

Robust clustering of variable-duration seismic waveforms using an incremental dynamic time warping framework

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SUMMARY

Different geophysical processes generate characteristic seismic waveforms. Identifying similar waveforms therefore helps to distinguish between different source mechanisms and to monitor seismic activity in settings ranging from volcanoes and glaciers to urban environments. In many applications, however, the seismic event types are unknown and no labelled training data is available. Then, unsupervised clustering is necessary. Most existing approaches require all input vectors to have the same length, which in seismology translates to a fixed event window. However, seismic signals can differ considerably in duration: This may require events to be cropped or padded to a common length, which may lead to a loss of important waveform characteristics. Furthermore, the approaches commonly rely on extensive feature engineering or machine-learned representations, which often require hyperparameter tuning and can reduce the physical interpretability of the resulting clusters. In addition, many clustering algorithms require the number of clusters to be specified a priori, limiting their flexibility when analysing previously unknown datasets. This study introduces Incrementally Buffered Dynamic Time Warping Clustering, a new unsupervised clustering algorithm that operates directly on seismic time-series data using a small number of physically interpretable parameters. The method is based on Dynamic Time Warping and is particularly suited to noisy and continuously active seismic environments, where overlapping signals and imperfect event catalogues are common. The buffered and incremental structure of the algorithm explicitly identifies outliers and allows new clusters to form during incremental updates, enabling continuous monitoring without reclustering the entire dataset. The algorithm is evaluated on a labelled volcano-seismic dataset, where it achieves a clustering accuracy of 69.39 per cent, comparable to previously published supervised approaches. A second application to Antarctic icequake data demonstrates its ability to identify meaningful waveform groups in a setting with limited prior knowledge of event types. These results show that the newly introduced clustering algorithm provides an interpretable and scalable framework for clustering large seismic datasets while retaining direct access to waveform similarity in the time domain.

Key words: Machine learning; Persistence, memory, correlations, clustering; Time-series analysis; Cryoseismology; Seismic noise

1 INTRODUCTION

Seismology has been collecting data on an unprecedented scale for decades. A variety of methodologies are employed to record ground motion, including networks of seismic stations and dense sensor arrays. In addition, there are novel technologies such as distributed acoustic sensing. These methodologies generate extensive datasets ranging from years to decades. The accumulation of such long-term and high-resolution measurements renders manual analysis impractical and underscores the need for automated methods.

Machine learning helps to work with such large datasets. Su-

pervised or semi-supervised learning is commonly used when labelled or pseudo-labelled training information is available, e.g. in earthquake detection (Zhu et al. 2023) and magnitude prediction (Asim et al. 2017) or classifying earthquake-induced building damage (Mangalathu et al. 2020), moment tensor inversion (Steinberg et al. 2021) and phase-picking (Zhu & Beroza 2019; Bornstein et al. 2024).

In the case of data with no labels, unsupervised learning methods are used. A typical application is to cluster different types of seismic signals produced by numerous sources. This is needed in volcanic settings to classify and differentiate between various types

of magmatic or fluid-driven seismic events as well as mechanically generated signals such as rockfalls (McNutt & Roman 2015) or in urban areas to identify human activity like machinery and pumps (Snover et al. 2021) or traffic (Martin et al. 2018). In cryogenic settings, interactions between ice-ice and ice-bedrock as well as glaciohydraulic processes (Aster & Winberry 2017) can produce different types of seismic patterns (Hammer et al. 2015; Kinzel et al. 2024).

The applications described above are carried out in noisy settings, where many seismic events can occur within short time periods, often overlapping due to the superposition of different signals recorded by the sensors. At the same time, there is little to no prior knowledge about the seismic signatures of all processes active at the study site. Therefore, unsupervised clustering is commonly used due to the absence of labelled event catalogues.

Clustering algorithms generally involve two fundamental aspects: the representation of the data and the configuration of the clustering algorithm. The representation of the data determines how the input observations are described and compared, including the choice of input features and any dimensionality reduction. The algorithmic configuration, in turn, comprises choices such as the clustering method, the number of clusters, the treatment of outliers and constraints on the input data. These two aspects are discussed separately below, starting with the representation of the data and subsequently addressing the algorithmic configuration.

The representation of seismic event waveforms is particularly challenging because events can differ in duration and exhibit similar waveform characteristics at different relative positions in time (Fig. 1). Seismic events are often represented through extracted features rather than directly in the time domain. Variations in the time window prevent a direct comparison of raw time-series representations in a fixed feature space, because the same event can be represented by different portions of the waveform at different positions within the input vector. Furthermore, the input feature dimension is restricted by the curse of dimensionality (Bellman 1961), which can cause distances between data points to become increasingly less informative as the dimensionality increases (Aggarwal et al. 2001).

Extracting suitable features is difficult, especially for previously unexplored datasets, and validating the resulting clusters can be challenging in the absence of ground truth or well-constrained prior information. As a consequence, parameter tuning becomes inherently dependent on assumptions about the expected cluster structures, which may not be valid in unknown or poorly understood environments. This creates a fundamental ambiguity in the clustering process, since suitable parameter choices cannot be objectively verified.

To address these limitations, dimensionality-reduction methods are commonly applied. Principal component analysis is a data mining technique that reduces the dimensionality of a dataset by computing the eigenvectors of its covariance matrix and projecting the data onto the directions that capture the largest amount of variance. PCA provides a linear and deterministic projection onto directions that capture the largest variance. As a linear method, however, it cannot explicitly represent nonlinear structure in the data.

This limitation has motivated the use of nonlinear methods such as t-Distributed Stochastic Neighbour Embedding (van der Maaten & Hinton 2008), Uniform Manifold Approximation (McInnes et al. 2018) and Pairwise Controlled Manifold Approximation (Wang et al. 2021), which aim to visualize more intricate patterns. However, these methods differ in how they preserve local

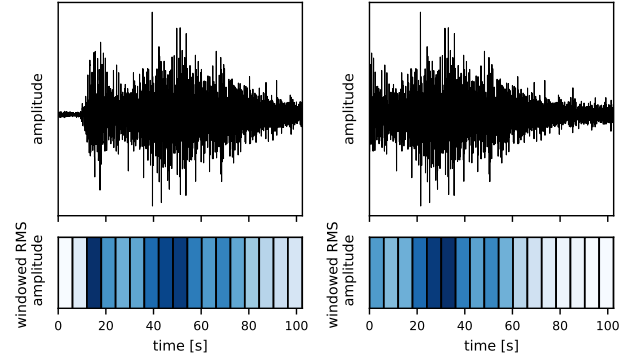


Figure 1. The same seismic event with two different time window cuts (top). The windowed root-mean-square amplitude shows the power within each window (bottom), indicating how the raw time series would behave as an input vector. The time-window variability of the same event shows ambiguity of the feature space.

and global structure, and the resulting embeddings depend on algorithmic design choices and hyperparameters (Wang et al. 2021).

While dimensionality-reduction methods facilitate the application of unsupervised clustering to low-dimensional embeddings (Chai et al. 2025, 2026) and provide valuable insight into seismic clusters, the resulting clusters can vary significantly depending on the selected method and its parametrisation. This limits their robustness as clustering features. Therefore, in this study, dimensionality reduction is used for visualisation only and not as a basis for clustering, in order to avoid introducing an additional dependence of the cluster structure on the selected dimensionality-reduction method and its parameters.

In many studies, seismic time-series data is transformed into the frequency domain to find seismic event types of similar frequency content. Time–frequency representations of seismic signals involve a trade-off between temporal and frequency resolution according to the Gabor uncertainty principle (Gabor 1946). To retain the complete waveform, including its temporal structure and phase information, the time series can instead be compared directly. However, direct comparison of seismic waveforms requires a distance measure that can account for differences in temporal alignment and event duration. Sequence-based models such as hidden Markov models (HMMs), long established in speech recognition (Young et al. 2002), have also been adapted to seismic detection and classification (Beyreuther et al. 2012; Hammer et al. 2015).

Furthermore, without prior knowledge about the data and without transparent, interpretable parameters, it is difficult to judge the reliability of the clustering results. By contrast, parameters with clear physical or intuitive meaning improve transparency and provide a basis for a more reliable interpretation of the obtained clusters. Therefore, transparent and physically or intuitively interpretable clustering parameters are a key requirement for the proposed approach.

The choice of clustering algorithm and its configuration introduces additional challenges. One way to cluster seismic data is to use deep learning methods. Deep Embedded Clustering (Xie et al. 2016) learns a low-dimensional feature representation while iteratively refining cluster assignments. Snover et al. (2021) applied this method to nearly one week of dense seismic array data in Long Beach, California, and identified five seismic clusters based on input spectrograms and related several of them to plausible anthropogenic sources. Still, the learned latent features have no explicit

physical meaning, making the resulting clusters difficult to interpret and validate, particularly when physical intuition is needed to assess their reliability in unexplored seismic surroundings.

To incorporate physical properties into feature extraction, Seydoux et al. (2020) developed a deep learning method that uses wavelets as convolutional filters and Gaussian mixture models for clustering. This preserves a physically motivated structure in the extracted features. However, these features are combined with dimensionality-reduction methods before clustering, rather than clustering the seismic waveforms directly (Seydoux et al. 2020; Steinmann et al. 2022).

In contrast, our method does not rely on a predefined or learned feature space and instead compares the seismic waveforms directly in the time domain. This makes it complementary to scattering-based approaches: while scattering offers physical interpretability and robustness, our algorithm enables the discovery of similarity patterns that are not necessarily captured by analytically constructed features. Together, these approaches can illuminate different aspects of the data.

Event extraction with STA/LTA detectors can be challenging in noisy, continuously active settings (Hammer et al. 2015; Kinzel et al. 2024). In the subsequent clustering step, methods that explicitly account for noise, such as DBSCAN (Ester et al. 1996), can avoid forcing every sample into a cluster. This motivates the need for clustering methods that can explicitly identify outliers and thereby enhance robustness in high-activity, noisy seismic environments.

Since many established clustering approaches assign every event to one cluster, noisy events may be incorrectly assigned to a specific cluster. This is also caused by continuous seismic activity (e.g. volcanic, urban and cryogenic settings), where closely spaced events lead to overlapping arrivals and superposed waveforms in the extracted events. Therefore, some seismic events cannot be assigned unambiguously to a single cluster.

Another drawback of many established clustering methods is the requirement for a fixed window length. Seismic signal durations can vary substantially, from short discrete events to sustained signals such as volcanic tremor, which can persist for minutes to days or longer (McNutt & Roman 2015). Cutting these events to a fixed length either causes the dominance of noise and increases the probability of multiple events occurring within one window, or results in a loss of coda information, respectively.

Additionally, many partitioning-based clustering algorithms, including k-means and k-medoids, require the number of clusters to be specified a priori. This imposes a hard constraint on the clustering process, as all non-outlier samples are assigned to the prescribed number of clusters regardless of whether this reflects the underlying data structure. Although cluster validation methods can provide guidance when selecting a suitable value, they cannot objectively verify the chosen number in the absence of ground truth. This is particularly restrictive for previously unknown datasets and monitoring applications, where new event types may emerge over time.

The proposed algorithm is designed to address these challenges by providing:

- support for events of variable length,
- a direct time-domain representation of the waveform data,
- automatic extension to additional clusters,
- automatic outlier classification and
- physically or intuitively interpretable clustering parameters.

These requirements motivate a clustering algorithm for un-

known datasets with high seismic activity and noisy data. The algorithm should be unsupervised, distinguish outliers from regular event clusters, process seismic events of varying duration and temporal alignment, and avoid reliance on a predefined feature space. Its parameters should have a direct physical or intuitive interpretation to facilitate reliable interpretation of the resulting clusters. The proposed method therefore prioritizes transparency and explicit control over clustering behaviour while retaining direct access to the waveform structure in the time domain.

The proposed direct time-domain representation is particularly relevant for single-component seismic measurements, where additional physically meaningful features such as polarization attributes are not available. Nevertheless, single-component measurements remain widely used due to their cost-effectiveness and ease of implementation and maintenance. This encompasses historical regional seismic networks that continue to utilise vertical sensors (Tauzin et al. 2019) and dense large-N deployments using inexpensive and easy-to-deploy nodal sensors (Wang et al. 2019). Distributed Acoustic Sensing (DAS) provides another example of dense single-axis sensing, allowing large numbers of measurements along fibre-optic cables and the use of existing telecommunication infrastructure (Dou et al. 2017; Lindsey et al. 2020). It also includes studies where vertical motion alone captures the relevant wavefield and deployments in remote or extreme environments, where single-component arrays are used for dense seismic observations (Hammer et al. 2015).

Single-component measurements offer the advantage of learning the structure directly from the seismic time series of each extracted event without requiring predefined features, although this may result in a loss of some waveform information. For single-component arrays, the beam of events can add spatial information, but it still relies on a single time-series input.

In this paper, we first introduce Dynamic Time Warping (DTW) as a distance measure for comparing temporally variable seismic waveforms and subsequently present a newly developed clustering algorithm based on this method. We then apply the algorithm to a labelled volcano-seismic data set to evaluate its clustering performance. To verify the applicability to different seismic settings, we additionally conduct a qualitative case study with seismic data from Antarctica.

2 DYNAMIC TIME WARPING

The methodological requirements naturally connect seismic waveform clustering to developments in other fields concerned with comparing and grouping variable-length time series. A prominent example is speech recognition, in which the classification relies on preserving the temporal structure of the signal while allowing flexible alignment in time. HMMs have become a standard solution in that context, because their state-transition framework explicitly models sequential dependencies and accommodates variable durations (e.g. Young et al. 2002). Similar ideas have been applied to seismic signal classification (Beyreuther et al. 2012; Hammer et al. 2015), which illustrates that accurate classification requires methods capable of capturing the temporal evolution of the signal. While these approaches highlight the importance of sequence alignment for seismological applications, they typically rely on supervised learning or parametrised probabilistic models, which limits their applicability for fully unsupervised clustering of raw seismic events.

The capacity of HMMs to exhibit flexible state transitions

enables the model to either remain, advance, or skip in a state, thereby implicitly defining a set of admissible alignments between sequences. The same principle can be applied without the probabilistic framework of HMMs by using DTW. This method allows for the comparison of sequences of different lengths under temporal variability, making DTW an ideal foundation for the development of our algorithm.

In the following, we introduce the DTW method. DTW was developed from early dynamic-programming approaches to time-normalised speech recognition (Itakura 1975; Sakoe & Chiba 1978). It allows local stretching and compression of sequences by comparing two vectors $\mathbf{X} = (x_1, x_2, \dots, x_N)$ and $\mathbf{Y} = (y_1, y_2, \dots, y_M)$ in a samplewise manner. To avoid amplitude-bias, the traces are z-normalised using

$$x_{\text{norm}} = \frac{x - \mu_x}{\sigma_x} \quad (1)$$

with μ_x being the mean of the trace and σ_x being the standard deviation. This comparison is performed through the cost matrix $\mathbf{D} \in \mathbb{R}^{(N+1) \times (M+1)}$, which is initialised as

$$\mathbf{D}_{i,j} = \begin{cases} 0, & i = 0 \text{ and } j = 0, \\ \infty, & i = 0 \text{ and } j > 0, \\ \infty, & i > 0 \text{ and } j = 0. \end{cases} \quad (2)$$

Since DTW identifies the minimum-cost alignment path, the first row and column of the cost matrix are initialised to ∞ to prevent any path from starting outside $\mathbf{D}_{0,0}$. The remaining entries are computed recursively by

$$\begin{aligned} \mathbf{D}_{i,j} = & \text{dist}(x_i, y_j) \\ & + \min\{\mathbf{D}_{i-1,j}, \mathbf{D}_{i,j-1}, \mathbf{D}_{i-1,j-1}\}, \end{aligned} \quad (3)$$

$i > 0, j > 0,$

where $\mathbf{D}_{i-1,j}$, $\mathbf{D}_{i,j-1}$, and $\mathbf{D}_{i-1,j-1}$ represent insertion, deletion and match operations, respectively. The local distance $\text{dist}(x_i, y_j)$ is added to the smallest of predecessor costs to obtain the accumulated cost at the current position.

These three transitions define the set of allowed local deformations between the sequences: insertions stretch the alignment horizontally, deletions stretch it vertically and matches move diagonally.

The final step is to extract the warping path, which is the sequence of matrix positions connecting $(0, 0)$ to (N, M) that yields the globally minimal cumulative cost. This path specifies the optimal alignment and determines at each step, which of the three transitions in equation 3 is applied.

This optimal warping path $\mathbf{w}$ is then obtained by backtracking from (N, M) through the matrix $\mathbf{D}$, selecting at each step the predecessor with the smallest accumulated cost.

Since the duration of the extracted events and therefore the warping path varies, the length-normalised DTW distance is used. This is defined as

$$\text{DTW}_{\text{norm}}(\mathbf{X}, \mathbf{Y}) = \frac{1}{L} \sum_{\ell=1}^L \text{dist}(x_{i_\ell}, y_{j_\ell}), \quad (4)$$

where L denotes the length of the optimal warping path and $\text{dist}(x_{i_\ell}, y_{j_\ell})$ are the local distances along the path. This normalisation avoids biases towards longer warping paths and ensures comparability across events of different durations.

To limit excessive temporal distortion and reduce computational cost, the admissible warping path is constrained using the Sakoe-Chiba band (Sakoe & Chiba 1978), restricting the alignment to remain within a fixed radius around the main diagonal of the cost matrix $\mathbf{D}$. Formally, a warping path element $w_\ell = (i_\ell, j_\ell)$ is admissible only if

$$|i_\ell - j_\ell| \leq r_s, \quad (5)$$

where r_s is the Sakoe-Chiba radius expressed in samples. Throughout this paper, r denotes the Sakoe-Chiba radius expressed as a time interval in seconds. For the DTW calculation, this time interval is converted to the corresponding number of samples according to the sampling rate.

This reduces the search space for the optimal warping path from $\mathcal{O}(NM)$ to $\mathcal{O}(r \cdot \max(N, M))$ and prevents pathological alignments, in which large segments of one sequence are matched to very short segments of the other. Within this band, the DTW recursion defined in Eq. 3 is applied only to indices satisfying Eq. 5 and all matrix entries outside the band are set to ∞ , ensuring they cannot be part of the optimal path. Physically, this Sakoe-Chiba radius defines the maximum local shift allowed to match two phases to each other.

We now have a clear time-invariant distance metric allowing for signals of varying length, which can be used for distance-based clustering. Since standard k-means computes arithmetic centroids, it cannot be combined directly with DTW without defining an appropriate average waveform. DTW-specific averaging methods provide one solution (Petitjean et al. 2011). In this study, we instead use k-medoids, which selects an actual sample as representative and therefore does not require a synthetic centroid.

Furthermore, DTW provides pairwise distances rather than an explicit feature representation. For the initial clustering used here, we therefore calculate all pairwise DTW distances and use the resulting distance-matrix vectors as clustering input. In this matrix, vectors of the same group are similar to each other and dissimilar to other clusters. Based on this, k-means can be applied using the columns as input features. A similar procedure was used by Ida et al. (2022) to classify 90 volcano-seismic events of different lengths, for which three distinct seismic event types with different waveform characteristics were identified.

This approach has been applied successfully to seismic waveform classification (Ida et al. 2022; Zeng et al. 2026). However, when each row of an $n \times n$ pairwise distance matrix is used as a feature vector, the input dimension increases directly with the number of samples. For larger data sets, this increases both the number of pairwise DTW calculations and the dimensionality of the clustering input (Aggarwal et al. 2001). Therefore, this study extends this method to work for larger data sets by combining established techniques into a single, robust DTW-based clustering algorithm.

3 INCREMENTAL BUFFERED CLUSTERING USING DTW

3.1 Initial clustering based on pairwise distances

We introduce a novel clustering algorithm that combines k-medoids clustering based on DTW distances with an incremental step, making it scalable to large data sets and mitigating the curse of dimensionality. Additionally, a buffer logic is incorporated to detect new clusters in the incremental step while allowing for outliers.

Since clustering the pairwise distance matrix has shown to

yield good results, pairwise distance matrix vectors shall be used as clustering input features. The dimension of the input features is therefore based on the number of samples used. To mitigate the curse of dimensionality while maintaining sufficient sample coverage of all clusters present in the data, a trade-off is required. In this study, the subset size n is limited to 500 samples as a practical compromise between sufficient coverage of the event groups and the dimensionality of the pairwise-distance representation.

The pairwise distance matrix of size $n \times n$ is obtained using the Sakoe-Chiba radius r (Eq. 5). The k-medoids algorithm is employed to identify k clusters within the subset. In contrast to k-means, which assumes an underlying metric space that supports the computation of centroids, DTW defines only pairwise distances between time series. As a consequence, the notion of a centroid is not well-defined and clustering approaches such as k-medoids, which rely on representative data points instead of synthetic cluster means, are required. The number of clusters k can be determined using established approaches like the elbow method applied to within-cluster distances. Using these methods, the initial subset is grouped using the DTW distance and the defined clustering parameters (Fig. 2, Step 1).

3.2 Incremental buffered update phase

After clustering the pairwise distance matrix using k-medoids, k clusters exist with one representative medoid for each cluster. Next, the missing samples have to be assigned to the existing clusters. Adding data incrementally is a common task in online clustering, where new samples are assigned to existing clusters without recomputing the entire clustering. Since this step allows for new clusters to be formed, the clusters from the initial step will be named core clusters labelled C .

For each new sample, the DTW distance to every medoid from the core clusters is calculated (Fig. 2, Step 2). This approach is computationally less expensive than constructing the full pairwise distance matrix, as it requires the evaluation of only k sample-medoid DTW distances. A simple strategy would be to allocate the sample to the closest medoid. However, this approach leads to a fundamental problem: since the initial phase may not contain representatives of all event types, new samples may originate from previously unobserved clusters. In such cases, a new sample may be substantially different from all existing medoids and assigning it directly would be inappropriate. Furthermore, noise samples would be forced to be assigned to a cluster but be better treated as outliers. Consequently, samples whose distances to the nearest medoid exceed a predefined threshold are not immediately assigned, but instead treated as potential members of a new cluster or outliers.

For this, a DTW distance threshold τ is defined. This value is derived from existing sample-medoid DTW distances from the initial step. Based on their distribution, the mean μ and standard deviation σ are calculated (Fig. 3). The threshold τ is then defined as

$$\tau = \mu + a\sigma \quad (6)$$

with a defining the threshold admissibility. If the DTW distance of a new sample to any medoid is below the specified threshold, the sample is assigned to the cluster of the closest medoid. A low threshold admissibility a describes a setting in which a significant proportion of samples is not allocated to a particular cluster, despite showing some degree of similarity. This approach serves to

maintain the integrity of the clusters by ensuring that they are well-defined and distinct. Conversely, elevated admissibility thresholds allow for larger within-cluster differences and reduce the number of detected outliers.

If the threshold is exceeded for every medoid, the sample is assigned to the buffer (Fig. 2, Step 2). Hence, we refer to this clustering method as Incremental Buffered Dynamic Time Warping Clustering (IB-DTWC). After assigning a sample to the buffer, the DTW distances to every buffer cluster medoid are calculated. Buffer clusters are temporary clusters that can be upgraded to core clusters if they contain at least $b_{\min}$ samples. If a buffer cluster has a medoid similar to the sample, it is assigned to the buffer cluster, else it creates a new buffer cluster. As soon as a buffer cluster contains at least $b_{\min}$ samples, it is treated as a new core cluster and the medoid is considered in the incremental step from the beginning. The number of new clusters is counted as l .

All samples from buffer clusters which were not upgraded are classified as outliers ultimately. A major advantage of this method is that it automatically classifies outliers, making the method robust for noisy or low-quality data, which was a key design goal of the algorithm.

3.3 Finalising step

After the sequential addition of all samples, each sample is assigned to a cluster or designated as an outlier. However, given that the initial phase does not permit the presence of outliers and that medoids of the l newly formed clusters may more accurately represent some previously assigned samples, a final clustering step is performed to reassign all samples (Fig. 2, Step 3). In this step, all medoids are treated as fixed cluster centres and the DTW distance to each of the $C = k + l$ core cluster medoids is computed for every sample. The DTW distance threshold is then recalculated based on the DTW distances between all samples and their respective cluster medoids (Eq. 6).

With this, every event is assigned to a cluster or classified as an outlier. This algorithm meets all defined requirements, ensuring robust performance on large, noisy datasets from continuously active seismic environments.

The IB-DTWC algorithm requires the following parameters as input:

- n : number of samples in the subset for the initial phase
- r : Sakoe-Chiba radius (Eq. 5)
- k : number of clusters for k-medoids in the initial step
- a : threshold admissibility (Eq. 6)
- $b_{\min}$: minimum number of samples in the buffer cluster required for upgrade.

All of these parameters have a clear physical interpretation and are intuitively understandable. Their practical implications will be illustrated in the proof-of-concept evaluation, which follows next.

4 PROOF OF CONCEPT: APPLICATION

4.1 Dataset and data preparation

To evaluate the performance of IB-DTWC, data of a suitable study area is required. A volcanic setting is perfectly suited due to its seismic conditions aligning with the target area for our method and the associated volcano-seismic event types are well understood (McNutt & Roman 2015). We use a labelled data set from Soufrière

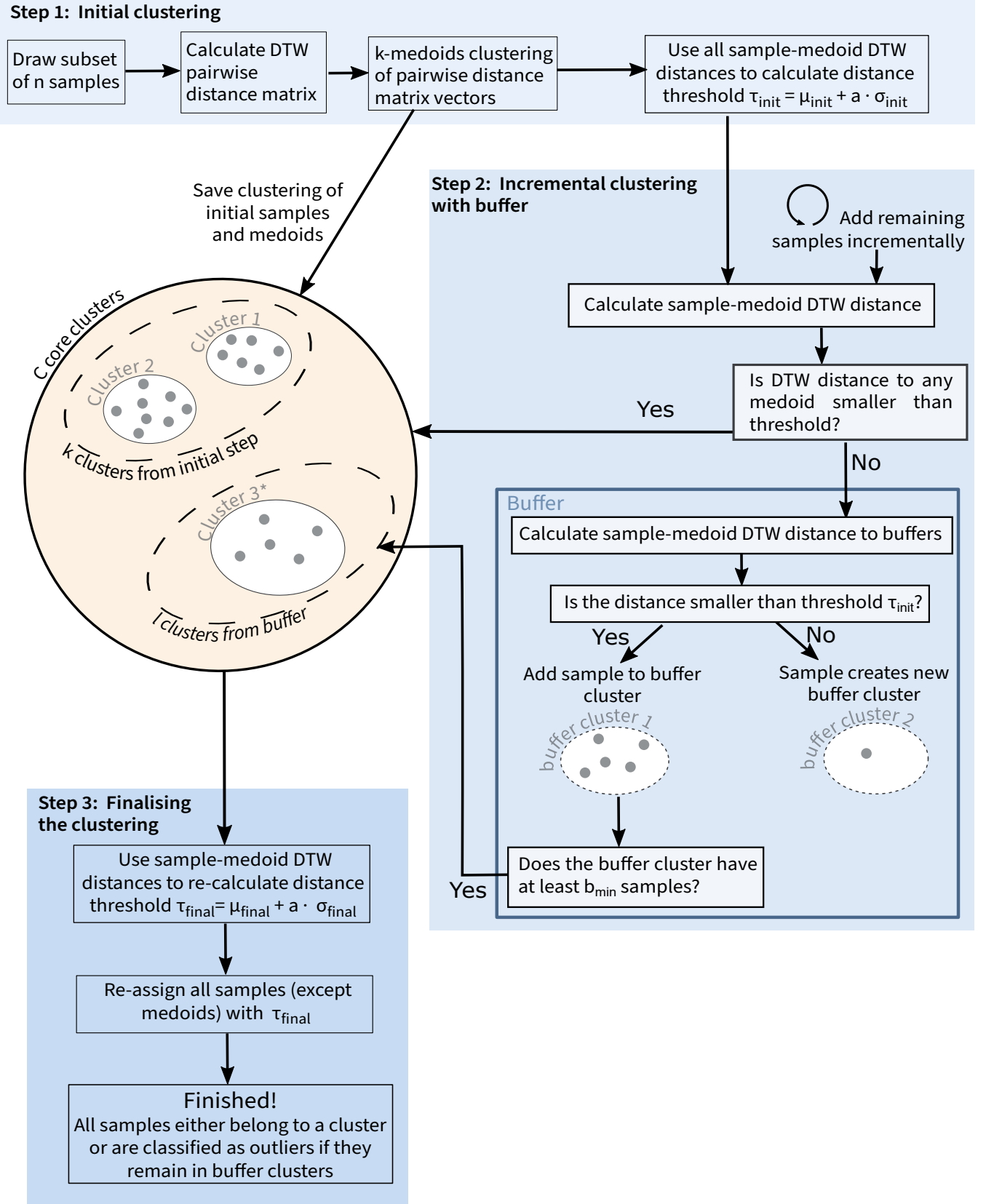
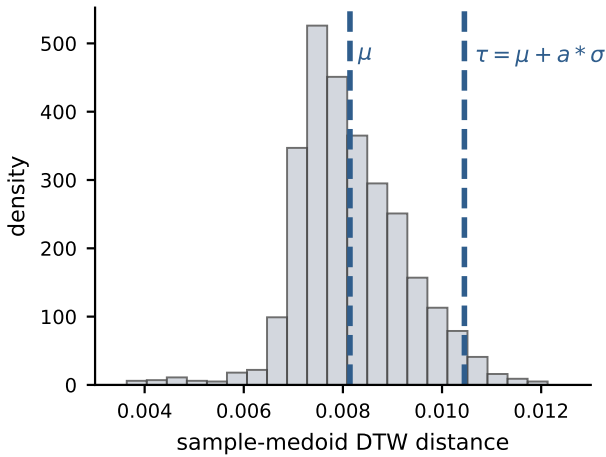


Figure 2. Flow chart of the IB-DTWC algorithm. Clusters with * were added during the incremental phase.

Table 1. Comparison of waveform characteristics and phenomenological descriptions for key seismo-volcanic event types at Soufrière Hills volcano, Montserrat, based on White et al. (1998); Neuberg et al. (2000); Calder et al. (2005); McNutt & Roman (2015).

Event type	Phenomenological description	Duration	Frequency range	Waveform characteristics
Volcano-tectonic event (VTE)	Brittle fracture within the volcanic edifice related to stress changes and magma movement	Few seconds (typically < 10 s)	Dominantly high-frequency, typically > 5 Hz	Impulsive onset with identifiable P- and S-wave arrivals
Long-period event (LPE)	Resonance in a magma- or fluid-filled conduit	Several seconds to a few tens of seconds	0.2–5 Hz	Smooth, emergent onset with low-frequency oscillatory waveform
Hybrid event (HYB)	Transitional or mixed event between volcano-tectonic and long-period signals	Several seconds to several tens of seconds	Onset: up to ~10 Hz; coda: 0.2–5 Hz	High-frequency onset followed by a long-period coda; no clear separation of P- and S-waves
Rockfall event (ROC)	Mechanical collapse involving dome material or loose blocks, ranging from small rockfalls to pyroclastic flows	Few seconds to several tens of seconds	Typically 1–10 Hz	Emergent, chaotic, cigar-shaped signal with no clear separation of P- and S-waves
Long-period + rockfall event (LPE+ROC)	Mixed event consisting of a long-period signal followed by a rockfall, likely triggered by the preceding long-period process	Tens of seconds	Onset: 0.2–5 Hz; subsequent rockfall phase: typically 1–10 Hz	Long-period onset followed immediately by an emergent, chaotic rockfall signature

**Figure 3.** Histogram of sample-medoid DTW distances. The distance threshold τ is calculated based on the statistics of these distances.

Hills volcano, Montserrat, analysed by the staff of the Montserrat Volcano Observatory. In this study, we use around 3000 labelled events from January 1997. The analysis is based on data from a single station, filtered between 0.2 and 10 Hz, covering the main frequency range of the event classes considered here.

This dataset was separated into groups related to different natural phenomena at volcanic settings. Six event types were classified: volcano-tectonic events (VTEs), rockfall events (ROCs), long-period events (LPEs), long-period and rockfall events (LPE+ROCs), hybrid events (HYBs) and miscellaneous events (MISCs). The event type description is similar to the standard volcano-seismic event discrimination by McNutt & Roman (2015), but adapted for the Soufrière Hills volcano by the researchers. In

the following section, the five seismic event types and their waveform properties are introduced. The event type descriptions are based on Langer et al. (2006) and Hammer et al. (2012) and summarised in Table 1.

Looking at the source mechanisms behind the event types, VTEs are produced by brittle fractures within the volcanic structure attributed to alterations in stress levels, magma pressurisation or stress relaxation. LPEs occur due to resonance of fluid- or magma-filled conduits and are therefore dominated by fluid movement, not brittle fracturing. The combination of brittle fracture and fluid-driven resonance produces HYBs. ROCs are attributed to a mechanical collapse of a lava dome or movement of loose blocks, ranging from small single-block falls to large collapses that can evolve into pyroclastic flows. They can follow after a long-period resonance in a magma-filled conduit, in which case they are classified as LPE+ROCs.

Event durations vary considerably between signal classes, ranging from less than 10 s for VTEs to several seconds or tens of seconds for LPEs, HYBs, ROCs and LPE+ROCs. The application of the duration-independent IB-DTWC algorithm is advantageous in this context, given that the events do not need to be cut and therefore their entire waveform information is in the clustering input. Furthermore, IB-DTWC is unaffected by event duration due to the normalisation in the DTW calculation.

Apart from this, the event types also differ in their frequency content, although these differences are not always sufficient for a clear distinction. LPEs are characterised by low-frequency energy in the range of 0.2–5 Hz, whereas VTEs are dominated by higher-frequency energy. ROCs typically occupy a frequency range of about 1–10 Hz, while LPE+ROCs combine a low-frequency onset with a subsequent higher-frequency rockfall phase. HYBs make the distinction even more difficult, as they exhibit a high-frequency onset of up to ~ 10 Hz followed by a low-frequency coda in the 0.2–5 Hz range. Frequency content alone is therefore not a reliable

parameter for separating the event classes, as several types overlap in frequency or combine both low- and high-frequency characteristics.

In contrast, the waveform characteristic is a useful indicator for event types. VTEs show impulsive P- and S-wave onsets, while LPEs exhibit smooth and emergent onsets. Consequently, HYBs, as a mixture of VTEs and LPEs, show a high-frequency onset followed by a long-period coda. ROCs show a cigar-shaped emergent onset and no clear separation between P- and S-waves. Their signal is rather chaotic due to the diffuse source mechanism linked to the number and size of rockfalls involved. LPE+ROCs combine both characteristics, typically consisting of an initial long-period signal followed immediately by a chaotic rockfall signature.

Since some event types overlap in their waveform characteristics and source mechanisms, an accuracy close to 100 per cent is not realistic as a clustering result. LPEs, HYBs and VTEs have similar underlying waveform characteristics and might therefore be mixed up in the clustering. The same goes for ROCs, LPEs and LPE+ROCs due to their similar physical nature. As a comparison, Langer et al. (2006) applied Artificial Neural Networks to data from the same study site, using about 6000 seismic records from approximately 1000 events recorded between 1996 and 1999. Their classification matched the original labels in approximately 70 per cent of the cases. After revising the reference classification, they obtained an accuracy of about 80 per cent. Since an in-depth reanalysis of the Soufrière Hills volcano is beyond the scope of this study, we do not manually reassign labels and thus consider an accuracy of about 70 per cent to be a realistic benchmark. Our goal is to obtain clusters dominated by a single event type, rather than to analyse how the underlying event types are distributed across clusters.

4.2 Application of IB-DTWC

Based on the expected outcome, IB-DTWC was applied using two parameter settings to highlight the physical meaning of key parameters (see Table 2). In the following, setting 1 is shown in orange shades and setting 2 in purple shades. For both settings, the initial sample size was 350, the admissibility threshold α was set to 2 and $b_{\min}$ to 5. In the first clustering, we used a Sakoe–Chiba radius $r = 3$ s and set $k = 4$ for the pairwise distance matrix. The second parameter setting is introduced later in the text, as it was developed only after an initial evaluation of the first setting. Every event was z-normalised to avoid amplitude bias (Eq. 1).

In setting 1, the algorithm detected six final clusters and one outlier class. 5.3 per cent (150 samples) of all events were classified as outliers. The clustering results are evaluated using the confusion matrix (Fig. 4). In addition, the corresponding cluster medoids and the distribution of samples among the resulting clusters are shown in Fig. 5 (second column).

Since our primary objective is to obtain internally consistent clusters, we focus on the purity of the detected clusters rather than the completeness of the reference classes (Fig. 4). Specifically, we assess whether each detected cluster consists predominantly of a single ground-truth class, whereas splitting a ground-truth class across multiple detected clusters is considered less detrimental for our application. In the following, the results of both settings are analysed in order of descending cluster purity.

All of the 26 events in cluster 6* correspond to LPE, showing the strong precision of newly formed clusters achieved by IB-DTWC during the incremental step. It is important to note that this cluster contains only 26 events. Its apparent purity should therefore be interpreted in the context of its small sample size. The medoid

Table 2. Parameter settings for the two starting conditions used to cluster the volcano-seismic data set.

Parameter	Description	Setting 1	Setting 2
<i>Set parameters</i>			
n	number of samples for initial clustering	350	350
r	Sakoe–Chiba radius [s]	3	10
k	number of clusters in initial step	4	3
α	threshold admissibility	2	2
$b_{\min}$	minimum samples in buffer cluster for upgrade to core cluster	5	5
<i>Derived during incremental clustering</i>			
l	number of clusters added in incremental step	2	1
C	number of core clusters (total number of clusters after incremental step neglecting outlier class)	6	4

of this cluster resembles the emergent onset and rounded waveform shape of the LPE example.

Of the 245 events in cluster 5*, 90 per cent (221 samples) are HYBs, with a smaller contribution of 5 per cent (12 samples) from LPEs. A negligible number of events belongs to ROCs and VTEs. This cluster is clearly dominated by an impulsive, high-frequency onset followed by a short coda. This aligns with the expected outcome of the mixture class HYBs being confused with LPEs and VTEs.

The same is evidenced by cluster 2, which has a very high detection rate of 80 per cent (440 samples) of HYBs and another significant contribution of 10 per cent (60 samples) from LPEs. The waveform resembles the medoid of cluster 5*, too. Both cluster 2 and cluster 5* contain a few events that do not match the HYB dominance. This could be due to wrong labels or waveform similarities with other processes.

Clusters 2 and 5* represent the typical HYB characteristics with an impulsive high-frequency onset followed by an emergent, steadily declining coda. Their shape is almost identical, but the time-variance is around 10 s, which indicates that the time-variance is larger than the chosen Sakoe–Chiba radius.

The largest cluster of setting 1, cluster 1, contains 47.6 per cent (1350 samples) of all events. It is dominated by 73.5 per cent (992 samples) of ROCs, but 12.6 per cent (170 samples) relate to HYBs and 12.5 per cent (169 samples) relate to LPE+ROCs. The medoid shows a rather emergent, cigar-shaped onset, which is typical for ROCs. The long coda and absence of clear P- and S-wave onsets also resemble HYBs. The misclassification of LPE+ROCs into the ROCs class is explainable because both share dominant high-frequency rockfall signatures, which can obscure the LPE components.

The least pure clusters are cluster 3 and cluster 4. While cluster 3 contains considerably fewer samples, only 2.4 per cent (67 samples) of all events, compared to 15.6 per cent (443 samples) in cluster 4, their purities are similar, with 49.25 per cent (33 samples) of ROCs in cluster 3 and 45.37 per cent (201 samples) of LPE+ROCs in cluster 4. In both clusters, the second most frequent event type corresponds to the dominant event type of the other cluster.

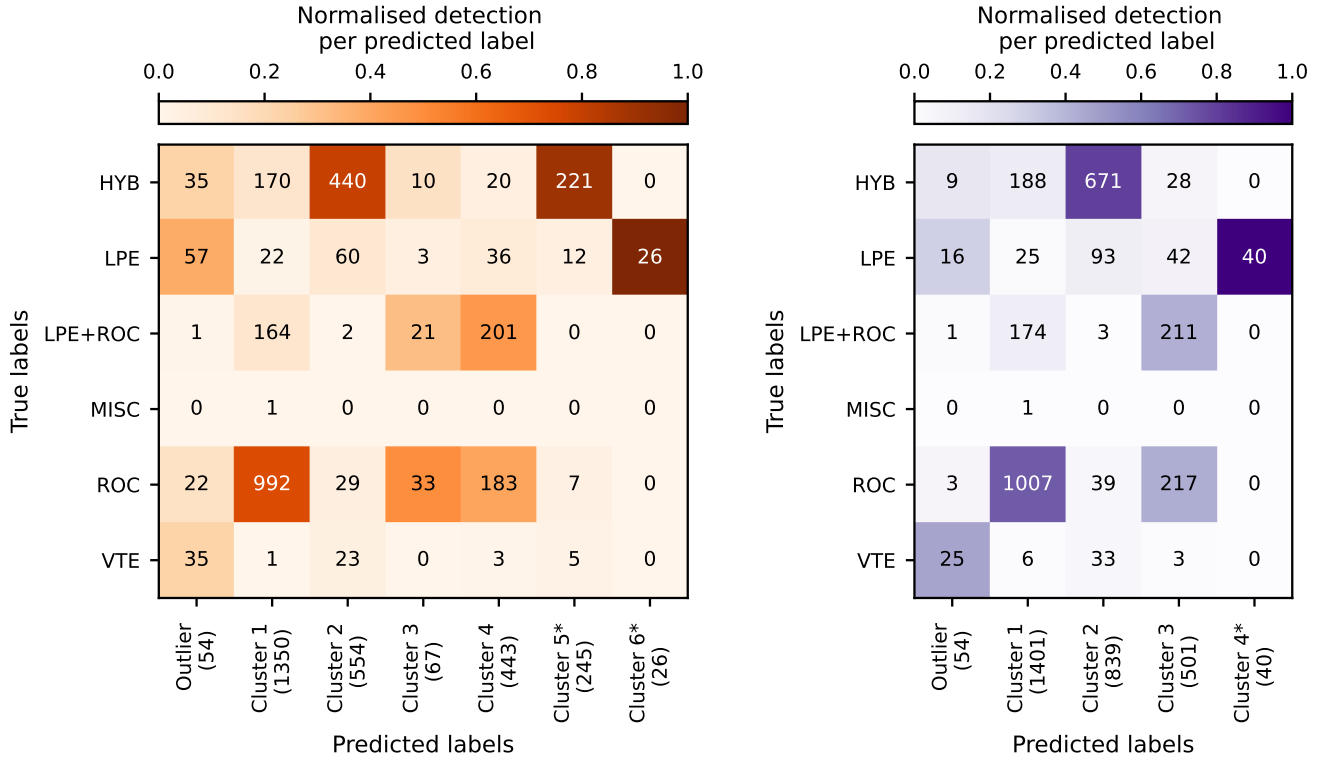


Figure 4. Confusion matrix between true labels (rows) and predicted labels (columns) for setting 1 (left, orange shades) and setting 2 (right, purple shades). The colour intensity in each cell represents the proportion of samples within the predicted cluster assigned to each true class (column-normalised), also referred to as cluster purity. The numbers in the cells show the absolute counts of samples for that combination of true and predicted labels, providing both cluster homogeneity and sample size information. * marks clusters added during the incremental phase.

ter, accounting for 31.34 per cent (21 samples) of LPE+ROCs in cluster 3 and 41.31 per cent (183 samples) of ROCs in cluster 4. Comparing the medoids of both clusters, the signals appear very similar, with an initial larger-amplitude recording of shorter duration followed by a longer, more continuous one. The difference is that cluster 3 exhibits a short amplitude decay over approximately 10 s, whereas cluster 4 does not. The Sakoe-Chiba radius does not allow for a local shift of more than 3 s, indicating that a higher value might lead to convergence of these clusters.

These observations suggest that the initial temporal constraint is too strict for the observed time variance. This is evidenced by the similarities between cluster 2 and cluster 5* as well as cluster 3 and cluster 4. Therefore, a second clustering was performed with a time variance allowance of $r = 10$ s. The decision of this parameter tuning is entirely based on the clustering results and no ground truth was required. Following the cluster validation procedure, the initial cluster number k was set to 3 based on the elbow method on the inertia values (see Table 2).

In setting 2, IB-DTWC detected four clusters and an outlier cluster (Fig. 5, third column). Here, only 1.9 per cent (54 samples) are outliers. A low outlier percentage is desirable, as the event catalogue contains only manually picked seismic events rather than noise recordings. In this context, outliers therefore represent rare events whose waveforms do not exhibit clear characteristics associated with any of the detected clusters.

The purest cluster is cluster 4*, which was added during the incremental phase. While it is also the smallest cluster, containing only 1.4 per cent (40 samples) of all events, all of these events are

related to LPEs. In contrast to cluster 6* of setting 1, the number of correctly classified LPEs increased almost by a factor of 2.

Cluster 2 is the second largest cluster of setting 2 with 29.6 per cent (839 samples) of all events and also shows the second highest purity. It is dominated by HYBs by 80 per cent (671 samples). The other samples are split between LPEs with 11.1 per cent (93 samples), 4.5 per cent (39 samples) for ROCs and 3.9 per cent (33 samples) for VTEs. The number of correctly identified HYBs in cluster 2 is nearly equal to the sum of HYBs in clusters 2 and 5 in the first setting, indicating that they merged in the desired manner by increasing the Sakoe-Chiba radius. Furthermore, the medoid of HYB cluster 2 of setting 2 is the same sample as in the HYB cluster 2 of setting 1, emphasising the robustness of the clustering algorithm.

In setting 2, cluster 1 contains the most data with 49.4 per cent (1401 samples). It is dominated by ROCs with a purity of 71.9 per cent. The misclassified samples in this cluster are mainly HYBs with 13.4 per cent (188 samples) and LPE+ROCs with 12.42 per cent (174 samples). Especially for the LPE+ROCs, this is plausible because both event types share similar source mechanisms and therefore show an overlap in seismic waveform characteristics.

Cluster 3 of setting 2 contains 17.7 per cent (501 samples) of all events. The samples are distributed nearly evenly between ROCs with 43.3 per cent (217 samples) and LPE+ROCs with 42.1 per cent (211 samples). This resembles clusters 3 and 4 from setting 1, associated with ROCs and LPE+ROCs, respectively, which seem to have merged into a single new cluster 3 in setting 2. This new cluster is now insensitive to the short, low-amplitude segment occurring during the event. This highlights the key advantage of IB-DTWC:

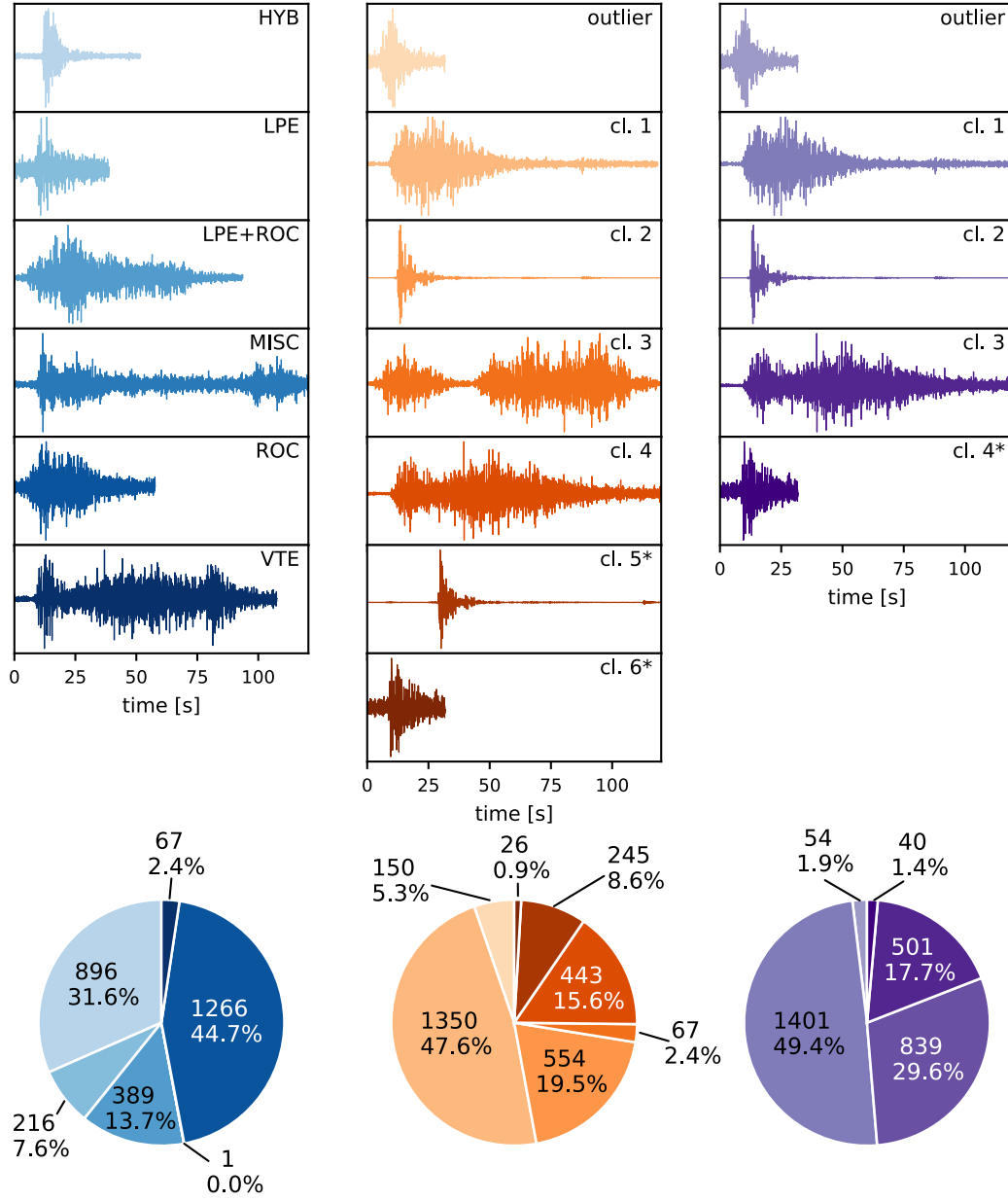


Figure 5. Event types in the labelled volcano-seismic data set. The upper panels show the seismic waveforms, the first column (blue shades) showing the labelled data from the Montserrat Volcano Observatory. Here, one representative example of each event type is displayed. The clustering results obtained using setting 1 (second column, orange shades) and setting 2 (third column, purple shades) are represented by the medoid of each cluster. As no medoid exists for the outlier class, a randomly selected outlier example is shown. The time axis is fixed for all waveforms to highlight differences in event duration and the vertical axis shows the normalised amplitude. The lower panels present the distribution of samples across the clusters, expressed as absolute counts and percentages. * marks clusters added during the incremental phase.

the tuning parameters have a physical interpretation and altering them leads to the expected effects.

Conversely, VTEs continue to exhibit ambiguity in their categorisation as a distinct event type and are therefore classified as outliers. It is possible that a different outcome would be observed if true noise samples were available, because the algorithm identifies VTEs as having no distinct waveform. The inability to detect the characteristic VTE waveform may also be related to the small number of available samples (67) in the catalogue.

The robustness of IB-DTWC is highlighted by the fact that the medoids detected with the higher Sakoe-Chiba radius are the

same as for the representative cluster medoids in the first parameter setting.

To investigate whether misclassification could be reduced by increasing the threshold admissibility α , we used setting 2 and compared the classification accuracy in relation to the DTW distance to the medoid of the respective cluster (Fig. 6). To assess accuracy, the clusters first had to be mapped to the corresponding event types. Based on the most frequent event type in each cluster of setting 2, cluster 1 was associated with ROCs, cluster 2 with HYBs, cluster 3 with ROCs and LPE+ROCs, and cluster 4 with LPEs. Cluster 3 was

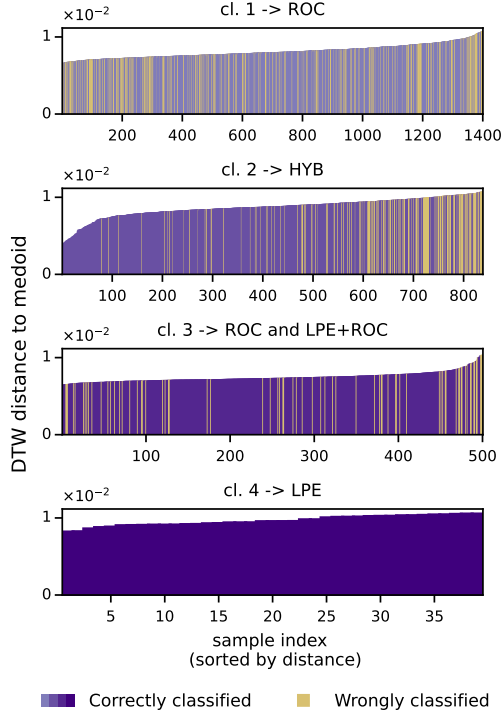


Figure 6. Misclassification of different clusters as a function of the DTW distance to the respective medoid.

allowed to relate to two event types because ROCs and LPE+ROCs overlap in their source mechanism and waveform characteristics.

With the exception of cluster 4, which does not contain any misclassified events, the trend shows an increase in misclassification at larger distances. This is expected since the signals deviate more strongly from the medoids with increasing distance. There are some misclassifications for lower distances, especially for clusters 1 and 3, which is expected due to the mixed seismic character of ROCs and LPE+ROCs. A lower value of the parameter α would therefore lead to higher clustering accuracy. This is an important finding, highlighting that the admissibility parameter must be carefully tuned when applying IB-DTWC. In this study, the admissibility parameter was not further adjusted because this would require labelled data, which are not available at other study sites and are not the focus of this study. The evaluation on labelled volcano-seismic data shows that IB-DTWC achieves a clustering accuracy of 69.39 per cent, which is numerically close to the approximately 70 per cent classification agreement reported by Langer et al. (2006) for a supervised ANN applied to data from the same study site, despite IB-DTWC not relying on labelled training data.

5 CASE STUDY: WATZMANN ARRAY IN ANTARCTICA

5.1 Data preparation

IB-DTWC proved effective for labelled volcano-seismic data, enabling a quantitative assessment of its performance. In real settings, however, such analysis is not possible due to the absence of labels. Therefore, we introduce a case study, in which the clustering is analysed qualitatively, with the aim of identifying distinct waveform characteristics between clusters. For this purpose, we use data from Neumayer Seismological Network in Antarctica. The network

consists of three three-component stations (VNA1–VNA3) (Fig. 7, left) and the Watzmann array (Fig. 7, right), with 15 additional vertical-component sensors around station VNA2 (Hammer et al. 2015).

The ice in Antarctica is highly dynamic and subject to interactions with bedrock, hydraulic interactions due to tides or filled cavities and interactions within the ice (Aster & Winberry 2017). Previous seismic studies in the Neumayer/Ekström Ice Shelf region investigated specific cryospheric processes (Hammer et al. 2015; Averbuch et al. 2025) or used machine learning to explore the broader event population at Neumayer (Kinzel et al. 2024). The data measured at Neumayer station are very noisy and event extraction and classification are challenging due to the diffuse nature of icequakes. It provides an ideal test case for IB-DTWC, because the data contain high noise levels and continuous seismic activity with multiple events occurring in short intervals with different durations.

Due to the data quality and the noisy environment, it is difficult to extract suitable seismic events. Kinzel et al. (2024) pre-selected events using an STA/LTA detector and used a higher trigger threshold for the training data to favour clear, high-quality events. Their contrastive-learning approach additionally uses data augmentation to learn a seismic feature representation. In contrast, IB-DTWC can retain weak or ambiguous detections in the event catalogue, since events that do not match an existing cluster can be assigned to the outlier class.

Since IB-DTWC focuses on one-component measurements, the vertical components of the Watzmann array were used. The data from the array were filtered between 3 and 8 Hz following the frequency band used for icequake analysis at Neumayer by Kinzel et al. (2024). Events were extracted using an STA/LTA trigger with an STA of 3 s and a LTA of 40 s, while the trigger threshold was 4. The event length depends on how long the trigger is continuously exceeded, with an additional 3 s before and 5 s after the event to include first arrivals and the lower-amplitude coda. This allowed us to include cryogenic signals with strongly varying durations, from short events lasting only seconds to long-duration tremor lasting minutes or longer (Aster & Winberry 2017).

Applying beamforming to the extracted events of the vertical array enabled a higher signal-to-noise ratio, which improved the signal quality. To do this, the event catalogue needed additional preparation. If an event was detected on less than ten of the sixteen stations, the event was disregarded. To avoid bias towards unphysical seismic recordings caused by e.g. the bad signal transmission in the harsh climate in Antarctica, single-station measurements of an event were set to 0 if their cross-correlation coefficient to the other stations was less than 0.4. These values were determined by inspecting the event catalogue for several settings, aiming for clean signals of high signal-to-noise ratio. Next, beamforming was applied and normalised to ensure all events were in the same value range. This resulted in a final dataset of 1464 events, which was subsequently used as input to IB-DTWC. Although some preprocessing was necessary to obtain clean beamformed signals, IB-DTWC does not use data augmentation to learn a feature representation, as done by Kinzel et al. (2024).

5.2 Application of IB-DTWC

Before clustering, we set the initial sample size to 350 and required 10 samples in a buffer cluster to form a new cluster. Investigating the event catalogue showed an average event duration of 15 s. As an estimate, the allowed time variation and therefore the Sakoe-Chiba radius was set to 20 per cent, corresponding to 3 s. Based on

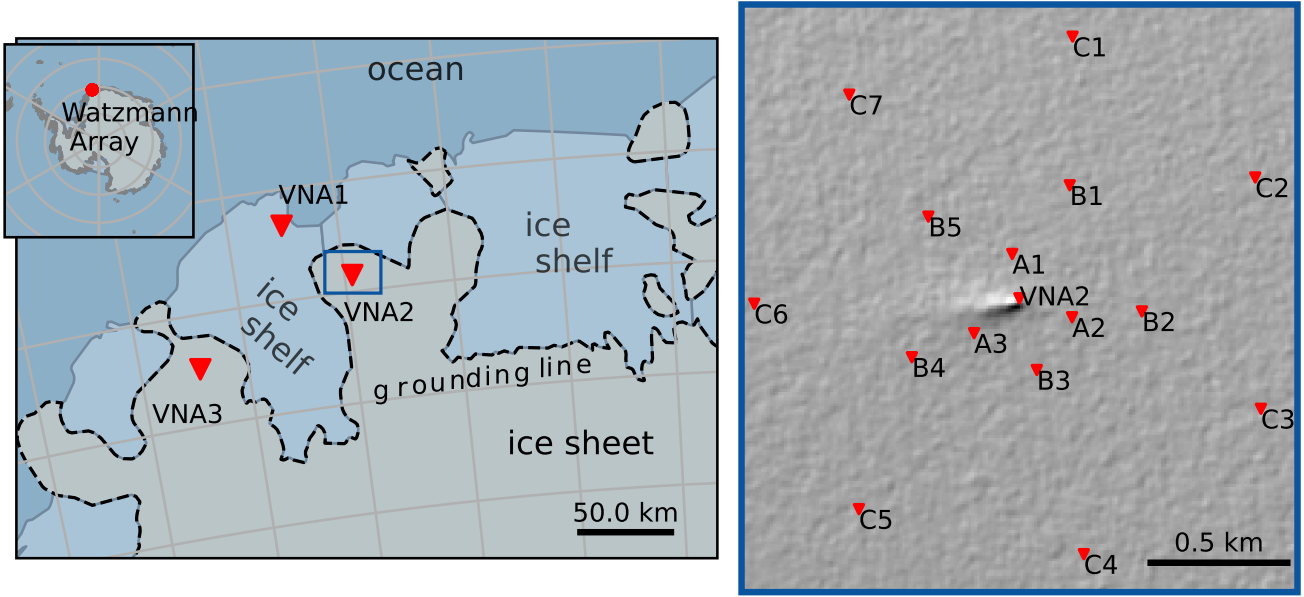


Figure 7. Map of the Neumayer seismological network (red triangles) and the local glaciological setting, including the ice shelf and the grounding line. The inset shows the regional location within Antarctica. Right: Close-up of the Watzmann array centred on station VNA2. Background topography is from the REMA 2 m DEM (Howat et al. 2022) and reveals local ice-surface variations as well as a small exposed rocky feature (Nunatak) within the array.

the cluster validation method of the pairwise distance matrix, the number of initial clusters k was set to 6. To tolerate a high number of outliers expected in such a noisy environment, the admissibility threshold was set to 1.5.

As a result, a total of eight clusters were detected, with two clusters added during the incremental phase (Fig. 8). 101 samples were classified as outliers, corresponding to 7 per cent. The seismic traces within the individual event windows of the outliers often showed two temporally adjacent high-amplitude arrivals, which may represent two closely successive events (Fig. 8, first row). This indicates that the allowance for outliers in IB-DTWC works well in regions of continuous seismic activity, preventing multiple events within a single time window from being assigned to clusters, which would otherwise worsen the clustering quality.

The waveform of cluster 1 is short-lived and exhibits high amplitude with lower-amplitude precursory arrivals occasionally preceding the main onset. While the main onset can appear impulsive, it is occasionally emergent with a rapid initial rise.

Signals assigned to cluster 2 display a short duration and often begin with a high-frequency impulsive onset, followed by a longer-lasting low-frequency signal. The amplitude of this low-frequency portion gradually decreases over time, although the total duration of the decay varies between events.

The seismic waveforms of cluster 3 are slightly more diffuse compared to the previous ones. They start with a distinct first arrival, mainly visible in the medoid and first examples, followed by gradually increasing amplitude with a subtle ramp-up. The main arrival is not continuous at a high level, but rather oscillates in intensity, giving a modulated appearance. Some high-frequency fluctuations superimpose the signal dominantly during the lower-amplitude modulated phases.

Clusters 4 and 5 exhibit similar waveform characteristics. They show an initial arrival of a smaller amplitude followed by a stronger main arrival. This resembles typical earthquake seismograms, which usually consist of lower-amplitude body-wave ar-

rivals followed by stronger surface waves. However, this is purely descriptive and does not imply that these event types exhibit this exact wave-type pattern. A formal event-type classification lies beyond the scope of this study. In comparison to cluster 5, cluster 4 shows a smoother and more symmetric, regular oscillation pattern. The difference may result from the allowed time variance of 3 s being too small, causing these events to split into two clusters.

The waveforms of cluster 6 have a compact, roughly oval or cigar-shaped envelope, with energy concentrated in a central burst and tapering off towards the edges. The signals are relatively high-frequency, with many oscillations within the main amplitude envelope. A clear onset is present, but the waveform shows a smooth, emergent rise with a slight amplitude modulation before the main rounded burst arrives.

Cluster 7 exhibits a similar seismic signature to cluster 6, but is missing the high-frequency oscillations and the rounded burst shape. It is similar in the smooth and steady increase and lack of distinct first arrival onset. Compared to cluster 6, the main energy burst is in a more similar amplitude range like the emergent onset.

Cluster 8 has a diffuse amplitude distribution and does not show any clear arrivals. The events seem to start with a high amplitude and are followed by a small decrease in amplitude, occasionally followed by a short amplitude-increase at the end of the event. Again, while the waveform differs from the other clusters, we do not interpret it in terms of specific seismic wave types. This study focuses on demonstrating that IB-DTWC can qualitatively separate distinct waveform characteristics.

As a result, IB-DTWC detected a number of waveform characteristics of cryogenic seismic data in Antarctica. The algorithm proved to handle this data set recorded in harsh conditions successfully. Especially the outlier class shows that the method is suitable for areas of continuous seismic activity, as it remains robust even when multiple seismic events occur in the same extracted time window. The clusters predominantly contain seismic waveform characteristics that reflect typical features of seismic signals like emergent

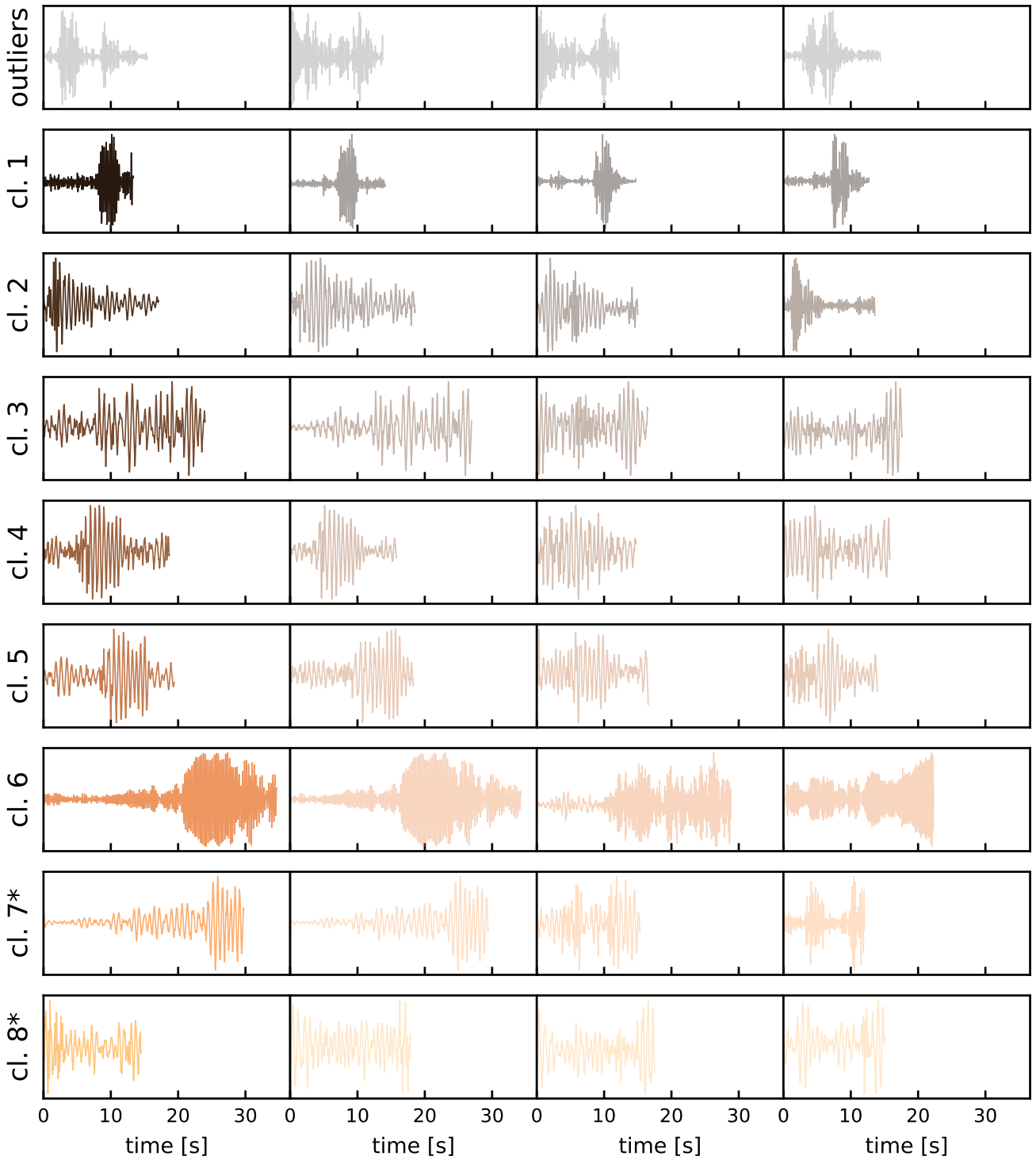


Figure 8. Exemplary normalised waveforms from January to July 2010 from the Watzmann Array following application of IB-DTWC. Each row corresponds to a different cluster, with the medoid shown as the first trace in each row, except for the outlier class, for which no medoid is defined. For each cluster, representative waveform examples are ordered from left to right according to increasing DTW distance to the respective medoid. For the outlier class, all waveform examples are randomly selected due to the absence of a medoid. * marks clusters added during the incremental phase.

or impulsive first arrivals followed by the main energy of the seismic event.

6 DISCUSSION

6.1 Strengths and limitations

In clustering, the two main components are the data and the clustering algorithm. The challenge is that the underlying event types contained in the data are generally unknown and therefore cannot be used directly to assess the clustering quality. One of the main challenges is selecting suitable parameter values. In many applications, this is done under the assumption of how meaningful clusters should look like, based on existing background knowledge of event types. The resulting clusters are then tested by varying parameters and comparing the outcomes to this prior expectation. This effectively means that parameter tuning is guided by an assumed structure of the data derived from prior knowledge.

However, clustering results are typically not directly evaluable in a strict sense and any assessment remains indirect. In the absence of reliable prior knowledge, this leads to a situation where clustering is still performed, but its quality cannot be objectively verified.

With our novel approach IB-DTWC, this uncertainty is reduced by design. All parameters have a clear physical meaning, which provides direct control over the clustering process. This allows us to bypass prior assumptions about event types, since meaningful clustering is achieved through physically constrained parameter choices rather than comparison to expected cluster structures. As a result, IB-DTWC can be applied even in settings where no prior knowledge about the event types is available, while still maintaining interpretability and control over the clustering outcome. This is achieved through a formulation in which all relevant parameters are directly linked to physically meaningful quantities.

A key strength of the proposed approach is that no fixed event duration is required. Seismic signals of varying length can therefore be included, as demonstrated by the seismo-volcanic ground-truth data, where event durations vary, but waveforms remain suitable for clustering. In contrast, fixed-length approaches typically rely on procedures such as zero-padding, which may introduce artefacts and limit the representation of the full signal. Preserving the complete waveform reduces signal truncation and overlap effects, particularly in continuously active settings such as urban environments, where multiple events occur within short time windows. This improves the quality of the extracted events and consequently enhances the clustering performance. To further increase the signal-to-noise ratio, array-based processing such as beamforming can be applied to incorporate spatial information.

Another strength of the algorithm lies in its incremental structure. The streamlined nature of the incremental and finalising step enables the regular addition of new samples as shown by the additional clusters indicated by the asterisk in this work. This methodology enables continuous monitoring, as new data can be added incrementally without recomputing the full pairwise distance matrix or rerunning the initial clustering. Furthermore, the ability to correctly incorporate emerging clusters during subsequent data additions highlights the suitability of the algorithm for monitoring applications.

A significant constraint of this algorithm is its emphasis on single-component measurements. In the proof-of-concept study, only the vertical component with the highest signal-to-noise ratio was used. This inherently excludes multi-component information

such as wave type characteristics and polarization. In cases where multi-component measurements are required, alternative methods such as deep scattering may be more useful. For single-component or Distributed Acoustic Sensing measurements, this constraint is not restrictive, as the data are inherently recorded in a single dimension.

Another limitation is that the number of buffer clusters can be high, depending on the data set and threshold admissibility, which can make IB-DTWC computationally expensive. This can be mitigated by increasing the admissibility, which reduces the number of samples stored in individual buffer clusters, by lowering the number of samples required for a buffer cluster to be upgraded to a core cluster, or by defining a maximum buffer age. The latter would mean that a buffer cluster is removed if none of a specified number of newly added samples is assigned to it. However, this may cause rarely occurring clusters to be missed.

In order to achieve a balance between the mitigation of the curse of dimensionality and a variety of cluster types when choosing n , it is possible to incorporate prior knowledge about expected event classes. While the present study concentrates on the clustering of unknown data sets, it is important to note that practical applications frequently offer a certain degree of physical insight and potential temporal occurrences. For example for cryogenic events in Antarctica, a number of potential source processes (Aster & Winberry 2017), likely relations to tides (Hammer et al. 2015) and other environmental factors (Kinzel et al. 2024) are known. This information helps select appropriate temporal subsampling strategies, thereby ensuring that the most relevant cluster types are included while keeping the sample size, and therefore the clustering dimension, small. Importantly, this type of prior information is limited to the expected occurrence and sampling of events, whereas no assumptions are made about the waveform characteristics themselves. This process can be further supported by more sophisticated bootstrapping techniques rather than simple temporally stratified random sampling.

The second parameter, the Sakoe-Chiba radius, is defined as the maximum time-variance of the same signals within an extracted window length. Determining this value can be achieved through two methodologies. Firstly, a review of several examples of the data set can be conducted to obtain an approximate estimation of the shift. This can be done by visually inspecting several events of supposedly the same type and estimating the time shift. Secondly, the length can be set to a proportion of the average event length. If uncertainty persists, it is best to choose a slightly longer length using more computing power. In a second step, the resulting clusters can be compared as shown here for the seismo-volcanic data set. If medoids of different clusters show an undesirable time-variance but a similar signal shape, as in clusters 3 and 4 or clusters 2 and 5* in setting 1, the radius can be increased. This leads to the expected outcome that these clusters are merged into a single, large one (clusters 3 and 2 for the second setting, respectively).

The number of clusters for the k-medoids clustering of the pairwise distance matrix is determined by employing validation methods like the elbow method on the inertia of different cluster numbers. It is recommended to select the lower end of the plausible cluster-count range provided by these methods, since they generally yield a range rather than a single definitive value. Choosing the lower value is justified because the incremental step and the buffer logic may introduce additional clusters later in the process. Consequently, the initial value of k is less restrictive than in standard k-medoids clustering.

The parameter that exerts the most significant influence on the

outcomes is the threshold admissibility a . For low-quality data sets, a low admissibility threshold can increase cluster robustness by preventing weak or ambiguous detections from being forced into existing clusters. Hence, standard STA/LTA triggering can be applied even in noisy environments where detections may include weak or ambiguous events, as the admissibility threshold and outlier treatment mitigate their influence on the clustering results.

In this context, the minimum number of samples required to upgrade a buffer cluster to a core cluster $b_{\min}$ is also a salient factor. It is imperative to select this value in relation to the total number of samples. In data analysis, a very low value can result in the formation of an excessively large number of small clusters. On the contrary, a high value may prevent the formation of clusters with only a few detections.

6.2 Conclusion

In this study, we first demonstrated the need for an algorithm capable of clustering single-component time-series data from continuously active seismic environments while accounting for time invariance, variable event durations and noisy signals. Such seismic datasets occur in cryogenic, volcanic and urban seismic settings. The high density and overlap of events, combined with limited prior knowledge of event types, make unsupervised clustering approaches essential.

Existing seismic machine-learning approaches often rely on extracted or analytically defined features (e.g. Seydoux et al. 2020; Steinmann et al. 2022; Karimpouli et al. 2024) or learned representations from neural networks (e.g. Rimpot et al. 2025). These representations can subsequently be combined with dimensionality-reduction techniques such as PCA, t-SNE or UMAP for clustering or visualisation. For learned representations, the resulting feature space depends on the selected network architecture and training procedure, which can make the physical interpretation of the clusters more difficult (Lu et al. 2024). This limits the ability to validate clusters in previously unexplored seismic environments.

In addition, many deep embedded clustering approaches jointly optimise feature representations and cluster assignments in latent space, making the resulting clustering structure dependent on the selected embedding strategy and training procedure (Mrabah et al. 2022). In contrast, IB-DTWC operates directly on raw time-series data, avoiding the need for engineered or learned feature spaces.

Seismic analysis commonly relies on either multi-component station data or multi-station array processing for wavefield characterisation. IB-DTWC was developed for single-component time-series inputs at the individual channel level and it does not operate on multi-component wavefield attributes used for polarization analysis. However, it can be combined with array processing techniques such as beamforming when multiple spatially distributed sensors are available, enabling the incorporation of spatial information without modifying the underlying clustering framework.

Waveform similarity methods, including template matching and cross-correlation-based detection, are widely used in seismic event analysis and compare waveform segments directly in the time domain (Gibbons & Ringdal 2006; Shelly et al. 2007). These approaches generally require representative templates and predefined comparison windows, which can limit their flexibility for data sets with strongly varying event durations.

DTW has been combined with clustering methods for seismic waveform classification (Ida et al. 2022; Zeng et al. 2026). Scaling pairwise DTW approaches to large data sets remains challeng-

ing because the number of waveform comparisons increases rapidly with the number of samples and, for the distance-matrix representation used here, the feature dimension increases at the same time. A robust extension of DTW-based clustering to large-scale continuous monitoring remains an open challenge similar to other pairwise waveform similarity approaches.

The proposed IB-DTWC algorithm introduces physically interpretable parameters that enable unsupervised clustering without relying on feature engineering or predefined templates. This is particularly relevant in settings where seismic event types are unknown a priori, allowing clusters to emerge directly from time-domain waveform similarity under explicit physical constraints. The parameter a controls admissibility and outlier tolerance, enabling robust performance in both noisy and clean data sets. This can reduce the need for extensive catalogue cleaning, as ambiguous or noisy events can be treated as outliers rather than being forced into existing clusters. The minimum cluster size parameter $b_{\min}$ and time-shift constraints further provide intuitive control over the clustering behaviour.

IB-DTWC is designed for large-scale seismic datasets and mitigates the curse of dimensionality associated with high-dimensional feature spaces. Its incremental formulation enables continuous monitoring, where new data can be incorporated without recomputing the full pairwise distance matrix or rerunning the initial clustering. The final reassignment step can be performed periodically after a batch of new samples rather than after each individual update, reducing the computational effort during continuous monitoring.

The evaluation on labelled volcano-seismic data shows that IB-DTWC achieves a clustering accuracy of 69.39 per cent, which is comparable to the approximately 70 per cent reported for supervised learning approaches trained on labelled data (Langer et al. 2006), despite not relying on labelled training data. The initial parameter settings in this work showed splitting of certain event classes, which was resolved by adjusting the Sakoe-Chiba radius to account for time variance within waveform classes. This highlights the importance of explicit time-invariance control in clustering performance. Importantly, the cluster medoids of the representative event types remained stable across the parameter settings, indicating robustness of the clustering structure.

Our case study on Antarctic icequake data further supports the applicability of IB-DTWC to environments with limited prior knowledge of waveform classes. Due to the lack of labelled ground truth, this analysis remains qualitative, but demonstrates the ability of the algorithm to identify meaningful waveform groups in cryogenic settings.

IB-DTWC is not restricted to volcanic or cryogenic environments, as it is applicable to any setting with continuous seismic activity and limited prior knowledge of event types. This includes distributed acoustic sensing applications and legacy single-component seismic networks.

While the method is currently limited to single-component input data, array-based extensions through beamforming can introduce spatial information without altering the core clustering framework. Multi-component polarization analysis remains outside the scope of the current formulation.

IB-DTWC therefore provides a waveform-native approach for scalable unsupervised clustering of continuous seismic recordings while retaining physically interpretable constraints.

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Author contributions: A.K. developed the methodology, performed the analyses, prepared the data and wrote the manuscript. V.S. and C.H. contributed to the scientific development of the study, provided guidance throughout the project and critically reviewed the manuscript. V.S. contributed particularly to the Antarctic icequake data and their interpretation, while C.H. contributed particularly to the methodological and structural aspects of the study. All authors reviewed and approved the final manuscript.

Conflict of interest: The authors declare no conflict of interest.

Data Availability

The software used for the analyses presented in this study is publicly available at <https://github.com/AntoniaKiel/IBDTWC>. The Antarctic icequake dataset used for the clustering analysis, including the waveform data and associated metadata, has been submitted as supplementary material with the manuscript to *Geophysical Journal International*. The Montserrat volcano-seismic data and the associated ground-truth classification are not publicly available because the data were provided by the Montserrat Volcano Observatory under restricted data-access conditions.

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