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The DeuteroNoise Dataset: An Initial Exploration of an Underwater Vessel Sound Dataset Within the Framework of a JPI-Oceans Project

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Abstract. The vast and largely unexplored underwater environment is a rich source of diverse sound events. These sounds, which range from the calls of marine life to the noise generated by human activities, create a complex acoustic environment. Research has been conducted on gathering and categorizing this type of data. However, only a few databases have been recently openly published focusing on anthropogenic sounds. This paper outlines the preliminary steps towards the creation of a comprehensive dataset for the detection of underwater sound events, with an initial emphasis on the sounds of vessels and boats. Within the framework of the JPI Oceans project, DeuteroNoise, a wide spectrum of vessel sounds under varying conditions has been captured and annotated with the necessary metadata for sound event detection tasks. Moreover, the proposed dataset will facilitate the development of more accurate and adaptable vessel sound event detection models and encourage further research in this area. The dataset contains raw audio files and the respective initial analysis based on labeled events, duration of the events, signal-to-noise ratio (SNR) and impact measurements. The retrieved data can be grouped into noisy and non-noisy spots. The noisy locations include the Port of Barcelona (Spain), the Port of Constanța (Romania), and the Lagoon of Venice (Italy). In contrast, non-noisy data was collected during two measurement campaigns at Pont del Petroli in Badalona (Spain). In addition to the dataset, to illustrate its potential application, a classifier for vessel/boat sound events is proposed. The classifier uses mel spectrograms as input data and is built on a pre-trained model that leverages a residual neural network. This system is capable of classifying vessel/boat related events from background sound environment.

Keywords. Data Mining and Knowledge Discovery from Databases, AI Applications.

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1. Introduction

Underwater sound events have attracted a lot of attention in recent years due to its significant impacts on marine life and its applications [1]. The primary focus of research in this area has been on the detection and classification of these types of acoustic events, which have applications in the classification and detection of marine vessels [2]. These studies are crucial in assessing the environmental impact of the sound produced by these vessels. However, the field remains challenging due to the few databases openly available. In the context of underwater research, obtaining a high-quality and comprehensive dataset is both challenging and costly. Factors such as recording equipment, permits, and environmental conditions contribute to the complexity. While significant efforts have been devoted to developing classification methods for underwater audio data, there remains a gap in the availability of publicly accessible, diverse datasets specifically focused on vessels.

Apart from the classification methods, datasets have a comprehensive approach to analyze and model underwater vessel noise. This involves distinguishing vessel noise from background noise but also the training of algorithms to automatically detect types of vessel noise. Furthermore, datasets can be used to assist calibrating commercial underwater acoustic modeling software, like dBSea [3], enabling us to map sound levels, predict noise levels, and assess noise variations based on ship density. In the framework of the JPI Oceans project, DeuteroNoise, we are conducting the creation of the DeuteroNoise Dataset, initially focusing on vessel/boat and background sounds.

The DeuteroNoise Dataset provides a valuable resource for training and evaluating various algorithms, advancing on the underwater event classification research gap. Currently, the dataset has been recorded across different locations in three different countries: Spain, Romania, and Italy. It comprises around 42 hours of real-world underwater recordings, labelled, right now, into two levels: background events and vessels/boats. This study also delves into the retrieval methods, recording systems, and labeling processes used and developed. While preliminary analyses and experiments demonstrate the dataset's promise, further investigation and adjustments are necessary. We aim to expand its coverage to include additional vessel types and refine the labeling process.

In addition to the dataset, we conducted experiments using an artificial neural network (ANN) algorithm to classify the proposed labels. The experiments were based on a ResNet architecture, a 50-layer convolutional neural network (CNN) [4]. The resulting model can effectively detect and classify vessel and boat sound events, as well as background noises (other events). Within the framework of the JPI Ocean project, DeuteroNoise, this dataset holds promise for applications in maritime traffic management and marine environment protection, it opens the possibility to model and reproduce noises of actual vessels based on the recorded sounds. Under controlled laboratory conditions, tests can be conducted to measure its impact on the physiology, reproduction, genetics and behavior of invertebrate animal models; research gap also addressed in the project.

This work is structured as follows. In Section 2, existing underwater event datasets are reviewed, with a focus on anthropogenic noise and classification techniques. This is followed by Section 3, where the data collection process, retrieval methods, and labeling procedures are described. Section 4 provides an overview of the analysis conducted on the dataset and insights from the trained model. Finally, in Section 5, the next steps are discussed and initial conclusions are drawn.

2. Related Work

2.1. Underwater Noise Existing Datasets

Datasets play a crucial role in the field of underwater acoustics, yet there is a lack of openly available resources. While some studies focus on anthropogenic and non-anthropogenic noise recordings, these datasets are often not publicly accessible. For instance, Bao et al. [5] utilized data from recordings of six boats for training purposes. Other works [6] extensively analyzed icebreaker-emitted noise data and on the other hand, M.Khishe and M.R. Mosavi [7] proposed a new underwater acoustical dataset based on passive propeller acoustic data collected in a laboratory. Unfortunately, these proposed datasets remain private.

However, there have been notable efforts to create publicly available datasets. One such resource is ShipsEar [8] presented by Santos-Domínguez et al. This comprehensive collection of underwater vessel noise recordings serves as a benchmark for researchers and professionals studying noise generated by vessels. The ShipsEar database provides open access to a diverse range of vessel noise recordings, including various vessel types, operating conditions, and noise characteristics. To target and classify the recorded vessels, visual identification was performed during recording. Additionally, most recording sessions were documented using annotated videos. Currently, the database comprises 90 records representing sounds from 11 different vessel types, with a total recording duration of 6189 seconds.

A recent milestone in underwater acoustic research is the DeepShip dataset [9]. Extracted from the Georgia delta near Vancouver, Canada. The DeepShip campaign spanned from May 2, 2016, to October 4, 2018. This benchmark dataset offers large-scale real-world underwater audio recordings from various vessel classes, each with different levels of background noise. DeepShip includes four commercial ship classes: oil tankers, tugs, passenger ships, and cargo ships. Automatic Identification System (AIS) data is used to obtain the location and timestamp of ships passing by the deployed sensor. This information is then used to automatically classify the ships into the mentioned classes. The total recording duration for these four ship classes amounts to 47 hours and 4 minutes. Across the dataset, there are recordings from 265 different ships, resulting in a total of 613 individual recordings. The duration of each recording varies—from approximately 6 seconds to 1530 seconds—depending on the ship's position relative to the hydrophone and its navigational speed. Both the ShipsEar and DeepShip datasets, capture sounds from specific locations—one from "Ria de Vigo" and the other from Georgia delta near Vancouver. The contribution in this paper extends the already proposed public datasets to different locations by incorporating sounds from Spain, Romania, and Italy. Furthermore, the dataset is expected to grow in the near future, incorporating additional locations and metadata.

2.2. Classification Methods in Underwater Acoustic

To address the classification of underwater acoustic events, traditional artificial intelligence algorithms such as K-Nearest Neighbors (KNN) [10] and support vector machine (SVM) [11], [12] have been utilized. However, recent efforts have shifted towards the application of deep learning techniques. These techniques, which employ convolutional

layers, feature-extraction filters that draw inspiration from biological processes, and machine learning methods for raw signal feature extraction, have demonstrated potential in enhancing the accuracy and efficiency of underwater vessel noise classification [13]. Progress in feature extraction methodologies has been pivotal in the analysis of noise radiated by ships. Methods such as multi-scale improved permutation entropy have been introduced to improve feature extraction from ship-radiated noise signals [14].

The creation of benchmark datasets like ShipsEar and DeepShip; not only provided a standardized datasets for the testing and comparison of algorithms, but also proposed classification models; setting their accuracy benchmarks. ShipsEar [8] focused the classification experiments on a Gaussian Mixture Model (GMM). The classifier was trained using different Gaussian models for each of the five vessel classes. The expectation maximization (EM) algorithm was used for training, and the classification was achieved by calculating the global likelihood of each audio file with each class model.

In contrast, the DeepShip [9] study undertakes an exhaustive analysis of a variety of extracted features and analyse four machine learning models and three deep learning models. These models are selected based on their widespread use and recurring application in underwater acoustic classification problems. The features analyzed in this study include the cepstrum, mel spectrogram, mel frequency cepstral coefficient (MFCC), constant Q transform (CQT), gammatone frequency cepstral coefficients (GFCC), and wavelet packets. The machine learning models explored are SVM, KNN, Naive Bayes, and random forest (RF), while the deep learning models are variants of a deep neural network (DNN), ResNet, VGG, and inception networks. Furthermore, they propose a unique method, a separable convolution autoencoder (SCAE). This method is inspired by the Xception network [15] but is adapted with a backbone for the encoder module.

3. Methods

3.1. Data Acquisition

The proposed setup has retrieved data from four different locations; two in Spain, Badalona and Barcelona, one in Italy and one in Romania, Constanța. Figure 1 illustrates the current setup used to record underwater sound at all the selected locations. The hydrophone used in this setup is a uRec384k, from Nauta Scientific [2], customized with the calibrated Aquarian Scientific AS-1 [3]. In parallel, AIS data was also collected to correlate the information, although it was not fully utilized in this study. Within the framework of JPI Oceans project; DeuteroNoise, the selected locations can be categorized as either noise-polluted or non-noise-polluted, as demonstrated in previous studies [16]. The distinction between these two types of locations is significant, resulting in notable differences in the recordings and sound characteristics. Suggesting that the presence of these vessels and boats directly impacts on the noise pollution of the areas; active listening of the audio recordings concluded that vessel and boat noise had the most significant impact; furthermore, no other significant noise sources were identified in the analyzed recordings. Three locations are proposed for the study: the noise-polluted port of Constanța in the Black Sea, two spots in the Catalan Sea (one noisy near the Port of

[2] https://www.nauta-rcs.it/SHOP/?product/page/230/uRec+384k, last accessed 2024-05-17
[3] https://www.aquarianaudio.com/as-1-hydrophone.html, last accessed 2024-05-17

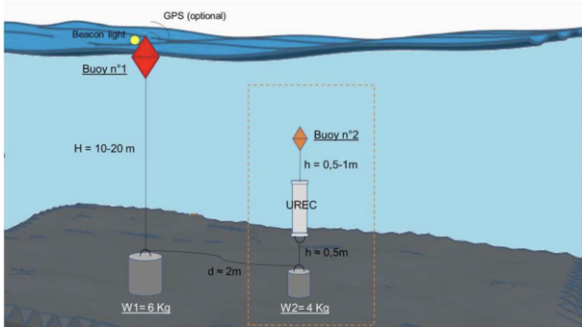


Figure 1. Proposed setup for the deployment of the hydrophone [17]

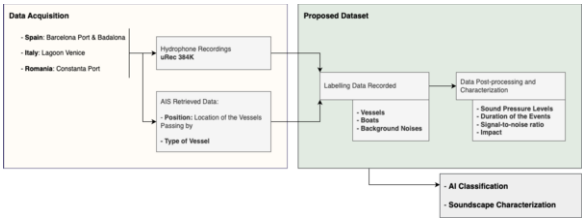


Figure 2. Methodology Flowchart from Underwater Recordings to Dataset Creation

Barcelona and a quieter one near Badalona), and a noisy location near the entrance of the Lagoon of Venice.

Most of the data was labeled manually, but the mentioned developed classifier was used as a supporting tool too. In the same way; the integration of the AIS system also helped as a during the labeling process, although the correlation of this information with the recordings has not been fully automated at the moment. Figure 2 illustrates the workflow of the proposed setup. Since AIS data was not employed for the automatic identification of vessels and boats in this study; vessels (passenger ferries, ocean liners and ro-ro vessels) and boats (motorboats, pilot boats and sailboats) are grouped into the same category: vessel/boat.

3.2. Post-Processing Analysis

We conducted sound analysis related to the retrieved dataset, providing us with initial insights into the complexity dynamics of the underwater anomalous noise events (ANEs), contributing to the broader understanding of this acoustic environment. The analysis, focuses on two key parameters: SNR [18] and the impact. In this particular case, the SNR, provides insights into the relative strength of the ANEs. The impact, on the other hand, is a measure of the effect of these ANEs on the overall sound environment. Not only is the salience of the event important in terms of its impact, but also the duration of the anomalous situation, therefore, duration is also a significant factor to consider in this preliminary analysis. In this research ANEs are defined as the manually-labeled events corresponding to vessels/boats. All other labeled sound events are classified as background noise.

Location	Label	Event Duration	Event Number	Duration	Total Duration
Port of Barcelona	Vessel/boat	2 hours 41 minutes	77	26 hours 5 minutes	42 hours 12 minutes
	Background	5 hours 48 minutes	30		
Port of Constanta	Vessel/boat	1 hour 23 minutes	17		
Lagoon of Venice	Vessel/boat	7 hours 46 minutes	62		
	Background	8 hours 27 minutes	57		
Pont del Petroli (Badalona)	Vessel/boat	9 hours	231	15 hours 43 minutes	
	Background	2 hours 53 minutes	12		
Pont del Petroli (Badalona)	Vessel/boat	1 hours 51 minutes	219		
	Background	1 hour 42 minutes	36		

Table 1. DeuteroNoise Dataset Details

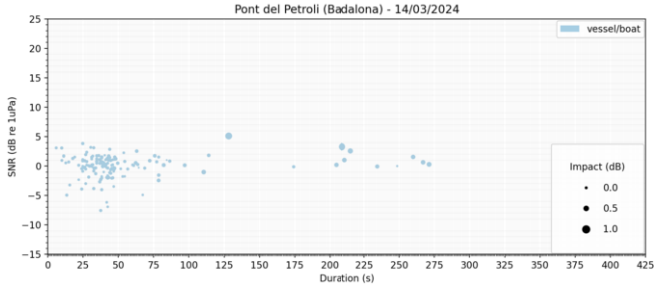
3.3. Classification Experiments

In order to validate the dataset, we trained and tested an artificial intelligence model using a subset of the labeled data. The model uses mel spectrograms as input data and ResNet neural network as the architecture. Mel spectrograms are computed by applying a Hamming window to the signal, taking the fast Fourier transform (FFT), and then applying mel filterbanks to the power spectrum. This transforms the frequency scale in a non-linear manner, converting frequencies to the mel scale [19]. ResNet, a classic neural network used in computer vision and deep learning, was introduced by [4]. Its key innovation is the introduction of "skip connections" or "shortcut connections", which allow the gradient to be directly backpropagated to earlier layers. These connections perform identity mapping, and their outputs are added to the outputs of the stacked layers, helping to mitigate the problem of vanishing gradient, a common issue in training deep neural networks. The primary objective in developing this model was not only to validate the dataset but also to use the model as a support mechanism during the labeling process for the remaining data. The model was relatively small as it was trained at the onset of this work. It comprises 3 hours and 33 minutes of recorded sounds, balanced into 2 hours; around 1 hour per label - vessel/boat and background - encompassing approximately 3192 data samples per label. Input data was derived from normalized mel spectrograms, taken from 1 second excerpts.

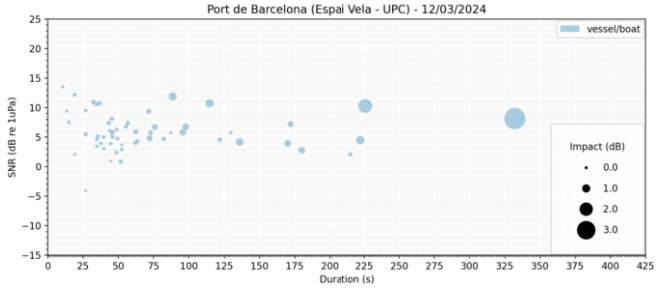
4. Results

4.1. Analysis of the Dataset

The Table 1 illustrates the proposed dataset, which was compiled from 104 hours of recorded data across various locations. The labeled data, accounting for a total duration of 42 hours and 12 minutes, considers the sound characteristics of both noisy and non-noisy locations. For the noisy locations, 26 hours and 5 minutes of data have been labeled. For the non-noisy locations, the labeled data amounts to 15 hours and 43 minutes. Duration of vessel/boat varies from around 03 s to 900 s. The recordings are saved as WAV files, each lasting 15 minutes. Label data is stored in TXT format, detailing the event's start time, end time, and label.



(a) Duration and impact of the Events in Badalona, Pont del Petroli - March 14, 2024.



(b) Duration and impact of the Events in Port de Barcelona (Espai Vela - UPC) - March 12, 2024.

Figure 3. Duration and impact of the Events in Badalona and Port de Barcelona.

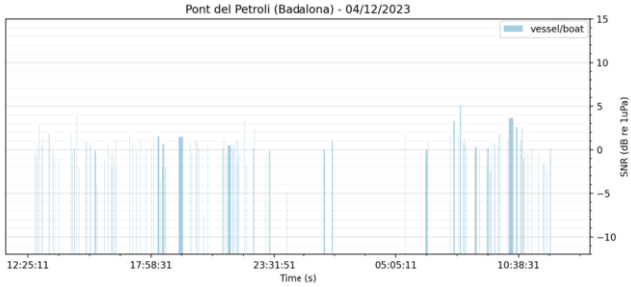
Analysis has been performed on the recorded and labeled data, visual representations of the impact, duration, and SNR from various locations are presented. Figure 3a highlight the results and evaluate the impact of the events, in these plots integration time has been set to 1 second for resolution purposes. Specifically, in Figure 3a and Figure 3b we focus on the SNR of the ANEs, showing the impact of the different labeled events. The x-axis represents the duration of the labeled events in seconds, while the y-axis indicates the SNR levels in dB re 1μPa. Figure 3b presents the same analysis for the Port of Barcelona. Other experiment conducted provide a comprehensive visualization of the events that occur throughout the course of the recordings in specific locations, like in Figure 4a. It not only depicts the sequence and timing of these events but also details the duration of each specific event. The figure also presents an analysis of the SNR associated with each event. This can serves as a valuable tool for dissecting the dynamics of a day's events, offering a granular view of their duration and signal quality. This representation can also be useful in the identification of trends. Two main observations can be drawn from Figure 4. First, Figure 4a corresponds to a location previously considered non-noisy (Pont del Petroli) based on earlier studies [16]. As expected, the Signal-to-Noise Ratio (SNR) levels are lower in this area. In contrast, at Espai Vela 4b, considered a noisy spot, SNR levels reach up to 10 dB re 1μPa. Secondly, both figures demonstrate a nighttime trend, also noted in previous studies, where ANEs decrease in both occurrences and intensity. This trend was consistently observed across all measurement campaigns.

4.2. Classifier

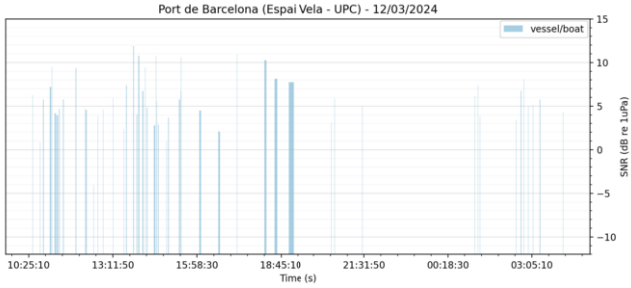
A ResNet50 model was used as a benchmark for validating the potential use of the proposed dataset but also to support in the annotation process. The task involved identifying vessels/boat or background noise utilizing data recorded on December 4, 2023, at Pont del Petroli. The input data, derived from resized and normalized mel spectrogram data, was obtained from audio excerpts of 1-second duration. During the evaluation phase, the model demonstrated an accuracy of 0.87. The F1 scores for the classes background and vessel/boat were 0.87 and 0.87 respectively, suggesting that the model performed well on unseen data. These results indicate that the model is able to generalize well to new data. Nonetheless, there exists potential for enhancement, which could be achieved by expanding the training to encompass the entire dataset and conducting a comprehensive evaluation. Furthermore, we anticipate significant performance differences when applying the model to noisy datasets. It's important to note that in the Port of Barcelona, detected vessels and boats were quite close to the sensor, in some occasions, less than 10 meters. Whereas at Pont del Petroli, detected vessels were rarely closer than 80 meters. Consequently, the sound profiles of these recorded events differ in both spectral distribution and intensity [20], making it more challenging for the model to correctly classify them. This is why datasets like DeepShip and EarShip emphasize the importance of the distance between the sensor and detected vessel-related events when applying classification models.

5. Conclusions

This paper introduces the initial exploration of the DeuteroNoise Dataset, a publicly available underwater sound dataset. Only two other studies, namely EarsShip and DeepShip, have previously focused on this area and their findings are openly accessible. The sounds in the DeuteroNoise Dataset were recorded in shallow waters under real conditions, encompassing both natural and anthropogenic background sound. The dataset currently includes data from various locations, with plans to incorporate and label more data in the coming year. This implies a notable changes from the state-of-the-art presented; collecting data from diverse locations not only provides a rich source of different anthropomorphic sounds, but it also uncovers a wide spectrum of non-anthropomorphic or background sounds. Currently, the volume of labeled data in the DeuteroNoise Dataset is nearly equivalent to that in the cutting-edge DeepShip dataset, with 47 hours and 42 hours respectively. Nonetheless, the precision in terms of labeling of this dataset has yet to reach the level of DeepShip. Future work aims to improve this by focusing on labeling data based on vessel type, by optimizing our AIS retrieval system, and also on non-anthropogenic noises. This dataset also opens the possibility to reproduce noises of actual vessels in water tanks, in laboratory controlled conditions, where we can test its impact on the physiology, reproduction, genetics and behavior of invertebrate animal models, which is also part of the work packages of the DeuteroNoise project. Moreover, the presented study outlines a methodology for recording sounds and retrieving additional identification information. We performed an analysis on the dataset, which provided us with a comprehensive overview of the collected data and its sequences of events; with a particular emphasis on the SNR and impact measurements. In addition, to validate the ef-



(a) Event sequence, duration, and SNR analysis throughout the recordings. Badalona, Pont del Petroli - December 4, 2023.



(b) Event sequence, duration, and SNR analysis throughout the recordings. Barcelona (Espai Vela - UPC) - March 12, 2024.

Figure 4. Event sequence, duration, and SNR analysis throughout the recordings in Badalona and Barcelona.

fectiveness of our dataset, we conducted an experiment where we trained a ResNet-based model nearly reaching an F1-score of 90% during the validation phase.

The DeuteroNoise Dataset, which will be **openly accessible to researchers**, facilitates detection, classification, identification, and tracking tasks through recorded underwater vessel sounds and their corresponding labels.

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