbitraire. [Wikipédia]



How to sort clustering results?

Sort the partitions by comparing expected and estimated timelines



Three new methods and a benchmark

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RAW SIGNAL-BASED CLUSTERING

**Is feature extraction mandatory? Can we
better exploit AE signals content?**

Collaboration with La Sapienza and INSA Lyon

[6] *Learning the representation of raw acoustic emission signals by direct generative modelling and its use in chronology-based clusters identification*, E Ramasso, P Butaud, T Jeannin, F Sarasini, V Placet, N Godin, J Tirillo, F Sarasini, X Gabrion, Engineering Applications of Artificial Intelligence 90, doi.org/10.1016/j.engappai.2020.103478.



Idea of the criterion for clustering proposed with University of Manchester

[7] Damage identification in composites through acoustic emission monitoring, N Chandarana, E Ramasso, C Soutis, M Gresil, 9th International Conference on Acoustic Emission, Chicago, 2019.

Modelling of AE signals using

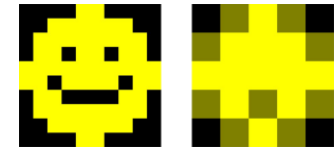
[8] Autoregressive Hidden Markov Models with partial knowledge on latent space applied to aero-engines prognostics, P Juesas, E Ramasso, S Drujon, V Placet, arXiv:2105.00211.

We want to build a damage scenario



Facts:

- Features are a compressed version of AE signals, with great loss!



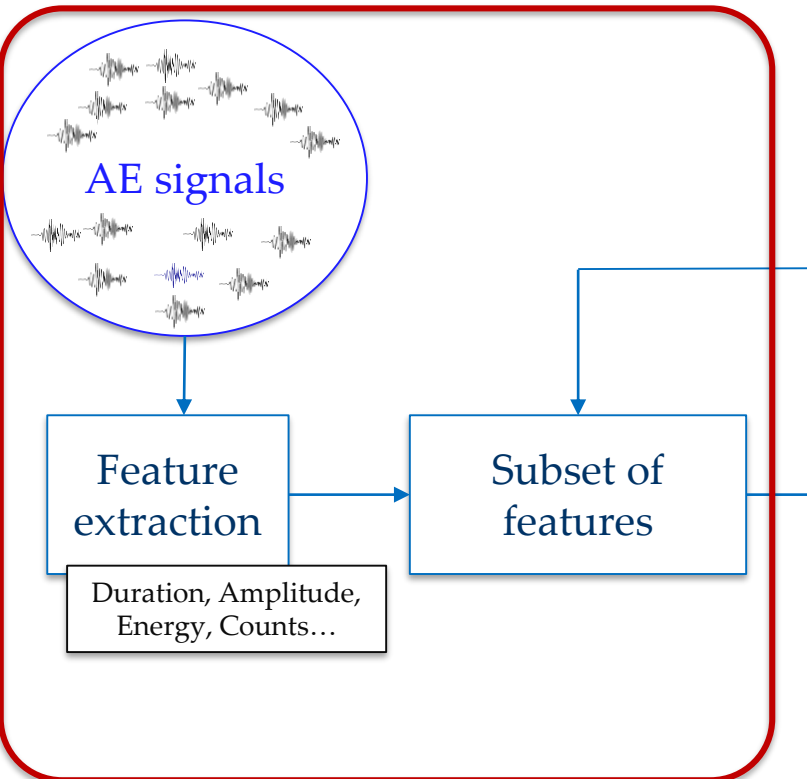
Futurelearn.com

- Feature extraction has become, with years, a must-to-do, but is not mandatory.

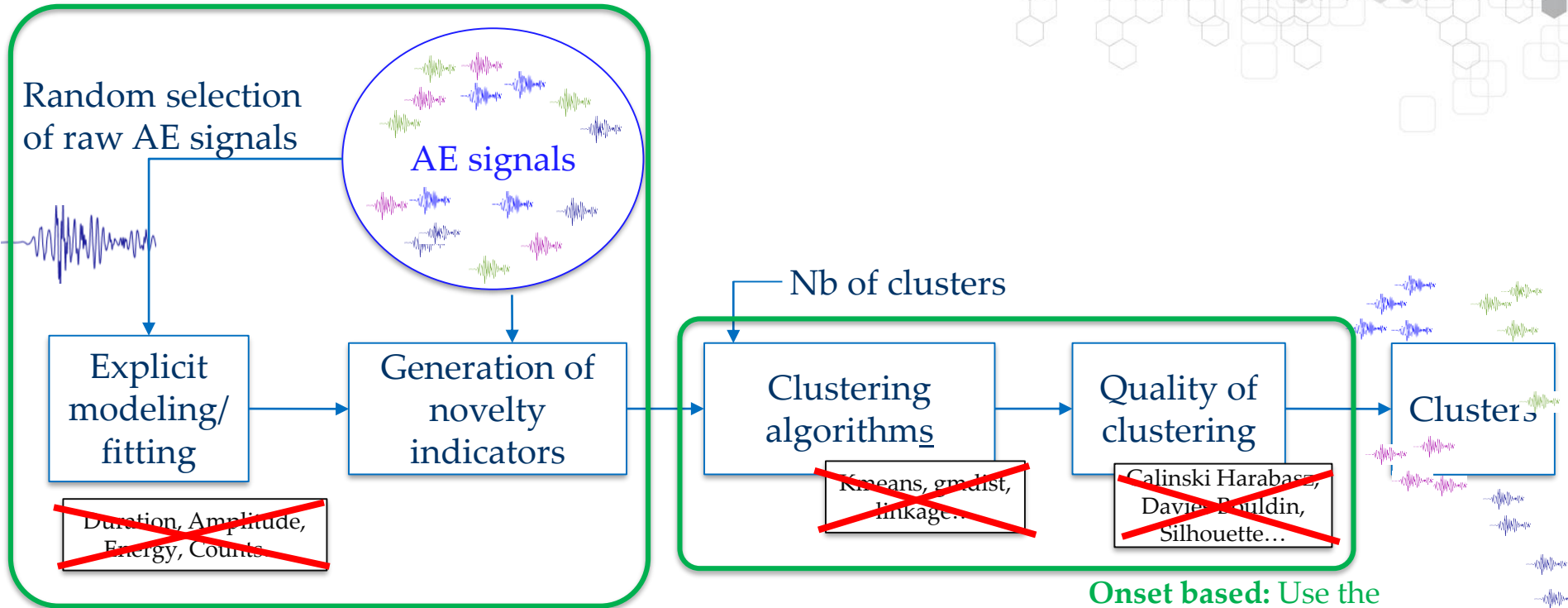
Topic of research: Can we extract more from AE signals? Can we perform clustering on raw signals? The problem is that signals have different length!

In other research fields like audio processing: several ideas were proposed based on FFT or envelopes of signals. Can be (were) used for AE.

New idea based on signal « modelling » proposed in [6].



Clustering of raw AE signals



Model fitting based on [8] (autoregressive Markov model)

Onset based: Use the method developed with Neha Chandarana, Matthieu Gresil, Costantinos Soutis [5,7]

Clustering AE signals with « shapelets »

1) Select a few signals. They will serve as references. Random selection can be fine but signals must be **representative** of AE signals.

2) For each reference signal $ref(j)$

$m(j)$ = build a model of $ref(j)$ able to predict sample k

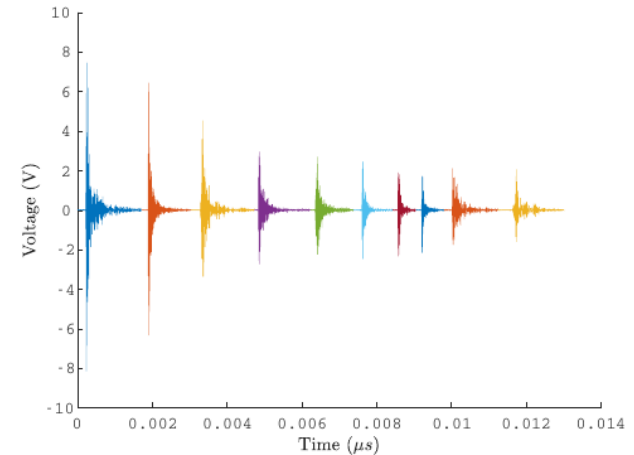
3) For each AE signal $sig(i)$ in the dataset

For each model $m(j)$

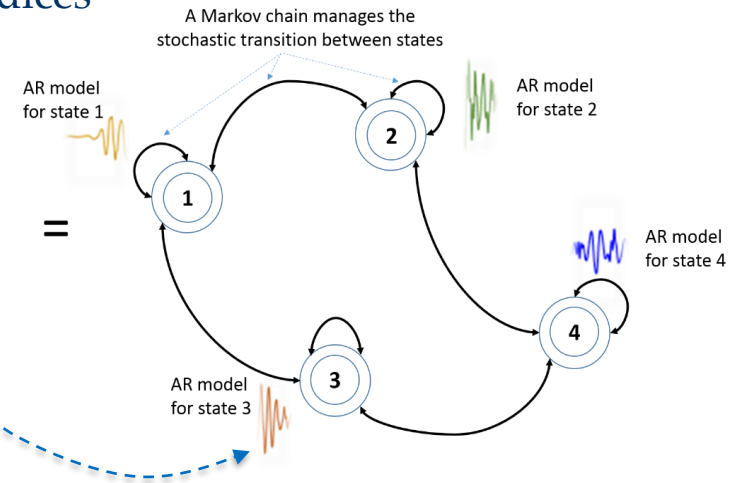
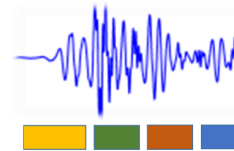
$p(i)$ = pass $sig(i)$ in $m(j)$ to predict samples in $sig(i)$

$e(i,j)$ = compare $sig(i)$ with $p(i)$ using discrepancy indices

4) Perform clustering on « e ».

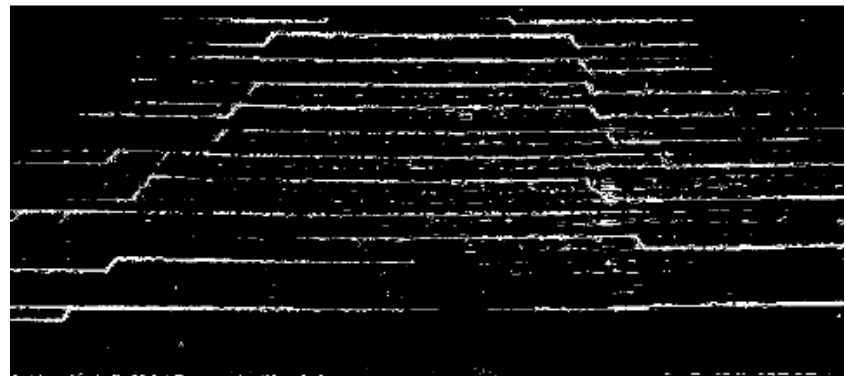
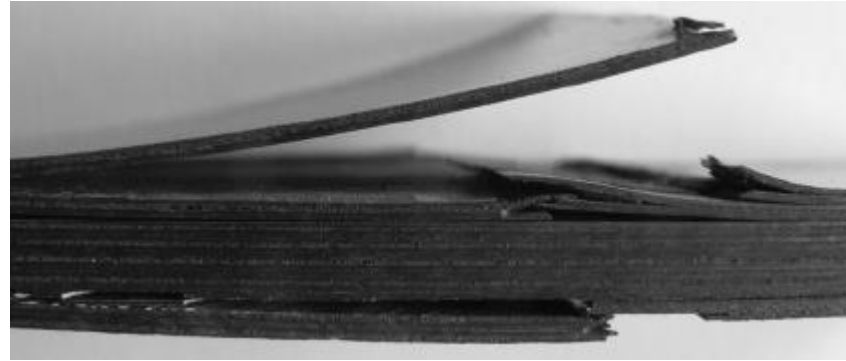
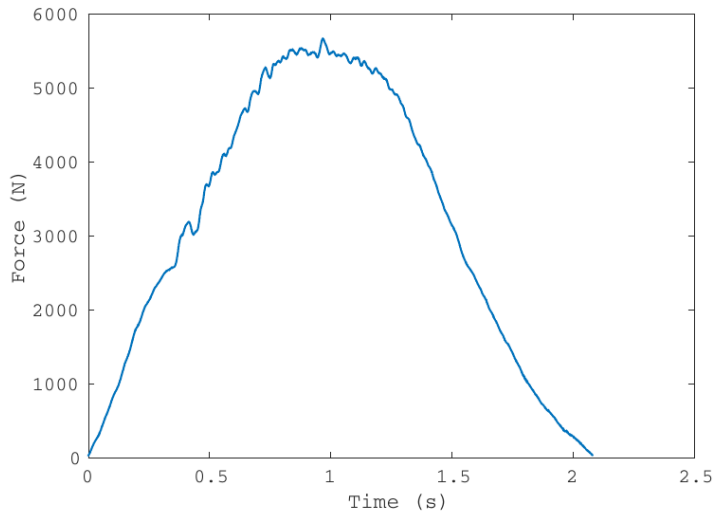


Proposed approach: An AE signal is represented by a mathematical model representing its time-dependent evolution.



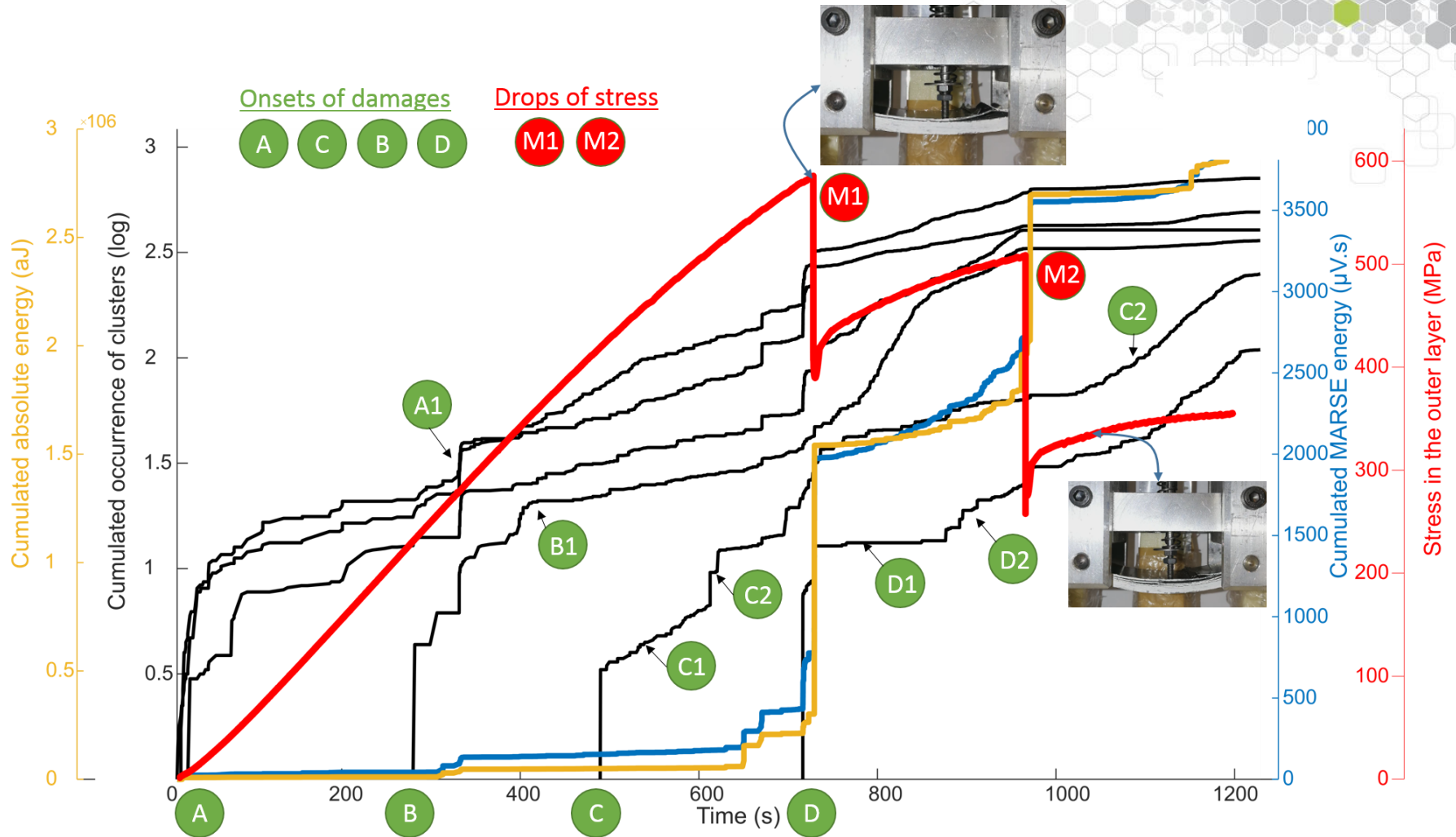
Application

Post impact QS and fatigue flexural tests of CNT-doped and undoped composite plates



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Results



- Clustering using consensus methodology applied on discrepancy measures « e »
- Energy features plotted, but **not used** in clustering

Three new methods and a benchmark

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Estimation of onsets from AE data

**Consider onsets as parameters, can we
estimate them from AE data?**

A collaboration with Pr. Thierry Denoeux (UT Compiègne) started in 2017. Applied to the monitoring of bolted structures with Pr. Gaël Chevallier (FEMTO-ST)

[9] Clustering acoustic emission data streams with sequentially appearing clusters using mixture models. Submitted in Mechanical Systems and Signal Processing, May 2021.

Parametric model of clustering including onsets, kinetics and damage growth



OBJECTIVE: Statistical description of damages onsets, kinetics and growth from acoustic emission data streaming by clustering

WHY?

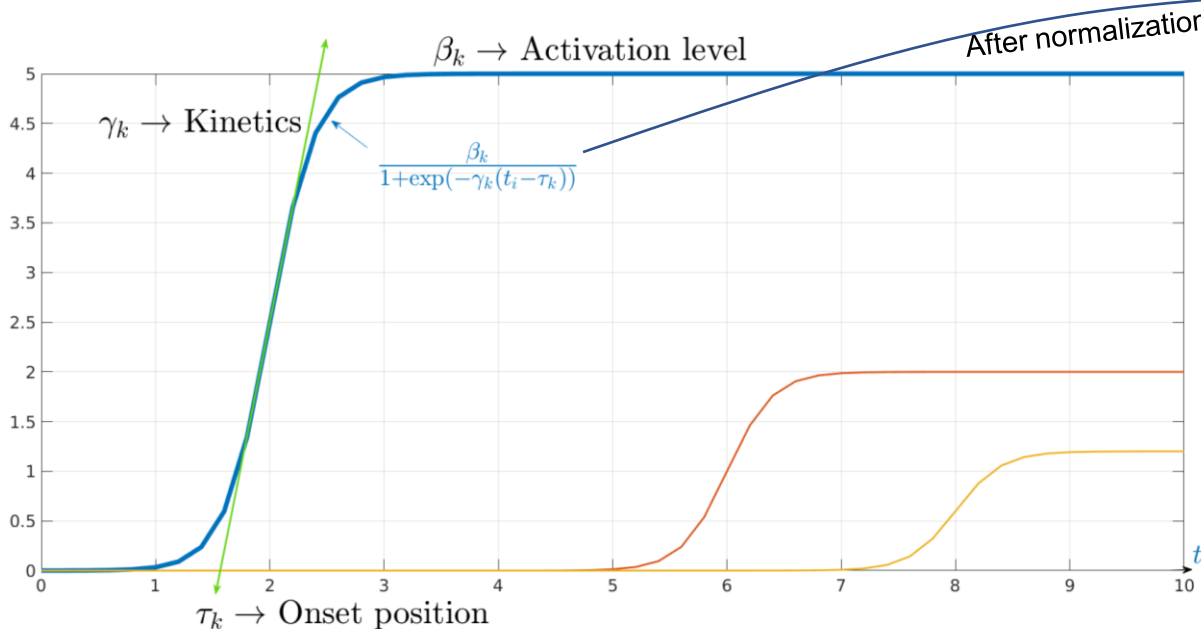
From a physical point of view:

- Because damages are **dynamical**.
- Because damages are **cumulative**.
- Because damages **occur gradually** or **suddenly**.



HOW?

Need of a **clustering method** specifically dedicated to acoustic emission data. The method must include **learnable** parameters associated to onsets, kinetics and growth within the clustering's objective function.



$$p(\mathbf{x}_1, \dots, \mathbf{x}_N; \theta) = \prod_{i=1}^N \sum_{k=1}^K \pi_{ik} \phi(\mathbf{x}_i; \mu_k, \Sigma_k)$$

A mixture model with modified proportions to **explicitly take time into account**.

Optimal (maximum likelihood) updates equations provided for all parameters including onsets.

Can be easily extended to other models.



MATLAB codes will be shared on GITHUB.



FINDINGS:

An **improvement of clustering** over 3 standard methods, evaluated on a **complex task** with 7 classes and 5 datasets providing useful insights. The selection of the number of clusters is circumvented by representing how **onsets** are **distributed with multiple parameterizations**. The method can be **physics-informed** through regularization by incorporating prior on parameters.



Conclusion: focus on onsets!

With *timeline-based clustering*

In 2D

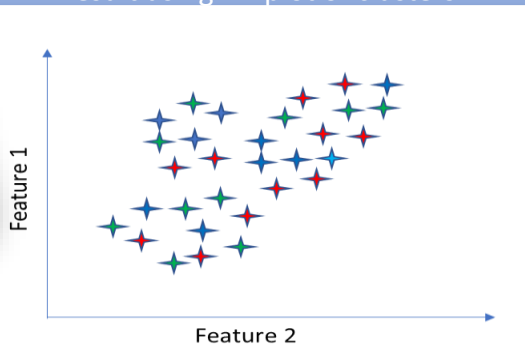
Selection of the clustering result with **shape-based criterion**



Visually speaking in 2D



Representation of the clustering result using 2D plot of clusters'

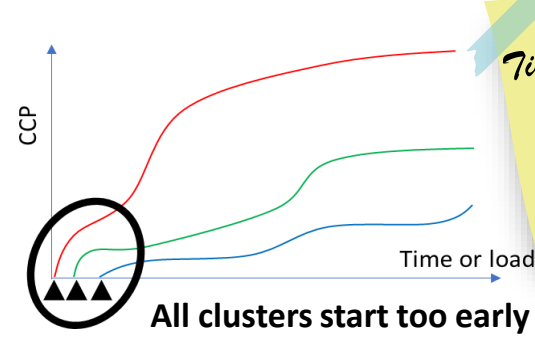


Visually not informative in 2D



Timeline

Representation of the clustering result using Cumulative Clusters' Plot (CCP)

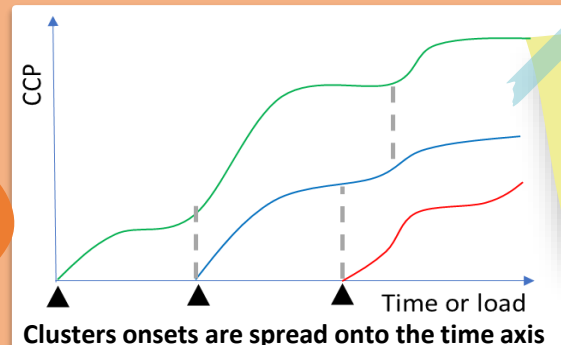


Timeline without interest for monitoring



All clusters start too early

Selection of the clustering result with **timeline-based criterion**



Timeline interesting for monitoring



Clusters onsets are spread onto the time axis

(2014) Reconnaissance des sources acoustiques dans les composites à matrice organique: quel (s) critère (s) utiliser pour une classification non-supervisée des signaux?. In Congrès Français d'Acoustique (CFA 2014) (<https://hal.archives-ouvertes.fr/hal-01145022/>)



Merci de votre attention

Academic environment



5 CNRS labs,
5 CNRS medals

5 ERC
Since 2012

11 EU
projects
since 2015
(5 ITN)


15
Platforms,
Open Labs

8
PIA




Graduate School EIPHI

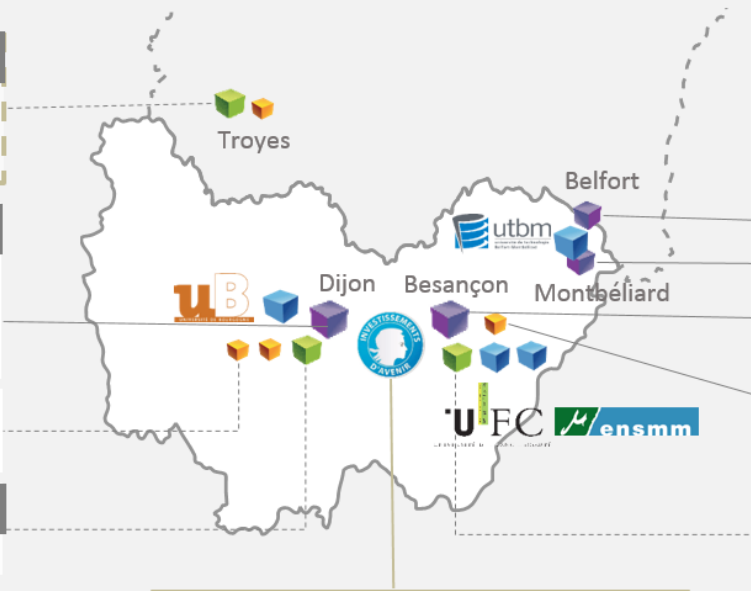
Univ. Bourgogne Franche-Comté, CNRS


 Institut Charles Delaunay **Lab. of Nanotechnology, Instrumentation and Optics NanoMat'** 60

 **Carnot Interdisciplinary Lab**
Materials, Nanosciences, Photonics 280

ARCEN & FLAIR
Nano & photonic characterization


 **Mathematics**
Institute of Burgundy 100



 **FEMTO-ST** 800

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- Time-Frequency
- Advanced control
- Mechatronics
- Computer sciences
- Materials & structures
- Energy
- Social and human sciences
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MIMENTO Clean room, **FCLAB** (Belfort, Fuel Cell), Mesocenter **UFC**, **MIFHySTO**, **FRILIGHT**, **Ametyste..**

 **UTINAM** Universe, Time-frequency, Interfaces, Nanostructures, Atmosphere and Environment, **Molecules** 130

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I-SITE BFC (Axis 1)
Labex ACTION, Labex FIRST-TF
Equipex Robotex, OSC-IMP, REFIMEVE+
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-  Associated labs
-  Staff
-  Main high-tech platforms
-  Universities, engineering schools