Team 117
12/3/2021

Earth Science Project Passive Acoustic Monitoring – Final Report

Introduction

The world's oceans are one of Earths most unexplored regions even today. Since their creation in the mid-1950's (Howe et al.) Passive Acoustic Monitoring (PAM) systems have allowed us to begin exploring these unknown parts of the ocean. Marine monitoring has occurred all over the globe (Haplin et al.), primarily as a method of determining what biota are present in the area (Browning et al.). PAM systems are beneficial because they can gather continuous data from multiple locations over a large amount of time without constant supervision. This type of monitoring has allowed researchers to determine populations of endangered species (Jaramillo-Legorreta et al.), generate a picture of the overall ecology of an area over time (Kaplan et al.), and establish the impacts human involvement has had on surrounding species (Tournadre et al.)(Schoeman et al.)(Kvadsheim et al.)(Cates et al.). Although many of the aforementioned papers are well done, they lack aggregation of multiple sources to provide a greater value than the sum of their parts. Additionally, while some of these studies have involved real-time analysis of sound signal (Baumgartner M et al.)(Baumgartner et al. 2019) most are short term or were not accessible to the public. None had interactive displays where a user can listen to the sounds being produced, either currently or historically (Johnson et al).

Problem Definition

Layouts of PAM data are only utilized by highly trained and knowledgeable experts, where we have provided high level analysis to a larger selection of the general population. Our Graphical User Interface (GUI) processes raw acoustic data identifying acoustic features such as marine life, provides an interactive module with a classification algorithm to determine if a sound clip contains sound features of interest, and plots interactions from many datasets combining locations of boats, buoys, and animal sounds. Because there is a large amount of data available, we limited our study to an area off the northern coast of Florida.

Survey

GUI layouts of PAM data are only utilized by highly trained and knowledgeable experts. Our project aims to cater to a larger selection of the general population by providing analysis/events of raw acoustic data, identifying acoustic features such as marine life, flagging selected animals and allowing the viewer to see and listen to the sound of identified anomalies. This GUI will help educate in an immersive experience to a broader, more general population. Additionally, exploration of aggregating other external information such as Automatic Identification System (AIS) will be investigated to see if further information of interactions between mammals and humans can be derived from raw acoustic data. Since there is a wide array of data rich areas, this study will choose a group of buoys.

WhaleMap (Johnson et al.) and Passive Acoustic Cetacean Map (Walker) are bleeding edge Free and Open-Source Software (FOSS) technology (with published papers) for aggregating data and animal tracks. However, the interactive map, even with documentation, can be extremely convoluted to a general population. Additionally, the projects' area of study is only whales off the eastern shores of the United States and Canada. Most importantly, many of the tracks and identifications of whales rely on non-automated, costly data collection methods such as plane flyovers and manual, line-of-sight identification. (Baumgartner et al.)(Nadir et al.)(Gibb et al.).

With numerous data sources found in multiple regions of interest, the planned expansion of species, and the integration of "listening" to audio clips; this project helps expand the population of interest, create an immersive experience, and use machine learning and processing to identify marine life. Combining multiple sources of data from different fields creates greater value than each separate part alone. There are ample areas of research in each separate field, and plenty of data to analyze. This creates a high pay off for communities of interest such as fisheries (Luczkovich et al.), and governments where processed or combined data has much more value than their separate parts. We plan to use SQLite to house our data and Python to analyze it.

Proposed Method

The world of oceanography and the related data collection continues to grow on a daily basis but unfortunately only attracts those that know exactly what they are looking for. We have provided intuitive and enjoyable interactions that will welcome audiences from various educational backgrounds. We have bridged this gap by providing an interactive visualization that will allow folks from K-12 and academia to use the data and effectively learn.

There are great visualizations that display PAM and AIS data ("MARS Hydrophone Data - MBARI", "MarineTraffic: Global Ship Tracking Intelligence"), there are great visualizations that help people learn about the various animal species that exist in the ocean, and there are great audio models that help identify species and population growth. These present two problems, one that they are siloed into their own specialties, and two the data is not presented in a way that is suitable for a wide audience. We have consolidated the data providing cross cutting analysis across many datasets.

Finally, there is a massive amount of data available for PAM projects but most layouts provide counts of sightings or a sound from a single animal. We have developed a process that efficiently and quickly processes and finds sounds in the ocean and separates it from ambient noise. This could revolutionize the acoustic monitoring industry by providing fast actionable insights.

Data Gathering

We scoured many sources for data in order to have as rich a dataset as possible, and work with "big data". After contacting several agencies, we received permission from NOAA to use several terabytes of PAM data from a set of buoys off the coast of Florida. We also found several open sources of data that were free to download directly. The data sets we used, and sources are described below.

- Passive Acoustic Monitoring data (PAM Data) – This data is more than 7 terabytes of raw sound files from the Atlantic Ocean that we were granted permission to use by NOAA (NOAA OAR)
- Combined animal sound truth data (Animal Sound Data) – We used this combined dataset to train the classification model. This data consists a combination of the following three datasets:
    - Manually sampled sounds from our processed PAM Data
    - Downloaded free ringtone data of whale and dolphin sounds (Source: https://voicesinthesea.ucsd.edu/index.html).
    - 6 GB of whale sounds a team member recorded during an acoustic study in Hawaii

- NOAA AIS data (AIS Data) – Data from the NOAA website that was downloaded using python. This data was filtered for GPS location and for ships that were seen several times. (Source: https://coast.noaa.gov/htdata/CMSP/AISDataHandler/)

Pre-Processing

We first preprocessed the data before it was classified, plotted, or played as sound. The PAM Data was heavily processed in order to isolate sounds of interest. We processed this dataset using the robust tools in the python scikit-maad package. The original .flac files were converted to .wav, and turned into spectrograms. The background noise was removed using a median equalizer filter and the power was converted to decibels. These files were then smoothed multiple times using a two-standard deviation gaussian filter in order to remove more background noise. After the data was as smoothed and filtered a Spectro-temporal based binary mask was applied on a double threshold to each image. This enabled us to create regions of interest (ROI) filtering on the min and max size of the features. A final filter was run to discard images that didn't match the desired parameters. Finally, functions were applied to each image to chop them into 10 second sound clips with the desired feature in the middle of the clip, and to extract the relevant metadata. After the processing was complete, we uploaded the PAM data into a sqlite database where the data was stored, with each clip represented by a single row.

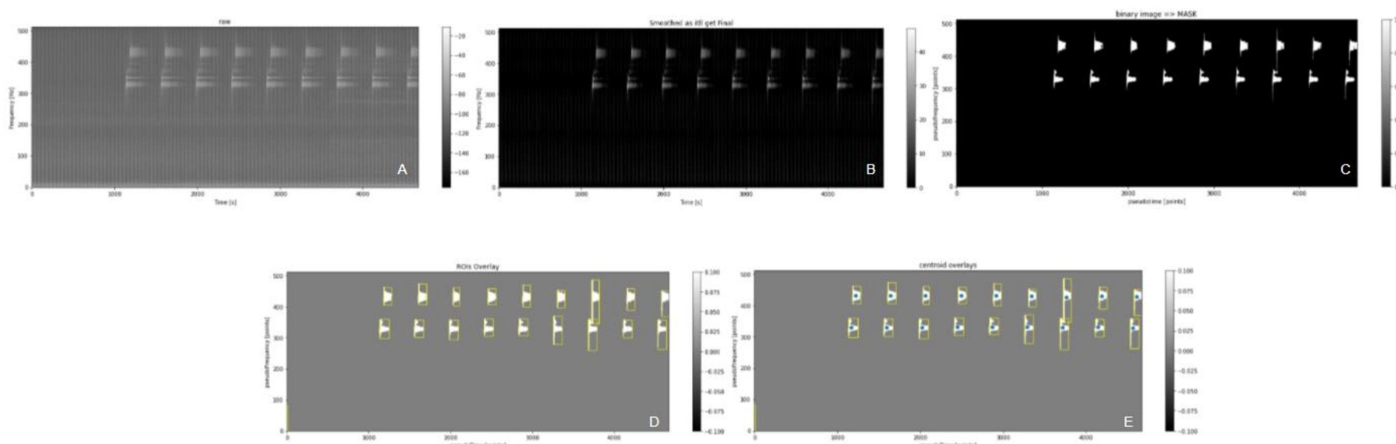

Figure 1: Spectrogram processing, initial spectrogram (a), smoothed using a gaussian filter (b), binary mask generated (c), Regions of interest (ROI) created based on parameters chosen (d), create centroids for sound clips based on ROI (e)

We combined the manually sampled PAM data, ringtone data, and whale sound data into a single dataset, which was normalized in order to build a consistent model to classify the sounds. To do this we downsampled the sampling rate of all audio files to 8 kHz (which provides 8000 data points per second). We clipped all audio files into 5 second chunks providing consistent vector length. For example, a two-minute clip of orca calls provided twenty four clips of five seconds that we used to train the model. Clipping at 5 seconds also helps capture the different acoustics that would come from the various animals appropriately. After this we fed the 5 second audio clip at 8kHz into a mel-frequencey cepstral coefficients (MFCC) to highlight the important acoustics found in the file.

Modeling

A model was built using the Animal Sounds data to classify whether a sound was an artificially generated noise or noise made by an ocean animal. Because of the potential for a non-linear irregularities that may make it easier to classify say a boat as opposed to a dolphin, we decided to create a deep neural network model that would be able to find these non-linear distinctions. The model that we built contained 7 layers, each approximately half the input of the previous layer so that with every layer we provide enough buffer that it will generalize well.

GUI

All processed AIS and PAM metadata was inserted into a SQLite database and .wav audio clips were stored in a directory. Both were hooked up to a django web server, which was used to render our visualization as well as provide data through REST API endpoints. Docker was used to containerize our application and scripts, which we ran locally.

Our world map was created using a D3 projection, and the buoys and boats were plotted using their respective latitude and longitude. There are four options for users to filter the data they will be seeing and listening to:

- The buoy audio samples to come from
- Which class of data you would like to listen to (boat, animal, ambient)
- Classes of boats you would like to see
- Slider bar for the date and time

Once they have chosen their parameters, the user can click to apply their filter and a list of sound files with a clip start time that falls within an hour of the chosen time along with a plot of all the boats with a logged location within 30 minutes of the chosen time will be rendered. The user may then select an audio clip that they can listen to, as well as view the audio's waveform and spectrogram.

Effort

All team members have contributed similar amounts of effort.

Experiments / Evaluation

We have found that there are large amounts of PAM and AIS data available and there is a lack of wholistic analysis on that data. This provides a rich environment for research in the field. We have tried to pursue several research questions with this project, and we have made significant progress finding observations on many of them. For ease we have laid out our questions, observations, and discussion below.

Can the process of finding interesting sounds in PAM data be automated, and/or made more efficient?

We have found that in our sample the process of finding interesting sounds; including animal noises, boat noises, etc. can be done quickly and efficiently with a high degree of robustness. Our sampling of the PAM data found many noises of interest, including boats, dolphins, seagulls, and orca whales within two hours of listening to audio clips. This is a considerable time savings from projects we researched including whale map (Johnson, Hansen, et al.), which was a PhD project that achieved largely the same result, but required an extensive list of contributors and time. Our process is mostly automated, raw .flac files can be run through our code and features of interest extracted in a matter of seconds, which can then be classified in a matter of minutes instead of scrolling or listening through years of acoustic data in real time. The ability to extract any audio features of interest from ambient noise is especially powerful when combined with the classification model below.

Can classification algorithms be used to label types of sounds?

We have made significant progress in labeling sound data with a neural network model. The model currently can predict whether a sound is artificially created (boat, oil, rig, etc) or whether it is an animal acoustic (dolphin, fish, whale, etc.). This can be very useful combined with tools like the process to smooth and binning of sound features developed above. The neural network modeling process allows us to further narrow down the true positives of sound features from ambient noise. The model we created had an accuracy score between 65% to 70%. A future project using a greater number of classified samples could increase the accuracy of this model and try to classify specific animal sounds, potentially focusing on endangered species or pinpointing certain types of boat traffic.

The application for this model can be expanded to several other projects related marine biology and marine traffic. The model provides a scalable way to feed wav files and identify animals which can lead to studies of thriving animal species based on acoustic data from various buoys across all the oceans. Once the model is further improved to identify specific species this will provide an easy, scalable, and automated solution to see whether certain species are growing or dying off based on the location and migration patterns in the ocean.

Another result of our model is that having such a scalable model will provide meaningful ways to audit boat traffic on various parts of the ocean. This will enable marine traffic security and validating shipping trails for cargo and other types of ships.

Can siloed AIS and PAM data be combined in a way that provides useful insights?

We believe the answer to this question is yes. We found many datasets representing different views of the AIS / PAM landscape and we leaned heavily on the algorithms and processes we describe above to analyze them. With these powerful tools we were able to provide interesting cross-cutting information such as frequent boat locations and the presence of animal sounds regularly near these boat locations. This data could be analyzed further to find more insights. A future expansion of this project could include tasks such as measuring distances from the buoy to the source of the sound which could provide boat or animal tracking capabilities, and finding clustered frequent locations of animals and migration patterns.

Can the above processes be presented in a way that is interpretable for all audiences?

We believe the answer to this question is also yes. We have created a visualization that reflects information from modern high level processing and modeling techniques, yet we have made it interpretable and usable by a wide range of ages and disciplines. We have tested this assumption by asking a sample of volunteers to give our tool a test try and report back. All volunteers enjoyed the tool and found it easy to use. A future expansion of this project could broaden this survey getting more feedback on things such as what functionality would be useful as well as user experience additions.

Conclusions and Discussion

We have heavily researched the topic of possible analysis and display improvements for acoustic monitoring data. We have also heavily searched for acoustic monitoring data. In the process we found that there are large amounts of PAM and AIS data but they have not been used to their full potential. We have asked if we can find ways to algorithmically enhance the processes of cleaning, filtering, and classifying raw sound clips, and if our enhancements can be displayed in a way that is digestible and useable, even to folks who are not experts in the field. We have succeeded in finding positive answers to these questions and further have found more questions to be researched by the next cohort. Further work can be done to hone the algorithms to processes and classify sounds. And more analysis can be done to increase the connection between data sets. We believe PAM and AIS data will be more readily available in the future and tools like ours will be useful to help in projects ranging from suspicious boat activity to endangered species identification and protection.

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