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SOURCE DETECTION AND TRACKING FOR UNDERWATER DISTRIBUTED ACOUSTIC SENSING

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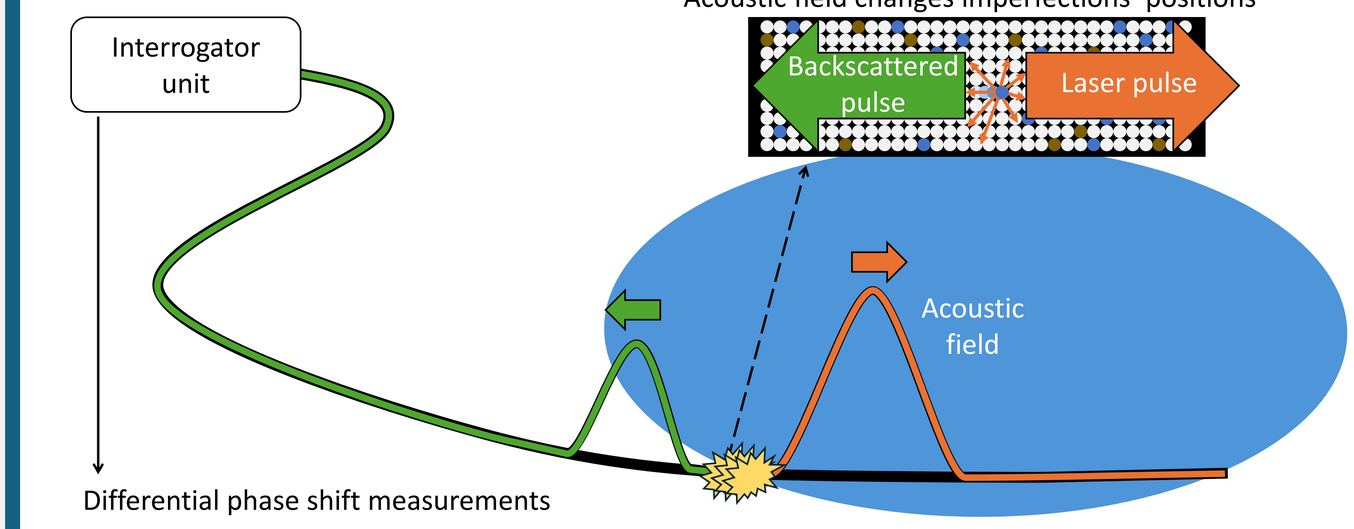
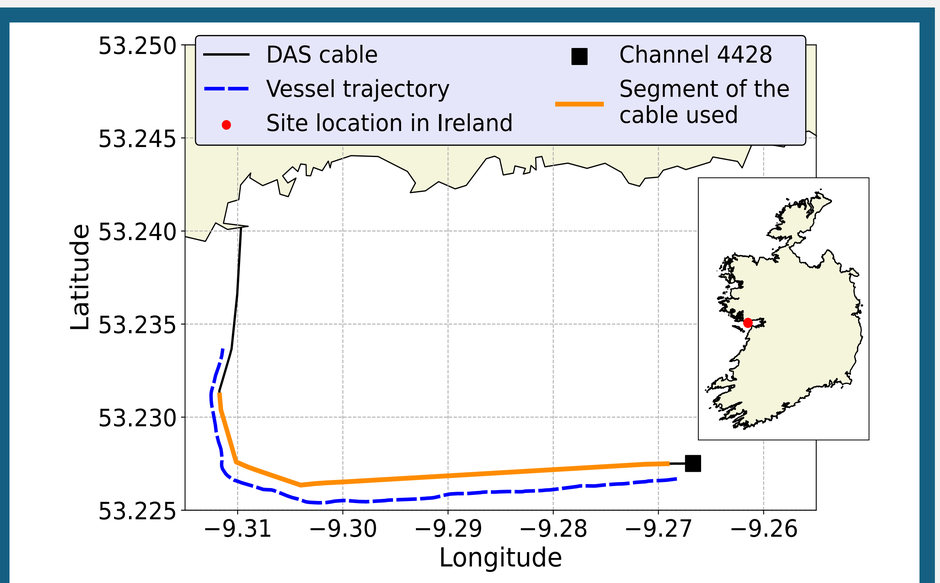
Context



Distributed Acoustic Sensing (DAS) uses fiber optic cables to detect vibrations by analyzing changes in the phase of backscattered light caused by external perturbations. Pulses of coherent light interact with imperfections in the fiber, which move in response to acoustic vibrations. This enables real-time monitoring of environmental changes with high spatial and temporal resolution, enabling tasks like sound event detection, classification, localization, and tracking of various acoustic events [1].



Real, novel marine DAS data, obtained from a 5,650 m offshore seafloor cable, were used to track an active source. A comprehensive framework based on **Principal Component Analysis (PCA)** [2] was developed, to extract relevant features, and facilitate real-time extraction of smooth trajectories from vessel track estimates.

Proposed approach

Filtering → **PCA decomposition** → **Component selection** → **k-means [3] clustering** → **GM-PHD filter tracking**

Low, high, and band-pass filters, are used to generate distinct versions of the data, based on uniformly spaced frequency bands. This step can help isolate different types of noise.

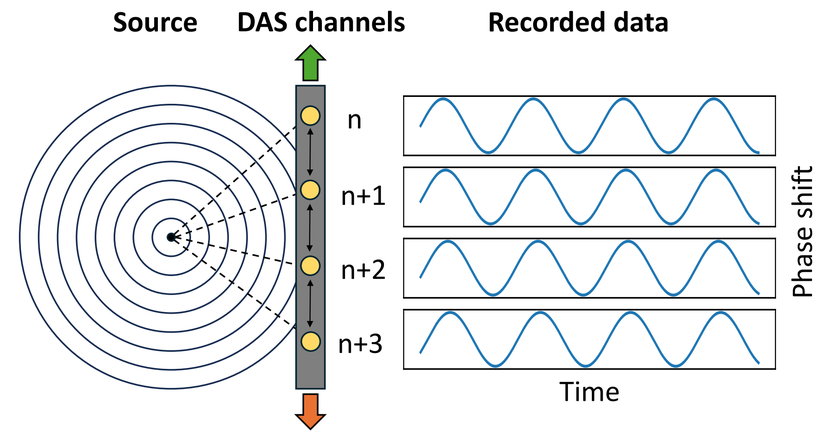
Each version of the m x n DAS data matrix is segmented using a sliding, r x c, non-overlapping window. PCA is performed on this set of r x c patches, upon flattening them into vectors.

We select components corresponding to structured, coherent signals with a locally dense energy distribution, using the **Pearson correlation coefficient** (PCC) and the **Shannon entropy**:

Each dimensionally reduced sample $\mathbf{d}$ is clustered based on its total energy in the selected principal subspace S :

$$e(\mathbf{d}) = \sum_{\mathbf{v}\in S} d_{\mathbf{v}}^2$$

The framework is completed with the aid of a Gaussian mixture probability hypothesis density (GM-PHD) [4] filter tracking algorithm, applied on the clustered data.



The PCC is used to characterize the **spatio-temporal correlations** among neighboring DAS channels. For a principal component (PC) $\mathbf{v}$ returned by the PCA, the average channel-wise PCC is defined as:

$$a(\mathbf{L}(\mathbf{v})) = \frac{\sum_{i=1}^{r-1}\sum_{j=i+1}^{r} PCC(L_i,L_j)}{C(r,2)}$$

where $\mathbf{L}(\mathbf{v})$ is the r x c matrix obtained by reshaping the relevant eigenvector of PC loadings, and $PCC(L_i,L_j)$ is the PCC between the i-th and j-th rows of $\mathbf{L}(\mathbf{v})$. The assumption is that PCs that correspond to **structured signals**, are expected to have **high values of** $\boldsymbol{a}$.

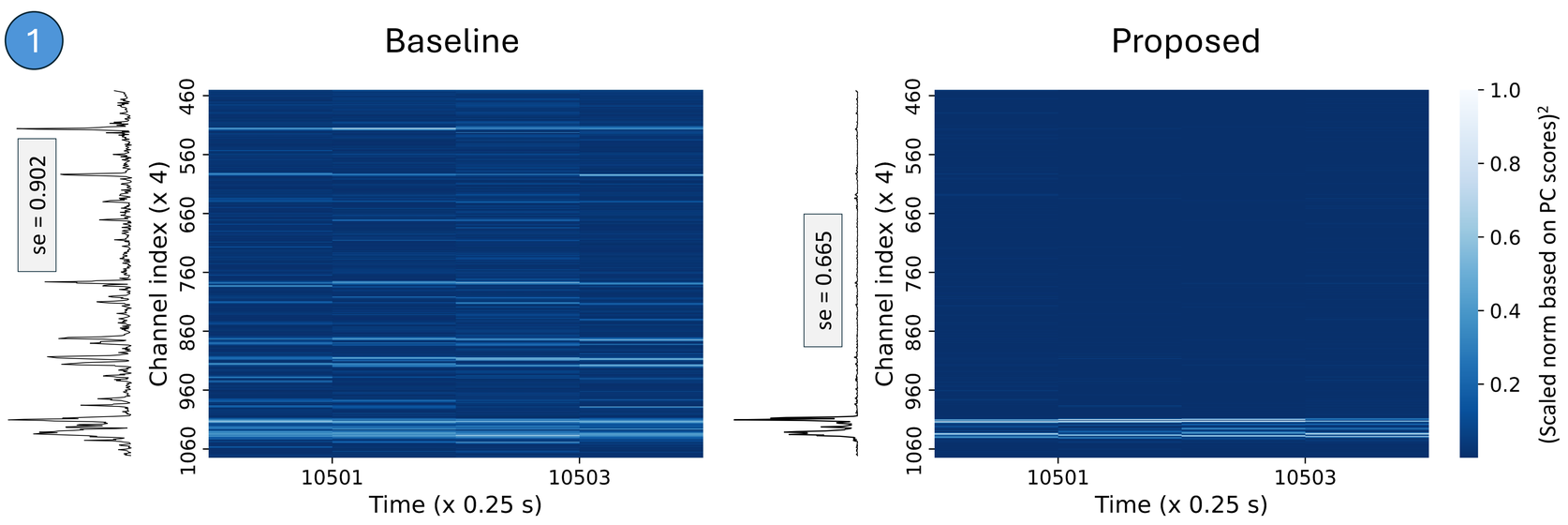
Entropy is used to examine whether a PC, when viewed as a spatial signal, has most of its **energy concentrated at a certain location**. Given a PC, $\mathbf{v}$, its spatial entropy can be computed using:

$$se(\mathbf{v}) = -\sum_{i=1}^{m/r} p_i \cdot log_{m/r}(p_i) \quad , \quad p_i = \frac{\sum_{j=1}^{n/c} v_{ij}^2}{\sum_{i=1}^{m/r}\sum_{j=1}^{n/c} v_{ij}^2}$$

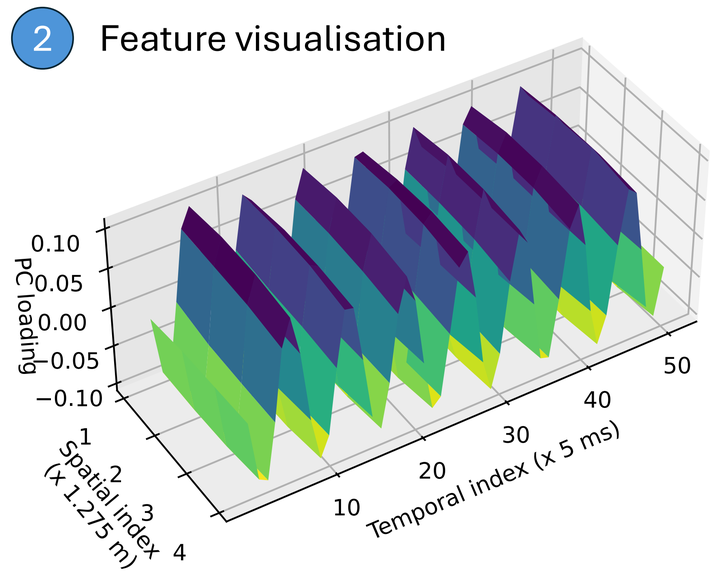
where v_{ij} is the relevant PC score on $\mathbf{v}$. The assumption is that PCs with **low values of** $\boldsymbol{se}$ will correspond to **sources of limited spatial range** in terms of the DAS cable response, e.g., a vessel, and comprise more interesting targets in tracking scenarios.

Results

1



2 Feature visualisation

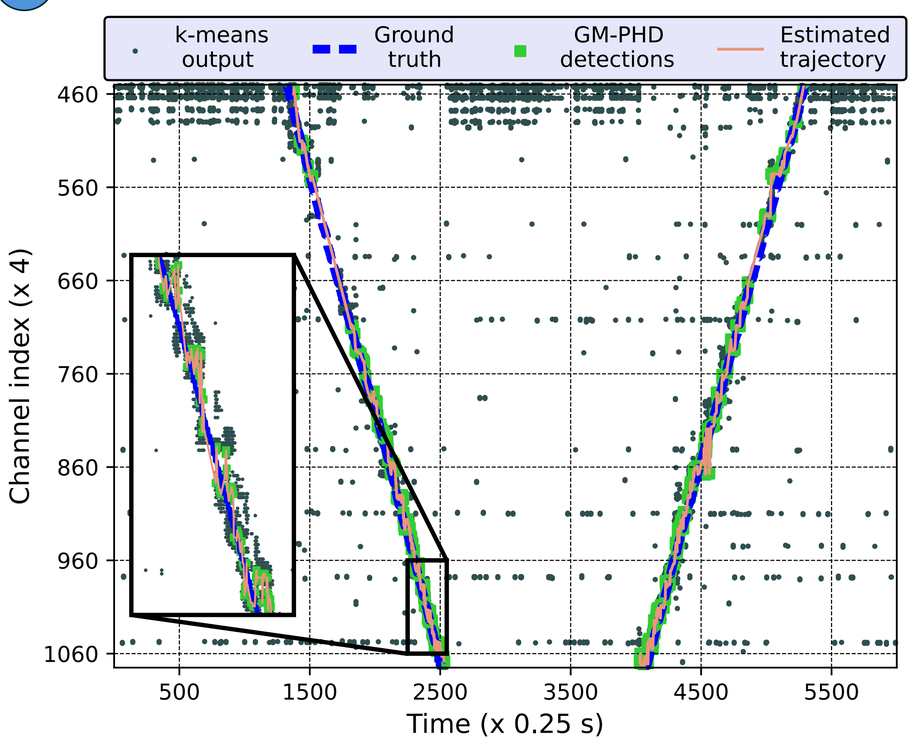


1 A **feature-level comparison** is made, between the proposed approach and this in [5], where the component selection is based on variance. As the signal of interest in this work is not the main source of energy, the approach in [5] leads to uninformative features. This can be quantified via the spatial entropy levels, computed based on the features extracted in each case.

2 An illustrative example of **PC loadings for a PC capturing a vessel** is provided. These loadings are the weights with which each spatio-temporal DAS sample is multiplied, based on the Frobenius inner product, to compute its value on the relevant feature. The 30 Hz eigenfrequency associated with the vessel's motion is captured by the proposed approach.

3 The **performance of the proposed framework, for a frequency band between 20 and 40 Hz**, for a subset of the data during which a vessel completes two traversals along the cable. Tailoring the GM-PHD filter to output only accurate detections, a **recall rate of 45%** is achieved, with an average error of 39 m and a standard deviation for the error of 31.7 m.

3 Final framework output



Conclusion

A novel and comprehensive framework for analyzing marine DAS data was proposed, employing PCA and two features in the PC space for tracking applications. Through successive filtering steps, marine DAS data were effectively denoised, enabling their utilization in tracking scenarios with a tracking algorithm. The framework's blind denoising and unsupervised data processing capabilities, advance underwater DAS data analysis, helping tackle new challenges in underwater real-time monitoring.

Acknowledgement

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References

[1] A. H. Hartog, M. Belal, and M. A. Clare, Marine Technology Society Journal, vol. 52, no. 5, pp. 58–73, 2018.
[2] T. Jolliffe and J. Cadima, Philosophical transactions of the royal society A: Mathematical, Physical and Engineering Sciences, vol. 374, no. 2065, p. 20150202, 2016.
[3] S. Lloyd, IEEE transactions on information theory, vol. 28, no. 2, pp. 129–137, 1982.
[4] B.-N. Vo and W.-K. Ma, IEEE Transactions on signal processing, vol. 54, no. 11, pp. 4091–4104, 2006.
[5] C. Wiesmeyr, M. Litzenberger, M. Waser, A. Papp, H. Garn, G. Neunteufel, and H. D¨oller, Applied Sciences, vol. 10, no. 2, p. 448, 2020.