SnT 2025
8 SEPTEMBER ONLINE DAY
9 TO 12 SEPTEMBER AT HOFBURG PALACE, VIENNA & ONLINE
CTBT: SCIENCE AND TECHNOLOGY CONFERENCE

P2.1-685

Characterizing Seismic Events in a Noisy Urban and Industrial Environment

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INTRODUCTION AND MAIN RESULTS

- Seismic event detection near the M3.2 Chicago area earthquake produced a high false positive and negative rate
- Improving detection in built environments like Chicago requires more dynamic, human-made noise as training data
- We developed a **simple workflow to detect and cluster seismic events** in two years of noisy, continuous data and **created a labeled data set of dynamic man-made noise**

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Introduction

- Curating AI-ready datasets of anthropogenic seismic events is a challenging and time-consuming task
- Aims: (1) Develop a semi-automated workflow to **detect** and **cluster** anomalous seismic events in a unique urban and industrial environment in the Chicago area (Fig. 1). (2) Build a **labelled dataset** from clustered events

Methodology

Stage 1: Detection via PSD misfit detector

- PSD misfit: an averaged, weighted difference between the power spectral density (PSD) of a given 10-s window and a dynamic background noise PSD [1]
- Detection: 10-s window with a misfit > 1

Stage 2: Clustering via k-means

- We trained a k-means clustering model (via scikit-learn [2]) on 20k+ anomalous events detected in a 3-week dataset
- Table 1 lists the features we explored for the k-means model. Features 1-4 were computed for all three components. We removed features that were highly-correlated (CC > 0.85).
- Selected a *k* (number of clusters) of 12 after qualitatively assessing clustering performance for *k* = 2 to *k* = 20 in a 3-week dataset

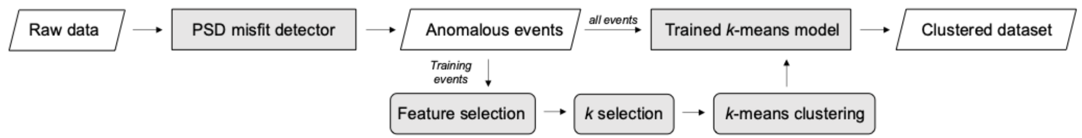

Figure 1. Concept map of study methodology.

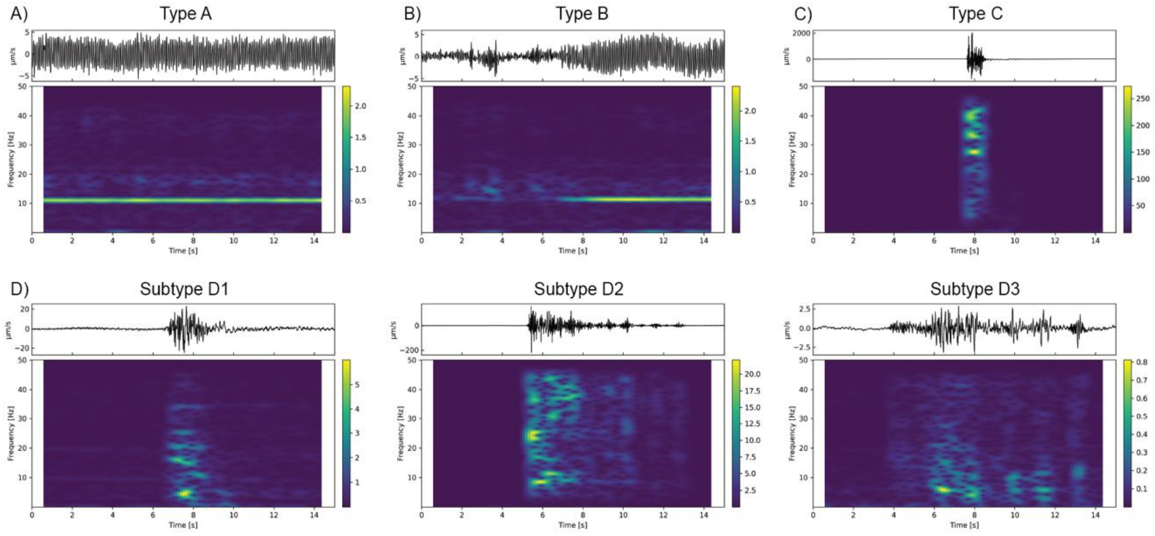

Figure 2. Examples of HQIL anomalous events in the four event types described in Table 2.Each example shows the event's vertical-component waveform and spectrogram. Color scales are in units of micrometers per second.

Table 1. Features for the K-means clustering model

Feature	Description
1. STA/LTA	Ratio of the average absolute amplitude in the 10-s to that of a preceding 40-s window [3].
2. Skewness	Skewness of the 10-s window
3. Kurtosis	Kurtosis of the 10-s window
4. PSD misfit	Misfit between PSD of 10-s window and a background noise PSD
5. Hour	Hour corresponding to the 10-s window
6. Day	Day corresponding to the 10-s window

Table 2. Description of detected event types

Type	Potential Source	Fraction of Events
A	Operation of industrial machinery with an 8-pole motor)	98.6%
B	Turning ON of type A machinery	1.20%
C	Surface blasts at the nearest quarry	0.10%
D	D1: Quarry blasts with source distances ≥1 km from station HQIL D2: Underground explosions at the nearest quarry D3: Wind interaction with local structures (requires more validation)	0.11%

Application & Discussion

- We applied our workflow to two years of continuous HQIL data and successfully produced coherent clusters of four event types (Fig. 2 and Table 2).
- Multiple clusters belonged to the same event type. Cluster 3 (Event Type D) needed to be manually subdivided into subclusters.
- We built a labelled dataset of 1000+ clustered events, including surface quarry blasts, underground blasts, machinery operations, and potentially-wind generated noise.
- Future work: Evaluate other clustering algorithms and frequency-based model features

References

[1] Vaezi, Y. and M. Van der Baan. Comparison of the STA/LTA and power spectral density methods for microseismic event detection. *GJI* 2015; 203(3): 1896–1908.
[2] Pedregosa, F. et al. Scikit-learn: Machine learning in Python, *J. Machine Learn. Res.* 2011; 12: 2825–2830
[3] Allen RV. Automatic earthquake recognition and timing from single traces. *BSSA*. 1978; 68: 1521-1531

See our publication for more details/references:
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