Transformer for Passive Acoustic Distance Estimation of Cetaceans

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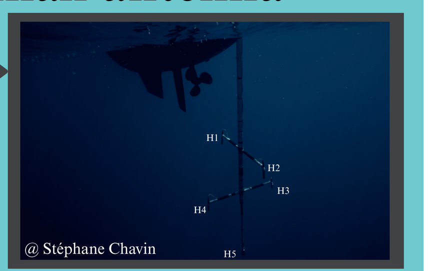
Introduction

- The underwater behaviour of sperm whales *(Physeter macrocephalus)* remains poorly understood, including their trajectories
- Passive acoustics readily estimate their directions, but range estimation remains challenging in case of small hydrophone arrays
- Existing methods based on time differences of arrival [1] or echoes [2,3] require large hydrophone arrays or lack precision

Can deep learning provide a way to estimate distances on a small hydrophone array by integrating various observables?

Materials and Methods

- To enable comparison with a reference track [1, 2], the deep learning method was first applied in the case of a large-aperture hydrophone array, and then to a small antenna
- Small, near-surface hydrophone array →
  Large case: Five bottom-mounted hydrophones spaced from 3.5km to 7.5km



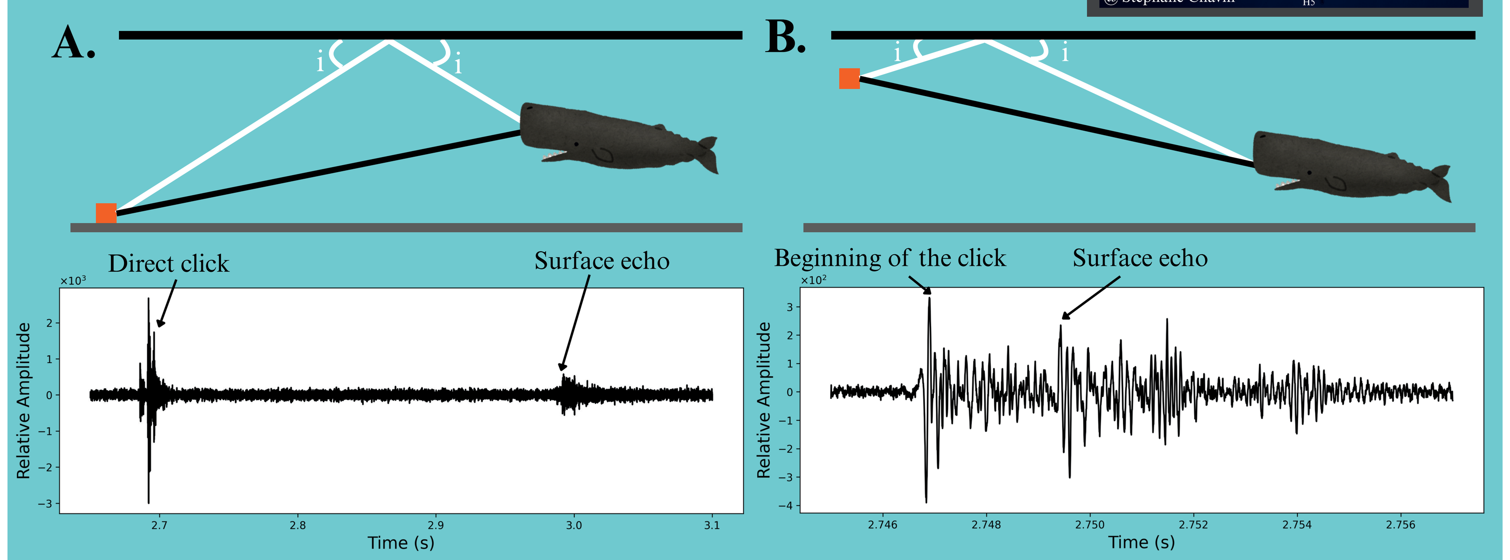
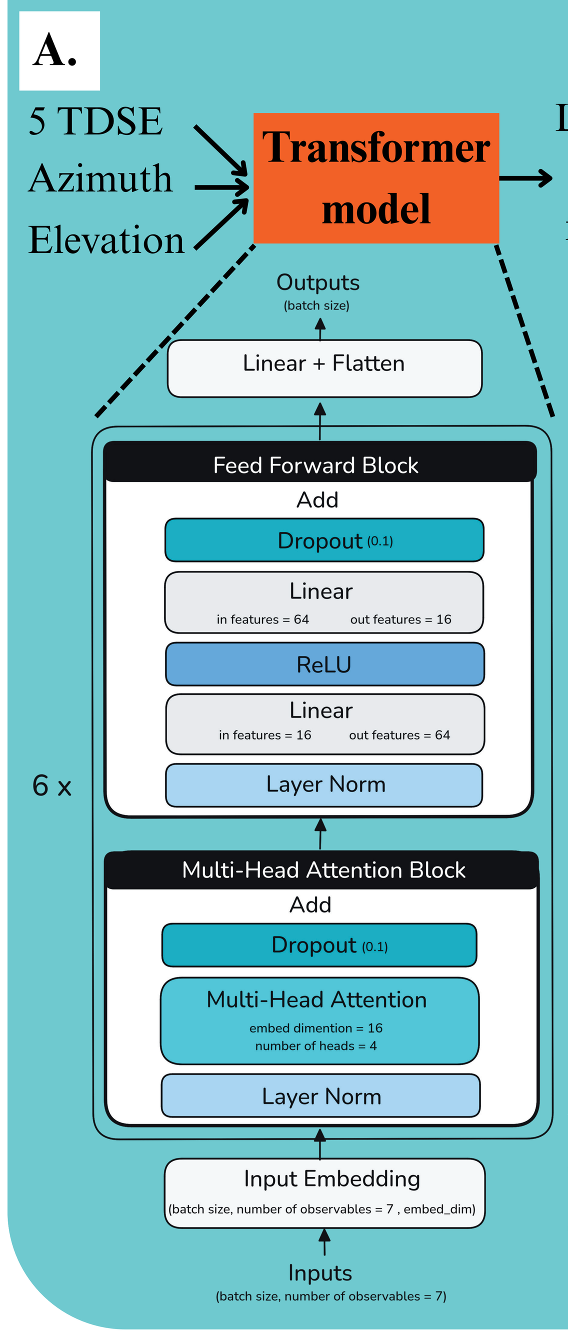


Fig.1: Surface echoes in case of (A) large and (B) small-aperture hydrophone array

- Due to the lack of labeled trajectories for supervised learning, the Transformer models [4] were trained on simulated sources, and then tested on both simulated and field datasets



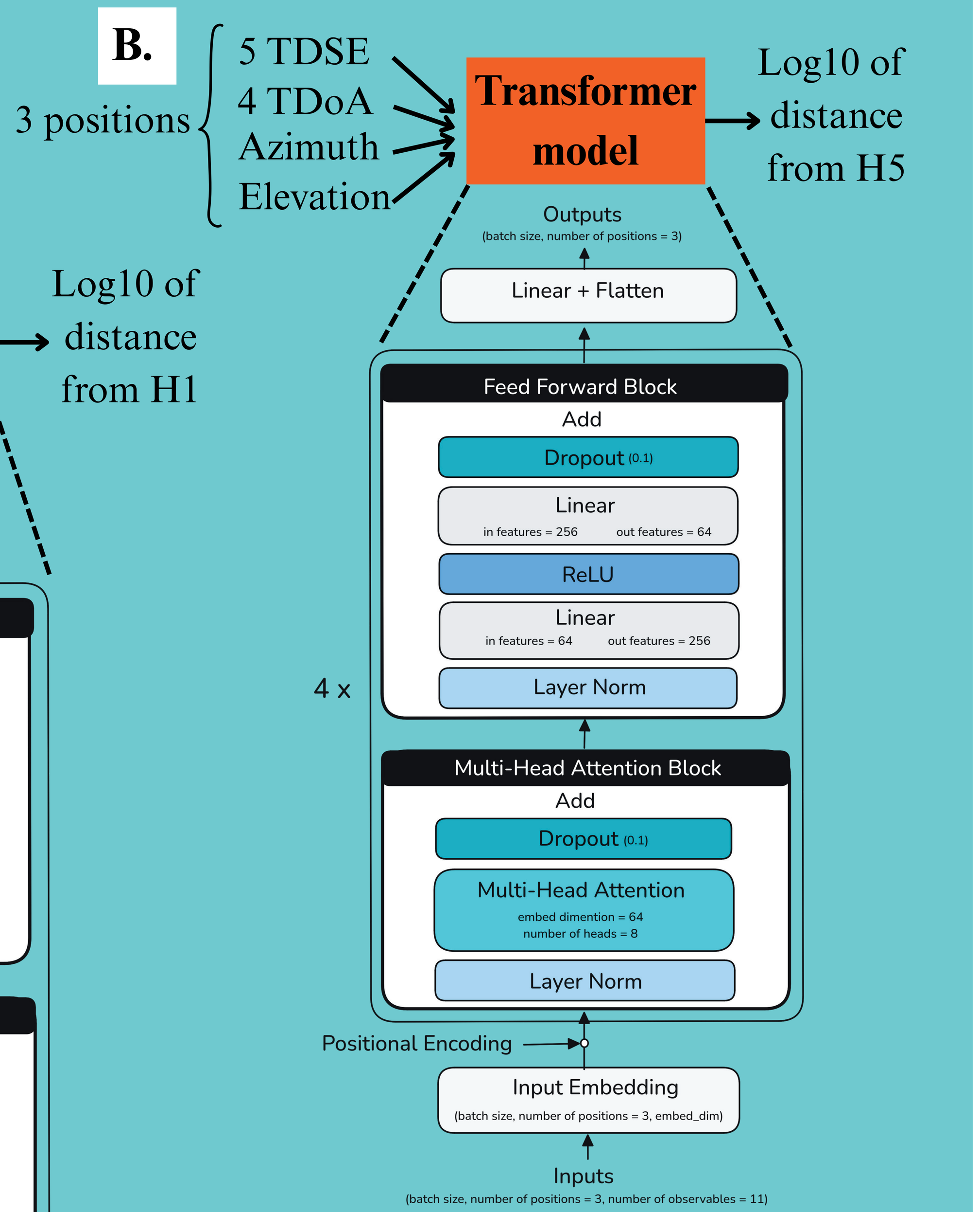


Fig.2: Selected Transformer training setup and architecture for (A) a large and (B) a small-aperture hydrophone array. TDoA: Time Difference of Arrival; TDSE: Time Difference Surface Echo

Results

- <u>Large-aperture hydrophone array:</u>
  - Simulated dataset : **MAPE = 1.41%** **R^2 = 99.8%**

The best performances are around 700m, due to the weights applied during model training

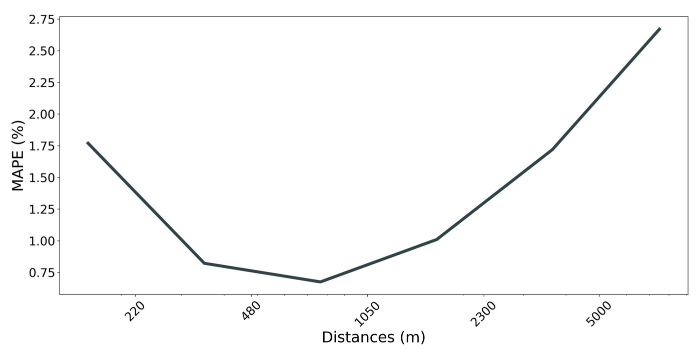
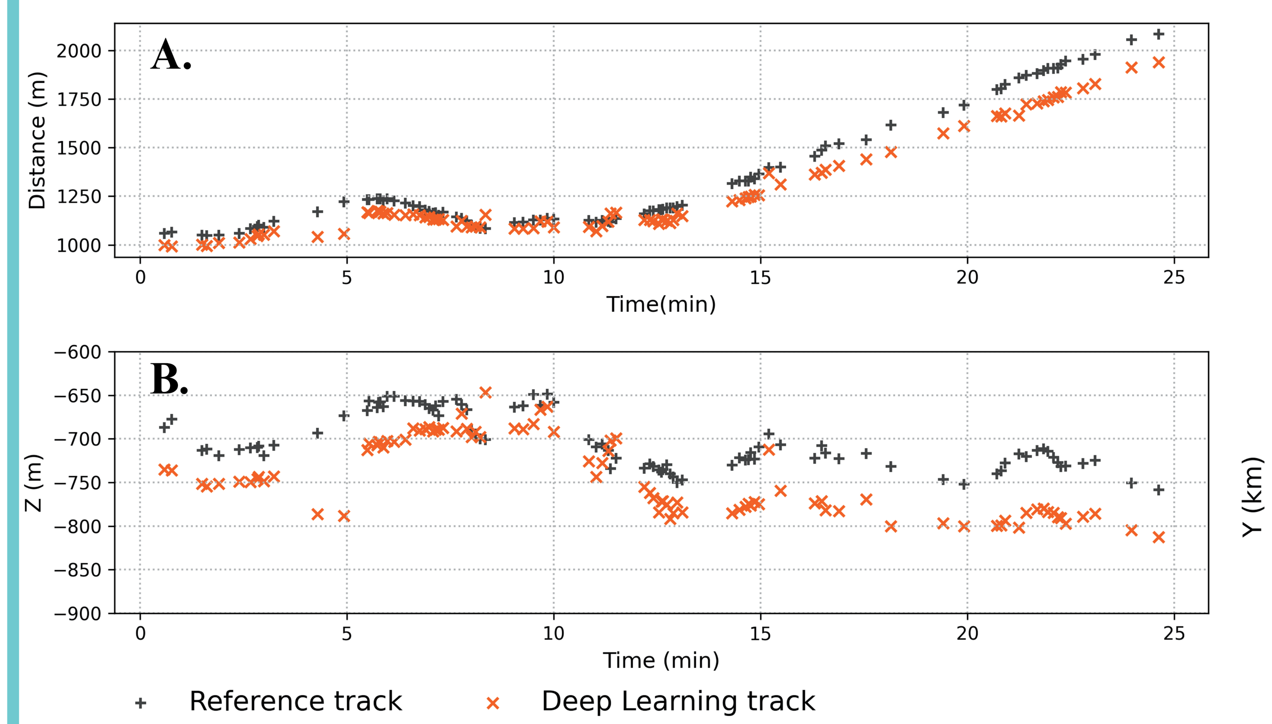


Fig. 3: MAPE on the simulated test dataset for the large-aperture antenna across different distance ranges

- Field dataset:

Comparison with reference track [1,2]: **MAPE = 5.29%**



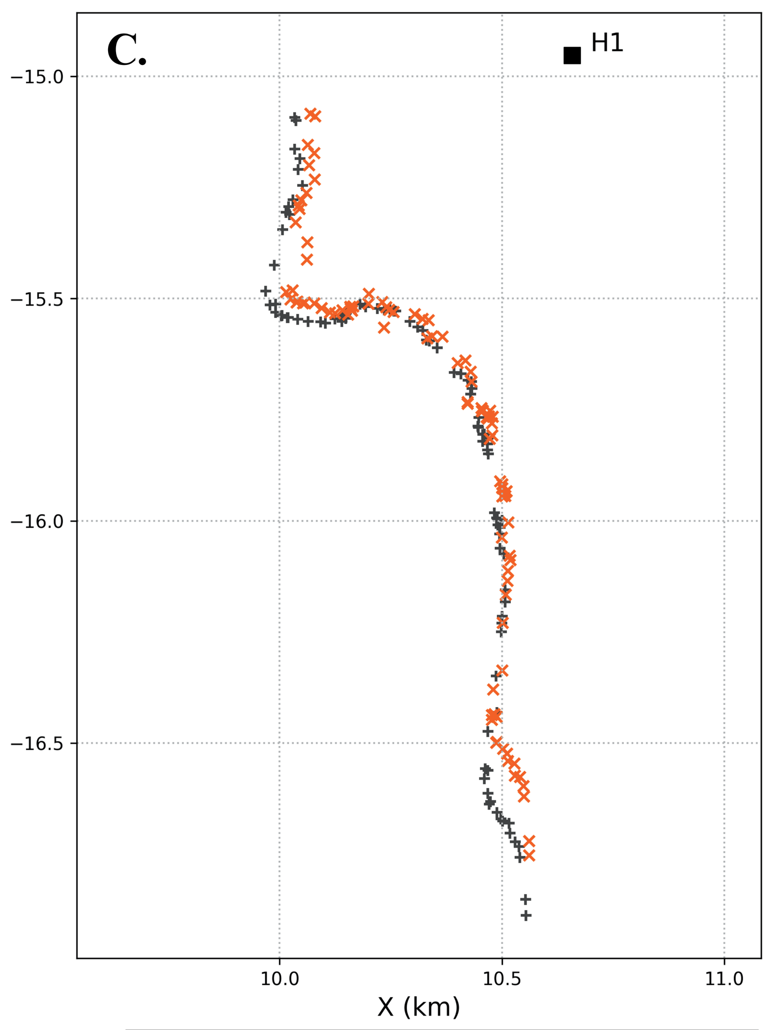


Fig. 4: Comparison between the sperm whale track estimated by our deep learning method (orange) and the multi-validated reference track (black). (A) distance from the first hydrophone, (B) depth profile and (C) 2D horizontal track of a single sperm whale

- <u>Small-aperture hydrophone array:</u>
  - Simulated dataset : **MAPE = 6.14%** **R^2 = 98%**

The best performances are from 200m to 1000m, due to the weights applied during model training

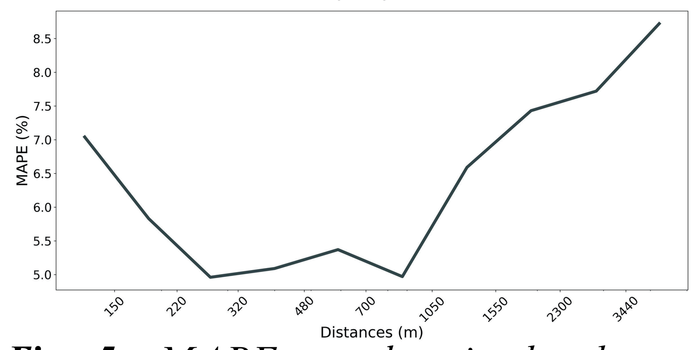


Fig. 5: MAPE on the simulated test dataset for the small-aperture antenna across different distance ranges

- Field dataset:

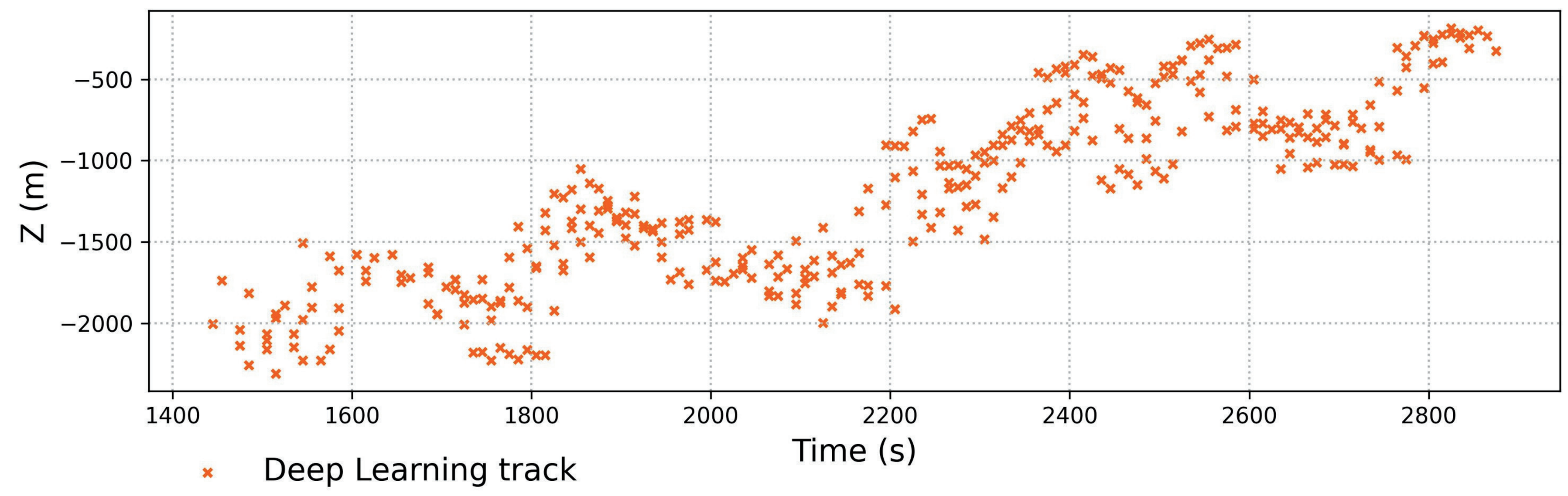


Fig. 6: Depth profile of a single sperm whale during the ascent phase, obtained with our deep learning method. Data recorded during Whale Way missions in the Mediterranean Sea.

Conclusion and Discussion

- With a large-aperture hydrophone array, the obtained track closely matches the multi-validated track and shows a similar temporal evolution
- These promising results, coupled with a MAPE below 10%, support the use of deep learning methods for range estimation in complex scenarios
- On simulated sources and small antenna, the method achieves a MAPE below 10% and an R^2 exceeding 95%, demonstrating its relevance
- On field data, although the estimated depth profile is broadly consistent, significant uncertainties remain in depth estimation
- This deep learning method for range assessment requires testing on more robust datasets, to be collected during future missions

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References

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