POSEIDON - Passive-acoustic Ocean Sensor for Entertainment and Interactive Data-gathering in Opportunistic Nautical-activities

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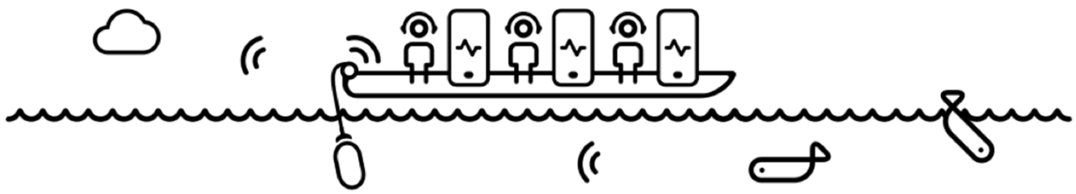

Figure 1. Graphical representation of the POSEIDON system

ABSTRACT
Recent years demonstrate an increased interest in low-cost Passive Acoustic Monitoring (PAM) in citizen science for ecological monitoring and environmental protection. However, most efforts have targeted land use, leaving ocean and nautical applications greatly unexplored. In this paper we present the design, deployment and testing of POSEIDON, a low-cost PAM system for nautical citizen science and real-time acoustic augmentation of whale-watching experiences. POSEIDON uses machine learning techniques to identify vocal acoustic samples of common cetaceans like whales and dolphins. When discriminating the calls, we find that Extra Trees and Gradient Boosting outperform other classifiers (>0.95 confidence threshold). The features extracted from the machine learning models are used to enhance the whale watching experience and provide citizen science data to marine biologists and environmental protection agencies. While this paper focuses on the design of the system, future work will focus on user testing and widespread deployment of open-hardware and software for nautical PAM applications.

Author Keywords
Passive Acoustic Monitoring; Ocean GUI; Citizen Science; Cetaceans; Machine Learning; Whale-watching; IoT.

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1. INTRODUCTION
The ocean is filled with sound. Underwater sound is generated by a variety of natural sources, such as breaking waves and marine life. It also contains a variety of man-made sources, from shipping, excavation to military sonars. Some sounds are present almost continuously and are called ambient noise. They range in: (i) low frequencies (<500Hz) from distance shipping, (ii) middle frequencies (500Hz-100kHz) from spray and bubbles associated with breaking waves, and (iii) higher frequencies (>100kHz) for thermal noise [69].

Sounds produced by marine mammals are numerous and diverse. Whales and dolphins use sound to obtain detailed information about their surroundings. From infrasonic calls of baleen whales to ultrasonic clicks of toothed dolphins, they produce vocal callings over a wide range of frequencies (10Hz-100kHz), overlapping with aforementioned sources. For these animals, underwater sound is one of their primary means of orientation, prey location, sexual display and short or long-range communication. For instance, dolphins use sound to individually develop more distinctive and versatile calls to keep in contact, while male humpback whales use long complex songs during the breeding season [31]. As our knowledge of this phenomena expands, more complex behaviors are detected. One notable example is the song patterns of humpback whales reported to be replaced rapidly and completely by the songs of the Australian west coast population of humpback whales, causing a dramatic change in their communication behavior [36]. Thanks to the oceans' interconnectivity and acoustics, the same baleen whale sounds can propagate across the continents [33].

Like many other ecosystems, the seas and the oceans are subject to intense human pressures. Examples include pollution (in particular plastic and acidification) but also the impact of anthropogenic noise [1]. Measurements from the North Atlantic show that average noise at 50Hz has increased about 5.5dB per decade from 1950 to 1970 and 2.8dB until 2013. A similar trend has been found in the North Pacific with noise increasing at an average rate of 2.5–3dB per decade at 30–50Hz since the 1960s [46]. Anthropogenic noise sources (e.g. shipping, seismic exploration for sub-sea fossil fuels or naval sonar exercises) cause cetaceans to adapt and even shift their vocal communication to higher frequency bands [57]. The same sources can also affect the cetacean growth population, as a side-effect of communication difficulties. This affects the cetaceans as marine biology studies show that a growth in separation between mother and a calf dolphin increases their intensity of whistling calls [49]. The pertained problem of noise pollution has been acknowledged by two European directives [12,13] which focus on means of the human activity impact on the marine environment, leading to sustainable marine strategies.

In this paper we describe POSEIDON which stands for Passive-acoustic Ocean Sensor for Entertainment and Interactive Data-gathering in Opportunistic Nautical-activities. POSEIDON is a novel acoustic monitoring application that enables a mix of citizen science data gathering and enhanced real-time interactive entertainment using on-boat mobile applications. In the following section we describe related work on acoustic monitoring and citizen science systems and identify potential gaps in the state of the art.

2. RELATED WORK

The work described here spans different areas of research. Technical aspects involve signal processing, hardware design and machine learning. Human-computer interaction and design aspects relate to citizen science and environmental sustainability. In the following we summarize the relevant related work on each of these topics.

2.1 Citizen Science and Acoustic Monitoring

Citizen science is the collection and analysis of scientific meaningful data by members of the general public, typically as a collaborative process with professional scientists. Facilitated by the growing availability of computing technologies such as mobile GPS enabled devices, capable of image capturing and processing, ecology and environmental science are now capitalizing on the “talents and geographical spread of non-specialists ‘citizens’, with spare time, curiosity and a smart phone” [2]. The potential resources available in terms of person-power have grown rapidly. Using social media, citizen scientists have been able to draw in large teams spread across vast areas [48]. Moreover, citizen scientists have shown to be competent with technologically sophisticated equipment, providing reliable recordings, and dealing with uncertainty.

The diversity of current citizen science projects is astonishing: from intrepid volunteers monitoring the night sky for light pollution [27]; to free divers capturing the extent of oceanic pollution [55]; and animal lovers identifying different types of animals from birds [10] to bats [17]. All these media are easily stored online, allowing the website visitors to take part in wildlife conservation (e.g. classifying bat calls from audible fragments). Acoustic monitoring used by citizen scientists has a great potential to engage people with animal calls. It can reveal hidden subtleties of animal lives and allow the health of populations to be monitored over long periods of time. One pioneering example of citizen science based on acoustic monitoring was conducted at the Cornell Lab of Ornithology. Their research program contains more than 7.5 million bird observations leading to more than 150 research papers based on bird related citizen science data. However, most of the research on citizen science using acoustic monitoring comes from ecology and environmental sciences.

Up to this point, the CHI and DIS communities have mostly focused their attention on people-centric issues [43] such us urban monitoring [25]. One notable exception is the work of Cappadonna et al, which explored novel ways to engage people with natural sounds. By using the exploration of the artefacts and practices of birdwatchers, they produced interactive user interfaces, allowing the website visitors to listen to the calls collected from the wild, while making ecological discoveries [8].

2.2 Whale Watching for Marine Wildlife Awareness

Whale and dolphin watching is a very prominent commercial touristic activity worldwide. This recreational activity can be used to raise awareness and implement conservation and protection strategies. Whale watching attracts not only the environmentally conscious, high-spending tourists, but also low-income communities, families and nature lovers. Whale watching is a USD 2.1 billion industry engaging more than 3 million people around the globe. Thus, it provides a unique opportunity for important educational, environmental, scientific, and other socioeconomic benefits. Spread over 119 countries and territories, whale watching is largely used for tourism marketing of coastal and marine protected areas, communities, regions and sometimes whole countries [20]. In Europe, the largest proportion of whale watchers are in Scotland (27%), Iceland (14%), Ireland (14%), Spain (9%), and Portugal (7%). Portugal as a whole (both mainland and Madeira and Azores islands) claim approximately 23% of total revenues in Europe. The focus of our deployment was Madeira Islands which accounts for 7% of the whale watching activity in Europe. In Madeira, the industry grew significantly since 1998 at a rate of 73% per year, attracting around 60 thousand whale-watchers in 2008 [40].

2.3 Passive Acoustic Monitoring for Cetaceans

With the rapid decline of biodiversity, scalable and low-cost monitoring technologies are critically needed to understand the effect of global changes on the wildlife ecosystem [6].

Until recently, acoustic wildlife monitoring relied on invasive multi-sensor and on-animal bio-loggers. In marine biology, cetaceans are mostly used as platforms for acoustic sensing using tagging [23,28,52]. Research in these fields is still contested because the methods are invasive and expensive raising ethical concerns.

Passive acoustic monitoring (PAM) is therefore the preferable non-intrusive method to study cetaceans. In general, acoustic monitoring uses sound recorders and refers to the non-invasive usage of surveys when monitoring wildlife and their natural environments. Obviously, this method assumes the animals emit some form of detectable sound. Generally, there are two types of acoustic monitoring: active and passive. Active monitoring requires the production of sound (e.g. a sonar) to detect objects. This is actually the mechanism used by the cetaceans to detect their preys. Passive monitoring (PAM) requires solely the recording of the existing sound and is the method mostly applied in cetacean observation. In fact, in recent years an increasing number of PAM applications have been developed to detect different cetacean groups [32]. Applications of PAM systems go a long way back to military uses during World War I, where the hydrophones (underwater microphones using piezoelectric transducers) were used for detecting submarines [51]. PAM applications usually compete between providing the long-term access to the collected samples, as well as in isolating the target signals from the rest of the acoustic ambient noise.

In our research, we focus on the design of a mobile PAM system which can be easily applied on the whale and dolphin watching boats, providing access to the real-time cetaceans' underwater calls.

2.4 PAM Applications, Hardware and Software Tools

The requirements for most PAM applications when studying cetaceans are to assess their: (i) dynamics, (ii) behavior, (iii) communication, (iv) diversity and the (iv) impact of human activity. Previous research on marine biology reports a diversity of PAM applications. One research project used an Autonomous Underwater Vehicle (AUV) as a sea glider for near-real-time acoustic monitoring of beaked whales and other cetaceans in Hawaii. Their deployment covered 390 km for three weeks, collecting 194h of acoustic data. This system allowed the collection of audio samples during various weather conditions [26]. Another research project involved deployment on buoys, towed arrays and a stationary autonomous array for monitoring the endangered North Atlantic whales [58].

In addition, several other systems generated spectrograms providing valuable insights in interpreting, storing and displaying the large amount of bio-acoustic data on demand. LIDO (Listening to the Deep Ocean Environment) [1] uses the real-time monitoring, acoustic detection and classification of marine mammal sounds at cabled and standalone observatories. LIDO provides acoustic data streams, spectrograms for visualization and audio, allowing wide areas of potential offshore applications such as in communication with ROVs, AUVs, buoy-to-buoy mesh networks, alert systems, among others. Another research project used Cetacean-PODs, underwater PAMs for odontocetes (toothed whales) [54]. They deployed 44 hydrophones (including 14 buoys) during the five-year project span and reported a 34% mean decline per year in cetacean population. This consequence imposed the Government of Mexico to issue a 2-year gillnet ban.

In terms of sensing equipment, state of the art ocean acoustic sensors remains still expensive and are mostly available for industrial and military purposes. Specific hardware is available commercially, including: Chelonia (C-POD and DeepC-PO odontocete) [9], High Tech Inc (HTI Marine Mammal hydrophone), Ocean Instruments (self-contained underwater autonomous recorders), Teledyne Marine (various hydrophones models) [18], Wildlife Acoustics (wide range of bioacoustics sensors and full spectrum analyzers) [65], among others. Despite the decline of hardware costs, these devices are still mostly proprietary and expensive for general purpose use.

In terms of software, several open-source software libraries for analyzing acoustic recordings became recently accessible to the wider public. A couple of free and open-source software for analytics and statistics, including the several open source GIT repositories can be found online such are: Pumilio [44], Seewave [47], Soundecology [50], WarbleR [60]; for self-annotation: AudioTagger [4], Ishmael [21]; for detailed spectrum analysis: Audacity [3], PAMguard [41], CPOD.exe [7], Tadarida [5], among many others.

The devices and systems mentioned previously demonstrate a growing trend towards the development of low-cost and customizable bioacoustics sensors for citizen science applications that take advantage of cheap microcontrollers and mobile applications. However, projects like Audiomoth [19] and Solo [64] are targeting large-scale biodiversity monitoring on land. For instance, mobile platforms for PAMs and for citizen science was reported in studies using bats [24], cultures at extreme locations [53], cicadas [66] and surveying the mobile applications which deal with digital conservation [22]. Another research project described the system using a mobile application that provides visual real-time feedback for assisting the cockpit crews, while conducting the aerial surveys of animals in Sub-Saharan Africa [14]. Similarly, other research developed the mobile application for forest rangers to capture the data of biodiversity and conservation in Indonesia [59].

3. POSEIDON RESEARCH OBJECTIVES

Madeira Islands are one of the oldest tourist destinations in Europe with almost 1,5 million visitor every year, including many that enjoy nautical activities and in particular whale watching. These islands also host one of the most important biodiversity and natural heritage patrimonies of Europe. Inspired by this unique environment, we decided to create POSEIDON, a novel PAM application that could be easily deployable and accessible by the visitors and locals, while engaged in whale and dolphin watching activities. POSEIDON combines low-cost acoustic monitoring with the pervasive availability of mobile phones in a growing community of tourists and citizen scientists.

3.1 Contributions

The POSEIDON system is to the best of our knowledge the first general purpose low-cost application for collecting and streaming acoustic signals from whale and dolphin watching boats. With this opportunity, we wanted to address an important gap in the state of the art which is the scarcity of citizen science PAM systems deployable in seas and oceans. POSEIDON goes beyond merely capturing acoustic data, deploying a novel on-board mobile application for augmenting the user experiences with real-time sound detection and classification of cetaceans. Our starting hypothesis was that tourists themselves can become citizen scientists during the whale-watching cruises, if they are provided with an easy to use and properly designed application available on their mobile phones. Therefore, our approach differs from previous PAM systems and contributes in several novel aspects: (i) POSEIDON provides a low-cost and open-source system for long-term deployment of acoustic detection and classification of cetaceans during whale-watching tours; (ii) POSEIDON enhances the visual surveying of cetaceans with a mobile PAM application which augments the experience with real-time sounds; and finally (iii) POSEIDON provides the continuously acquired dataset, available for download, visualization and further research by the scientific community and environmental conservation authorities.

3.2 Classifying Cetaceans from Acoustic Data

In the region of Madeira, 21 diverse species of cetacean are reported and sighted yearly [15,34]. Marine species usually found in this archipelago are Bottlenose Dolphins, Bryde-Whale, Common Dolphins, False Killer Whale, Fin Whale, Pilot Whale, Risso's Dolphins, Sperm Whale, Spotted Dolphins, Stripped Dolphins, etc. Most of their vocalizations are located in infra as well as in human hearable sound spectrum. Cetaceans in Madeira region can be therefore grouped in three families: (a) Delphinidae (e.g. bottlenose dolphins, using clicks and whistles); (b) Physeteridae (e.g. sperm whale, using special kind of repeating clicks); and (c) Mysticeti (e.g. baleen whales, producing moans).

However, the real-time detection of the exact cetacean within the single family remains a very challenging process due to the several constraints: (i) most common hydrophones are limited to the range of 100Hz to 20kHz which excludes some of the baleen and sperm whales (Figure 2); (ii) European and Portuguese government regulations applied to Madeira islands enforces that boat engines (around 4 KHz depending on the propeller design) should be switched on during the whole whale-watching activity. These limitations reduce the detection range and cause additional noise which is targeted at reducing the risk of hurting the animals.

In addition, other external factors can make acoustic detection more challenging, such are proximity to the whales, earth tectonic movements and additional noise pollution from nearby shipping. Due to these constraints, POSEIDON was developed to collect, analyze and classify the cetaceans by using their tonal sounds (moans and whistles, depicted in Figure 2) and echolocation clicks (shown in Figure 3) using supervised machine learning techniques. Previous research provided algorithms for detecting whistles, moans, and other frequency contour sounds [30]. However, they mostly focus on minke and other humpback whales from near Hawaiian coast, as well as that they avoid the clicks in audio processing.

We designed POSEIDON to combine all three categories and thus including the clicks which are typical of sperm whales and other cetaceans found in Madeira Islands. POSEIDON therefore records, models and classifies the sound to one of these three categories. An example of our collected sample of clicks, moans and whistles can be seen in the spectrograms in Figure 3, where the vertical axis depicts the frequency of 24kHz and horizontal axis represent the sample time, in this case 5 seconds.

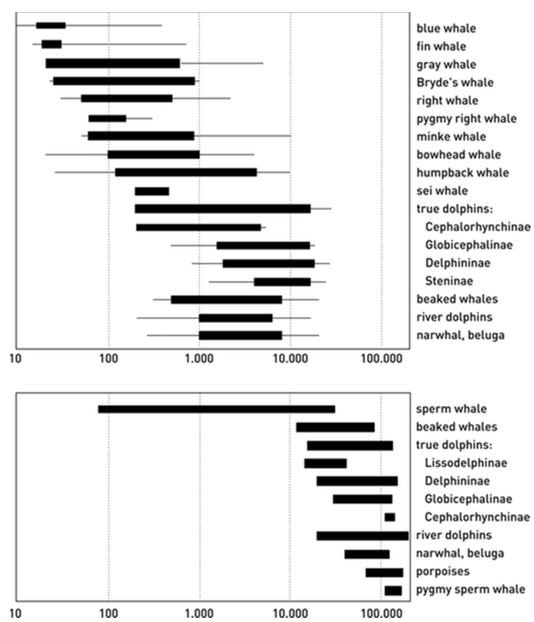

Figure 2. Cetacean frequencies (Hz). Moans and whistles (top) and clicks (bottom). Adapted from Mellinger et al. [29]

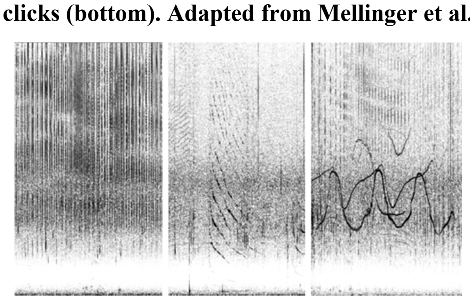

Figure 3. Spectrograms of the collected samples. From left to right: cetaceans' (1) clicks, (2) moans and (3) whistles

As we can observe from this sample (Figure 2 and Figure 3. left), clicks cover the whole frequency spectrum, including a repetitive pattern which becomes denser as the distance to the cetacean is shorter. Sperm whale is the main protagonist of clicks in the Madeiran waters. Moans carried by baleen whales (Figure 2. frequencies on top and Figure 3. middle), contain overtone harmonics which seem as similar tones propagated to the higher frequencies in the same time unit. Finally, whistles are usually transmitted by the dolphins (Figure 2, frequencies to the right from 1 kHz and Figure 3. right). They have the longer time signature and are represented as continuous oscillating lines.

In the remainder of this paper we describe the architecture and instrumentation of POSEIDON (section 4). Subsection 4.1 describes the POSEIDON station (hardware), 4.2 the classification pipeline for machine learning, 4.3 the server backend. Subsection 4.4 details the design of the interactive on-boat mobile application. Finally, subsection 4.5 outlines the system performance and machine learning preliminary results when recording, detecting and classifying the cetaceans offshore Funchal, Madeira island, in Atlantic Ocean. Finally, in Sections 5 and 6 we present the discussion, conclusions and future works.

4. POSEIDON DESCRIPTION AND PERFORMANCE

This section contains several figures. First, we describe the main characteristic of the POSEIDON system including all the components (Figure 4). We also depict the POSEIDON Pipeline, portraying the techniques used for sound analysis, feature extraction and machine learning techniques (Figure 5). In addition, we also present how POSEIDON includes a server backend, providing Python scripts for recording, classifying and dissemination of acoustic cetacean samples through on-boat wireless connection. Conversely, from the user-end side, we explain the POSEIDON UI, portraying the design of the mobile application interface to be used on boat by the tourists (Figure 6). Finally, we describe the POSEIDON Machine Learning Techniques, depicting the preliminary performances of models, testing the sound classification and overall machine learning performances of diverse algorithms applied to cetacean samples (Figure 7).

4.1 POSEIDON Station

The sensing hardware component of POSEIDON is responsible for collecting and recording the cetaceans' vocal calls in real-time. In order to reduce interference from movement and friction with the boat the system is deployed as a buoyant POSEIDON station (Figure 4. a, b and c). The station is connected to the boat and contains the following components:

- **Capsule**—attached to the boat with a cable a styrofoam capsule reduces interference from the engine noise, providing adequate buoyancy and thermal insulation of electronic hardware equipment (see Figure 4). The reusable capsule is covered with glue, preventing disintegration in smaller marine debris, harmful for the aquatic animals.

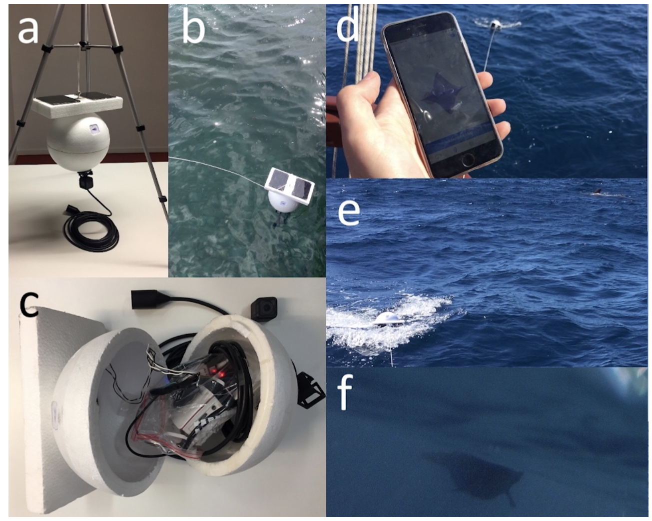

Figure 4. POSEIDON System: (a) in-vitro; (b) in-situ; (c) used components; (d) app; (e) capsule and Pilot-whale's dorsal fin; (f) Pilot-whale captured from the capsule

- **Media**—The capsule contains two main media acquisition devices (Figure 4. c): (i) a hydrophone (dolphinHyd DL-1) and (ii) an action camera (GoPro Hero 5 Session). This component is the most expensive part of the POSEIDON equipment, enabling the collection of high quality acoustic and video samples. The hydrophone is connected to the USB sound acquisition device via a 10m cable submerged into the water. The adapter converts the acoustic signal from analogue to digital by the low-cost Raspberry Pi 3 (RPi3) microcomputer. The action camera collects underwater media (Figure 4. f) communicating via a wireless connection with the RPi3 which relays to the mobile phones (Figure 4. d).
- **Power, RTC and GPS**—The station is powered by two solar panels providing the energy to the local power bank. They feed the RPi3 and the remaining hardware components as the solar panels extend the autonomy of the station, supporting the longer durations of whale-watching trips (up to 6h). In addition, we attached a RTC (Real-time Clock) module to the system, allowing the collection of exact timestamps, and GPS for obtaining the geolocation of the capsule.
- **Processing**—A low-cost RPi3 microcomputer acts as a general purpose local server, recording, classifying and streaming the collected samples of the cetaceans to the tourists' smartphones over WLAN. Once the sample recording is completed, it saves locally acoustic data to the internal SD card storage. The audio samples are then used for signal processing and classification. Once the acoustic features (clicks, moans or whistles) are detected, they are broadcasted through a local Wi-Fi connection to the tourists' smartphones. With this approach we overcome the absence of network coverage on sea, while reducing the usage of mobile GSM data. Finally, we designed a mobile application to be used by

the tourists on boat (Figure 4. d and Figure 6). The application polls the media samples directly from the local RPi3 server, including the sounds, spectrograms and images.

4.2 POSEIDON Pipeline

In this section, we describe the treatment of acoustic samples, including the way how we train the models from gathered offline acoustic cetacean samples. We also explain how these models are used for on-boat real-time classification during the whale-watching activity. In total, we collected the 1h dataset of the whales and dolphins found in Madeira after spending five days on diverse sea vessels, during the months of November and March. For classifying the cetaceans, we turned to predictive analytics and machine learning techniques for segment classification. We trained three models (clicks, moans and whistles) using supervised learning techniques. The following pipeline was inspired by existing acoustic analysis processes found in literature of used PAM systems for cetaceans [67] (Figure 5):

- **1. Sample recording**—Sound recording was obtained in the time-amplitude domain with sample rate of 48kHz, stereo, 32-bit. After consulting with the local marine biologists, we collected acoustic samples in three diverse settings: (i) while the engine was switched off; (ii) while the engine was switched on and in neutral position; and (iii) while the engine was on and the ship moving. We used this approach, so we could compare the performance of samples in order to apply the algorithms for noise removal.
- **2. Spectrogram**—The spectrogram is generated from the frequencies using Fast Fourier Transformations (FFT), and time and amplitude are depicted with color intensity. Additional spectrogram color settings were performed in Audacity (open-source audio software) where we set the gain and range to 40 db. This was the setting leading to easier visual detection of the cetaceans.
- **3. Noise Filtering**—An additional band pass filter was applied to remove the engine noise around the 4kHz frequency. Noise detected was mostly caused by the friction between cable and boat as well as by the ocean waves slamming the boat on the surface.
- **4. Event Detection**—In order to create a training dataset, we manually inspected the histogram for each captured audio file. We then annotated the events, which were then confirmed and certified by expert marine biologists from the Madeira Ocean Observatory. We distinguish between detected acoustic underwater events and those that are clearly related to the cetaceans' features.
- **5. Sound Labeling**—Sound recording was done in five second sample chunks stored in WAV format. The WAV file was labelled (observing the differences in spectrogram among clicks, moans, or whistles). This labeling was also confirmed by the expert marine biologists from the local Ocean Observatory.

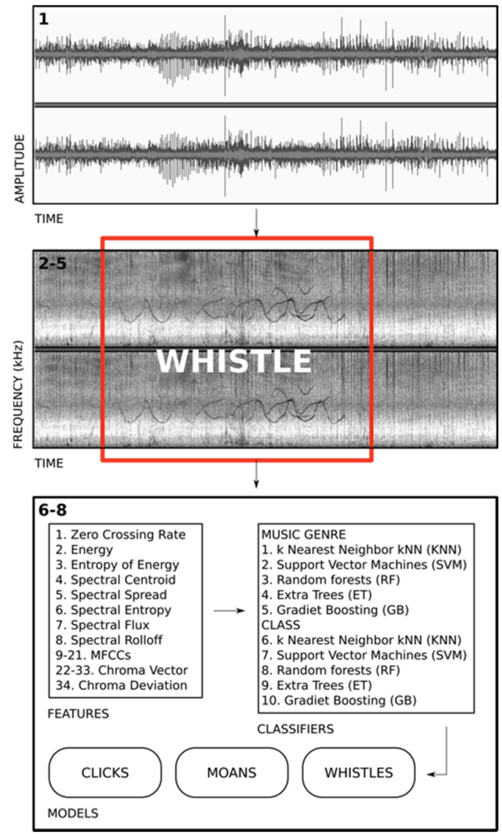

Figure 5. POSEIDON Pipeline

- **6. Feature Extraction**—This step was accomplished using automatic segment classification. From each category of sound sample (moan, whistle and click) we extracted 34 feature vectors: (i) zero crossing rate—the rate of sign-changes of the signal during the duration of a particular frame); (ii) energy—the sum of squares of the signal values, normalized by the respective frame length; (iii) entropy of energy—the entropy of sub-frames' normalized energies, interpreted as a measure of abrupt changes; (iv) spectral centroid—the geometric center of the spectrum; (v) spectral spread—the second central moment of the spectrum; (vi) spectral entropy—the entropy of the normalized spectral energies for a set of sub-frames; (vii) spectral flux—the squared difference between the normalized magnitudes of the spectra of the two successive frames; (viii) spectral rolloff—the frequency below which 90% of the magnitude distribution of the spectrum is concentrated; (ix-xxi) MFCCs—Mel Frequency Cepstral Coefficients form a cepstral representation where the frequency bands are not linear but distributed according to the mel-scale; (xxii-xxxiii) Chroma Vector—the 12-element representation of the spectral energy where the bins represent the 12 equal-tempered pitch classes of western-type music (semitone spacing); and finally (xxxiv) Chroma Deviation—the standard deviation of the 12 Chroma coefficients. We used these feature vectors as they are suggested in the literature as common features for human readable audio and can be easily obtained using the open-source Python library [16] which provides wide range of audio-related functionalities focusing on feature extraction, classification, segmentation and visualization.

- **7. Model Training**—the model was trained using 10 classifiers: five for music genre and five for classes which are used in general audio signal processing, including k Nearest Neighbor (KNN), Support Vector Machines (SVM), Random Forests (RF), Extra Trees (ET) and Gradient Boosting (GB). The full description between the classes and music genre classifiers is out of the scope of the paper. In total, we trained and obtained three models for clicks, moans and whistles, which will be used for prediction. The rationale for using these classifiers was that they are a standard in the machine and supervised learning for music and speech. We wanted to verify how the existing classifiers perform for the acoustic signal obtained underwater and, in our cases, for detecting the cetaceans.
- **8. Classification**—From all aforementioned steps, this was the only one performed in real time. The incoming acoustic signal was checked against our three models where the confidence rate is generated. This number is portrayed in further in our app as an accuracy of predicting the cetacean (Figure 6. f). More details about the classification methods can be seen in POSEIDON Server Backend section.

4.3 POSEIDON Server Backend

As aforementioned, the RPi3 microcomputer acted as the server backend providing a local wireless connection and web services to the boat occupants. The server was implemented in Python running on the default Raspbian OS (Linux based). Our main criteria were to implement as compact code possibly, gaining the more storage space on SD card for the samples. Among other, the most important server scripts include:

- **Sound Recorder**—using the local Linux recorder function, this script collects the audio signal from the hydrophone and stores it to the 5 seconds chunk audio files in WAV format. The script can be modified to accommodate two hydrophones by recognizing the additional USB inputs.
- **Cetacean Classifier**—this script compares the raw audio chunks with the trained models of click, moans and whistles. The classifier returns the confidence interval where everything above 0.95 is stored and prepared for the mobile application polling. In addition, local GPS coordinates are stored and made accessible for citizen science purposes.
- **Web Services**—in order to serve the mobile phone application over the local Wi-FI connection, we implemented web REST API services using the CherryPy Python Library, acting as a local web server which can handle HTTP connections (in particular GET and POST requests). The mobile application contacts the server every five second to verify whether cetaceans have been detected. When there is a positive reply from server, it returns a JSON data structure with three values: (i) the link of the previously classified recording sample for the mobile application to download; (ii) confidence rate from the cetacean classifier (percentage rate of the clicks, moans or whistles) which is portrayed inside of the mobile application (Figure 6. f, accuracy of the prediction); and finally (iii) the spectrograms (Figure 6. b, c, d) to be kept inside of the gallery of collected samples.

4.4 POSEIDON User Interface

As previously introduced, the POSEIDON User Interface (PUI) was designed to augment the tourists' experiences on boat during the whale watching tours. The design was inspired by our prior design works: (a) a treasure hunt mobile game tailored for ocean museums where we used passive proximity Bluetooth Low-Energy (BLE) beacons as sensors [45]; and (b) using routers as passive Wi-Fi monitors to understand touristic flows [37]. The PUI consists of two core components: (i) a Machine Learning component, which portrays previously collected and classified sounds of cetaceans in real-time (Figure 6. a, b, c, d); and (ii) a Whale Reporter component, which fosters citizen-science, allowing the tourists and marine biologists to report, gather media, and classify cetaceans' vocal calls (Figure 6. e, f, g, h).

Machine Learning: Portraying the Underwater Acoustics

Once onboard, tourists receive a pair of wireless headsets and are prompted to download the application using the simple QR code sticker found on the boat. Once installed, the application starts sending the HTTP POST requests to our RPi3 server and receives the reply from the server should any cetaceans are detected. When detection occurs, the application proceeds with downloading the audio file to the phone using the onboard Wi-Fi connection. While the mobile application is polling the data, it also demonstrates the visual and animated wavelength with 5 peaks of the probability of detected and classified cetacean (Figure 6. a). Peaks stand for (from left to right): (i) clicks only, (ii) clicks and moans combined, (iii) moans only, (iv) moans with whistles, and (v) whistles only. In case of the presence of clicks and whistles combined, the second and fourth peaks increase. We used the visual metaphor of the wavelength, in order to keep the consistency with the visual representation of water, waves and sea creatures. Color stands for the classification and shifts from detected cetaceans: (i) clicks (depicted in red, Figure 6. b), (ii) moans (portrayed in violet, Figure 6. c), and finally (iii) whistles (in blue, Figure 6. d). The container window showing these visualizations is a popup window, which appears in case the machine learning model detects cetaceans. In the absence of detected or classified cetaceans, the application shows the short animating wavelength mimicking a search mode. When the detected sound contains two or more of the categories (combined clicks, moans and whistles), the intermediate second and fourth wavelengths' peaks increase. The height of the wave is proportional to the confidence level, with higher waves match higher confidence. When the probability of detecting the cetaceans reaches the 95% (obtained from our previous tests with classifiers) the application demonstrates in real-time the spectrogram and the audio signal of clicks, moans and whistles (Figures 6. b, c and d). The depicted spectrogram contains very minimal information, using time on the horizontal axis and frequency on the vertical axis, covering the whole application window. The audio file is played on top of the spectrogram, showing the vertical line of the sound location. Tourists on boat can tap the spectrogram and replay the sound, while simple swipe gesture hides the popup.

Whale Reporter: Citizen-Science Activities

The core of the application UI is the tab group encompassing four main windows, represented to the right side of Figure 6, and organized to foster participation by the tourists. The first window is a map (Figure 6. e) portraying: (i) the current location of the person; (ii) the current location of the capsule; (iii) the reported sightings by other tourists (as blue pin), as well as (iv) the reported sightings by the current user (as red pin). To report a sighting, the user selects the button "I SAW SOMETHING", after which it is prompted with the interface to select the seen specie (Figure 6. h). The sighting is then displayed with the type, coordinates and main information about the cetacean. The second window consist of a similar interface to the sound wavelengths machine learning popup. Users can classify the sound by themselves, by pressing the "I HEARD SOMETHING" button. After this action, they are presented with the option to classify a sound by selecting whether they heard a click, moan or a whistle. The third window displays the underwater media from the action camera. Users can collect images or record video samples, which get stored onto the RPi3, while keeping the copies on their mobile phones. The last window includes the cetacean gallery with the detailed information and acoustic samples of the vocal callings of 21 cetaceans [68]. All aforementioned media and collected acoustic samples are stored on the phone and can be replayed from the RPi3 unit and shared on social media. One exception is that GPS location is prevented to be shareable on social media as the system can notify in real-time the exact coordinates of the spotted cetaceans. We omitted this information after suggestions from the marine biologists concerned about the possibility of this information leading to increased human presence around whale sightings.

4.5 POSEIDON Machine Learning Performance

In general, the analysis of the audio data is a trade-off between the time and frequency resolutions where larger sliding window lengths provide improved frequency reducing the time resolutions. Parameters related to the performance of the machine learning algorithms include different sliding window sizes, training of datasets as well as taking care of not overfitting the model data. In the following, we demonstrate solely the feasibility of the machine learning system for real-time cetacean classification. We accomplish and report the prediction accuracy of each of the three used models (Figure 7).

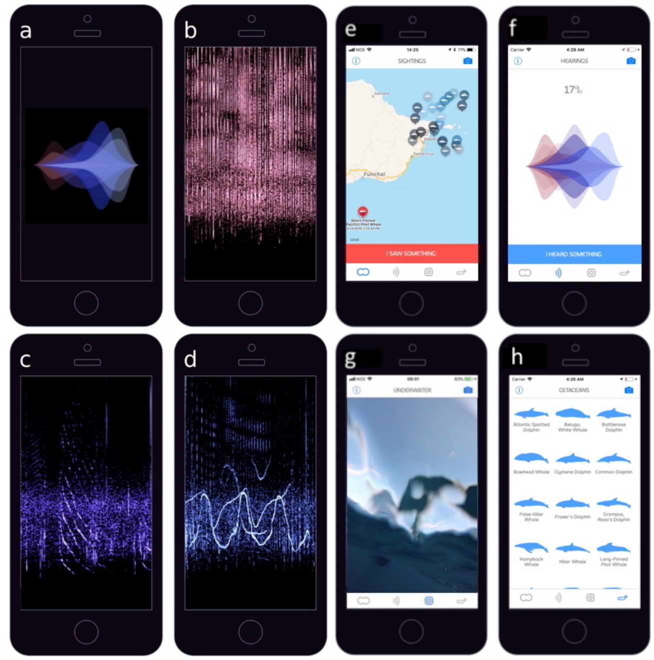

Figure 6. POSEIDON UI: (a) probability wavelength; (b) clicks; (c) moans; (d) whistles; (e) sightings reporting; (f) sound classification; (g) media collection; (h) cetaceans

In total, our training dataset included 16 collected audio samples of cetaceans from Madeiran sea. Samples were five seconds in length and included five clicks (Figure 7. c1-c5), six moans (Figure 7. m1-6) and five whistles (Figure 7. w1-5). We used one more additional vocal sample for moans to test the behavior of the models. When playing back the same audio files to all 10 classifiers, and comparing the three model performances, we found that ET and GB classifiers (for both music genre and classes) outperform all other classifiers reaching the highest confidence level (>0.95). The following classifier in line was RF reaching a medium tolerance level above 0.95 when detecting the clicks (Figure 7. bottom). The SVM classifier for classes proved also to be significant, however only when recognizing the clicks. From this input, we decided to use the threshold of 0.95 and focus solely on ET and GB classifiers for real-time detection on boat, aiming at reducing false positives. Of course, we need more tests to be conducted and more collected samples to test the models and to avoid the overfitting.

5. DISCUSSION

To the best of our knowledge POSEIDON is the first general purpose system aiming at collecting and streaming acoustic signals during whale and dolphin watching activities. The "In the wild" deployment of such applications raises numerous interesting design challenges, from hardware to software issues to the many possibilities in terms of end user engagement and citizen science. In the following, we discuss limitations and future work on POSEIDON.

We collected 16 samples of vocal calls from cetaceans found in Madeira sea. We used 10 classifiers to extract 34 features and train 3 models to distinguish the three types of calls:

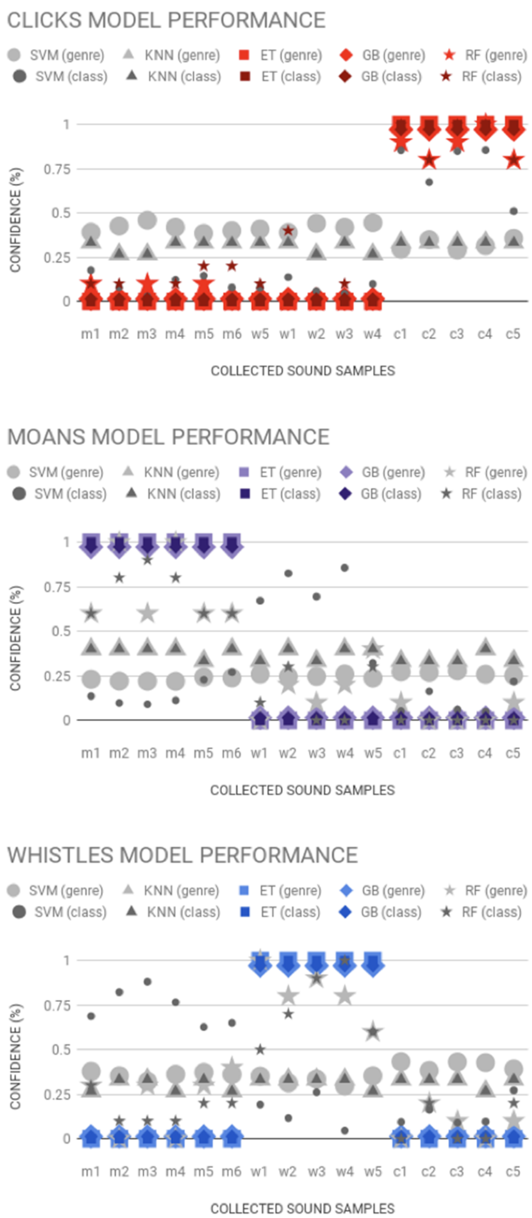

Figure 7. Performance of 10 classifiers using our 3 models: clicks (top), moans (middle) and whistles (bottom)

(i) clicks, (ii) moans, and (iii) whistles. Once the models were successfully trained, we found the best classifier performance (Extra Trees and Gradient Boosting) to define a confidence level (> 0.95) which we used as our tolerance threshold for detection of different cetaceans. POSEIDON was successfully used for onboard real-time recording and classification streaming data to mobile devices and producing useful scientific data for marine biologists. As a low-cost system, POSEIDON proved the potential of becoming an important citizen science platform for increasing the information about these marine species and their habitats.

Whale and dolphin watching is a growing touristic segment and concerns on the impact of direct and indirect human activity on marine environment. Requiring the implementation of sustainable strategies for the usage of marine goods and services. In the following, we highlight topics for discussion and future work.

Citizen Science and Open Datasets—several citizen science initiatives are mentioned targeting cetaceans, even suggesting a mobile app for hearing ocean sounds [39]. The same applies to promising initiatives collecting and studying cetacean samples [38]. However, very few initiatives have moved beyond small experiments and very few datasets are available online covering the diverse cetacean species. For this reason, we had to perform our own sample collection, obtaining the limited sample size and baseline for the system to 16 distinctive calls (with 34 features each). These initiatives need to become widespread in order to support widespread deployment of POSEIDON-like systems. Future studies will collect more cetacean samples and combine them with the existing dataset of pilot whales [62].

Software Improvements—the main limitation of the mobile application was the effect on battery life of GPS usage, screen brightness and the long polling of the data through constant POST requests to the server. Nevertheless, the design of our POSEIDON system is feasible and functional for the typical three hours whale-watching activity. However, future work should optimize the battery life and implement server push services instead of the pulling from the mobile phone, where the server side will notify the phones of detected cetacean calls. Concerning the machine learning algorithms, future studies should also do additional tests. Further comparisons are needed how these classifiers benchmark with other machine learning techniques and neural networks. We believe that such a system should be able to recognize and discriminate the cetacean instead of just discriminating the event (clicks, moans and whistles).

Hardware Limitations—in POSEIDON we used a single hydrophone, future studies could explore multi-hydrophone arrays in order to approximate the exact GPS and depth location of the cetaceans. In addition, two hydrophones combined can be used for source separation, subtracting the engine noise from the other underwater sounds. Additional comparisons of sounds will be made with other affordable underwater recorders, such as action waterproof cameras, as they can also record the sounds. Moreover, the distance from the cetacean is very important in collecting the samples, thus exact minimum distance should be analyzed. Regarding the weather conditions, POSEIDON hardware was tested in fairly calm ocean (ranked up to 2 on Beaufort Wind Scales) [63] and its' performance should be also verified across a wider range of weather conditions and water temperatures. One particular important concern is the placement of the hydrophone since in our experiments noise peaks from friction are one of the most important limitations. Also, POSEIDON should be tested with diverse boat sizes and engines' horsepower and the presence of multiple boats as all of these influence noise. One important suggestion from the marine biologists was to develop a version of POSEIDON that could be attached to observation buoys. This raises issues such as power and transmission of data to shore and opens up interesting possibilities for creating new applications where people offshore interact with acoustics.

Interface Design—the current POSEIDON User Interface uses spectrograms and probability wavelength and is therefore very limited to the sole visualization of sound. Additional effort will be made for portraying the visual representation of the cetacean, e.g. using the 3D models of the cetaceans and augmented reality to point towards the exact underwater location of the species. Also, it could be possible to leverage waterproof action cameras, for the purpose of depicting the real-time video of the cetaceans. Conversely, application could also portray additional description of the cetaceans as well with more descriptions about the clicks, moans and whistles. Moreover, bridging HCI and wildlife seem to cause an interest [61], the POSEIDON User Interface might also scale-up, by providing the direct connection from the whale-watching boat to the on-shore totem, which can serve as a real-time video-projection of the sound samples. Finally, for the purpose of improving awareness about the noise pollution, users in future POSEIDON system could interact with audio data through in-depth sensors, merging the live observer location points with cetacean vocal tones, affecting the visualization and sound of the cetacean vocal tones. This idea was inspired by previous research on using the sculptural projection mixing depth images of viewers with pre-captured footage of birds in natural and architectural environments [11].

User and Impact Evaluation—although the user evaluation was out of the scope for this research, future work will analyze the tourists' feedback and their engagement levels. We envision using physiological and emotional modelling, while applying the user experience scales during the usage of system. It could be least obtrusive that during the whale-watching tour, users are prompted with tiny animated questions, where they can rate their levels of excitement. We also foresee the usage of wearable applications (e.g. a smart watch application) due to the potential effect of weather conditions on sea. POSEIDON provides a good platform to understand more complex issues related to human impact on nature, starting with the impact of anthropogenic noise on cetaceans all the way to wider issues such as ocean pollution. Future studies will also compare the analysis of cetacean sightings reported by the user, by the machine learning algorithms, as well as how well do they perform together as previously done in similar studies [35].

Ethical Considerations—although whale-watching activity has demonstrated significant benefits for the tourism worldwide, recent research evidences suggest that these events can translate into population-level effects such as reduced reproductive rates of cetaceans. Also, whale and dolphin watching activities can cause direct mortality through collisions between vessels and cetaceans [42]. Although these activities on Madeiran coast have guidelines, more attention and awareness should be given to future activities using our POSEIDON system, e.g. through shared route calendars among the competitive companies and local sailors. While designing our system, we use the missing acoustic element of portraying the sounds of cetaceans, by allowing the collected samples to be more accessible to the persons. We sincerely hope that by providing the cetacean calls to the public, we are able to raise more the awareness about the anthropogenic impact. Future studies should discuss more about the potential ethical concerns.

6. CONCLUSIONS

We designed POSEIDON to become the first general purpose low-costs application for collecting and streaming acoustic signals from whale and dolphin watching boats. We wanted to address an important gap in the state of the art which is the scarcity of citizen science systems applied in the wild to seas and oceans. POSEIDON goes beyond merely capturing the acoustic data, deploying a novel on-board mobile application for augmenting the user experiences with real-time sound detection and classification of cetaceans. As a low-cost system, which enhances the onboard whale and dolphin watching experience, POSEIDON has the potential of becoming an important citizen science platform for increasing the information about these marine species and their habitats. Whale and dolphin watching is a growing touristic segment and concerns about the impact of direct and indirect human activity over the marine environment are requiring the implementation of sustainable strategies for the usage of marine goods and services. In this paper, we demonstrated the practicability of designing and deploying a Passive Acoustic Monitoring (PAM) system capable of collecting and classifying data opportunistically, while providing information to enhance the onboard experience. These two factors are key for a wide adoption of citizen science platforms for marine and ocean environments.

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