Whale Detection and Avoidance

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Abstract

Current on-vessel technology to avoid whales is insufficient. Ship captains need a way to detect and avoid whales more accurately and consistently. This project uses image processing to differentiate whales versus other sea noises as well as triangulation in order to locate the position of the whale and the direction it is moving in. Phase one of the project allows for whale detection, but there is a lot of space for future work.

1.0 Introduction

90% of all right whale deaths were caused by trauma from line entanglement and ship collisions (Milka, 2019). Current technology existing on boats consists of human spotting, plotting, and informing of whales. The human eye is prone to making mistakes and this method in widley unsuccessful, proven by the vast numbers of striking every year as well as the fact that most whales can hold their breath upwards of sixty minutes, resulting in a majority of their time spent underwater. There are apps that help communicate whale sightings. However, ultimately, these devices still rely on chance spotting and sufficient report of such sightings to reliably track whales. Boaters need on-ship detection to avoid whale collisions.

Using static detection, current research is focused on detecting and plotting patterns in whale's routines as well as their location throughout the day in an attempt to schedule boat routes around densely populated waters as well as to better understand the nature of whales as a whole. Currently there are two major whale detection methods being used in the research field. The first is visual. John Durban, a Marine Mammal Biologist from the Southwest Fisheries Science Center,

> "[flies] a small hexacopter to hover 100 to 200 feet above whales to take overhead photographs: from these [he] can do photogrammetry (taking measurements from photographs) to monitor growth, assess body condition, and identify pregnancies. These metrics allow [augmentation of] traditional stock assessments to not only focus on abundance trends of whales, but to also understand the underlying causes of population dynamics" (Noaa. (n.d.)).

Other researchers are using satellite data to plot population density of whales. The second method is auditory. Jessica Crance, a Research Biologist at the Alaska Fisheries Science Center, created a small sailboat drone that is able to go into the ocean for long periods of time and record sound. She describes her project by saying,

> "Our interest in the project was to determine if the Saildrone would be a suitable platform for passive acoustic monitoring of marine mammals, in particular the critically endangered North Pacific right whale. We attached a small, autonomous acoustic recorder called the Acousonde to the keel of each Saildrone, and set it to record continuously up to 4 kHz, which covers the frequency band of most marine mammals in the Bering Sea" (Noaa. (n.d.)).

Google is also conducting similar research. They use stationary hydrophones to pick up on sounds passing them and, using an AI system, are able to detect whether or not the sound is a whale. ("Acoustic Detection of Humpback Whales Using a Convolutional Neural Network." (2018)). Using this research, they have identified patterns in whale calls and in population behavior and density throughout the waters of the pacific.

This project attempts to bring these locating techniques into the boat world and locate whales in real time using an AI system to detect whale vocalization and a set of microphones to sense distance and direction of the whale. This information will be relayed to the captain who can maneuver away from the whale, avoiding collisions.

In the following, software to address whale collisions as well as an outline for hardware implementation and validation in section 2. Results for these plans are in section 3. In section 4, the evaluation of the results leads to a proposed application for the current phase of the project along with suggestions for future work. Finally, section 5 offers a summary of the project.

2.0 Methods

In order for a ship to automatically detect whale presence and avoid collisions, a process needs to be able to a) detect underwater sounds (section 2.2.2), b) identify the sounds as whales (section 2.1), c) calculate both the location of the sound source (angular position and distance) and the direction it is moving (section 2.2.1) and then d) make a decision based on the data about potential courses of action for the ship (section 2.3).

2.1. Whale Sound Identification

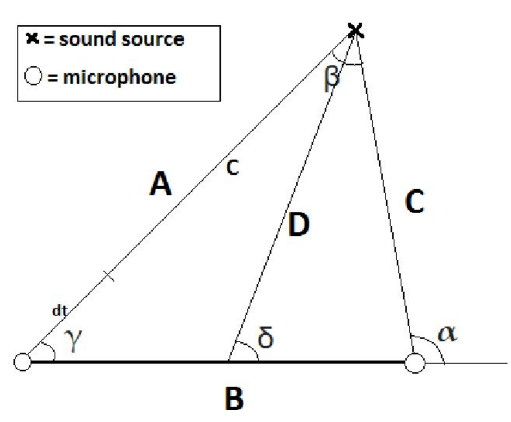
The sounds are categorized using an image processing Convolutional Neural Network (CNN) AI software from fast.ai. This particular software was pre trained to an extent with generic images that increased its speed in being able to correctly predict image categories. The software was initially trained for this project using sound files from (Mellinger & Clark, *MobySound: A reference archive for studying automatic recognition of marine mammal sounds* 2006) they were converted into images in order to be categorized by the image processor using audacity and sonic visualizer and then loaded into a jupyter notebook which is where the code for the AI is stored. The files fell into five categories: not whale (75 images), whale with no background (324 images), whale with background quieter than the whale (8 images), whale with background equal to the whale (7 images), and whale with background louder than the whale (2 images). The background whale images are less prominent than the others in terms of numbers because there did not need to be more of these types of images for the AI to successfully classify images. The whale with background louder than the whale category is the smallest because the images were almost unrecognizable. After the AI has been trained, the software can be fed any image and classify it as a whale sound or another sound.

2.2 Triangulation

After the sound has been identified as a whale, the sound source is found using three microphones and triangulation to find the angle at which the sound is coming from and the distance of the source from the boat. The figure below shows an example of triangulation in two dimensions. This system will need to work in three dimensions because the depth of the whale will need to be noted. So far, this system involves 2.2.1 theoretical triangulation code with a single input channel and 2.2.2 a prototyped microphone.

2.2.1 Triangulation Code

A program written in Processing (see appendix 3.2) demonstrates proof of concept for calculating the time delay



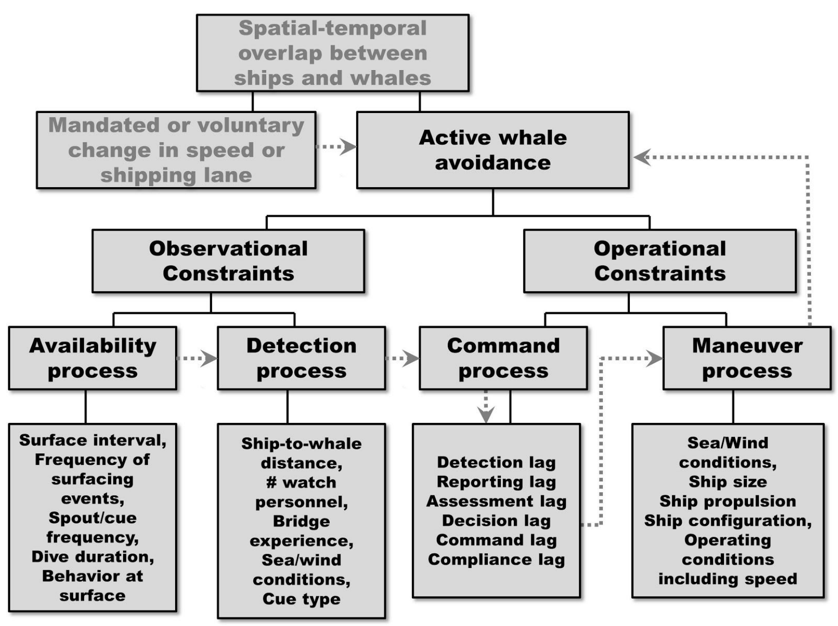
between sound signals to find a source angle. The code uses a threshold value to detect sounds over that value and interpret them as peaks. These signals are recorded and then the software find the time difference between two peaks. The speed of sound is theoretical so as to obtain values by tapping the microphone. The slope of a singular line is outputted.

2.2.2 Microphone

A prototyped hydrophone was built using a tin can and a lapel microphone. The mic is fed through a hole at the top of the can and is sealed with caulk. Washers were placed both on the outside of the microphone and the inside to keep the mic submerged. The lid of the can was secured to the bottom of the can using caulk.

2.3 Course of Action

Once the location and identity of the sound has been found, a decision is made on the safest measure the boat can take, based on work done by Gende, S. M., Vose, L., Baken, J., Gabriele, C. M., Preston, R., & Hendrix, A. N..



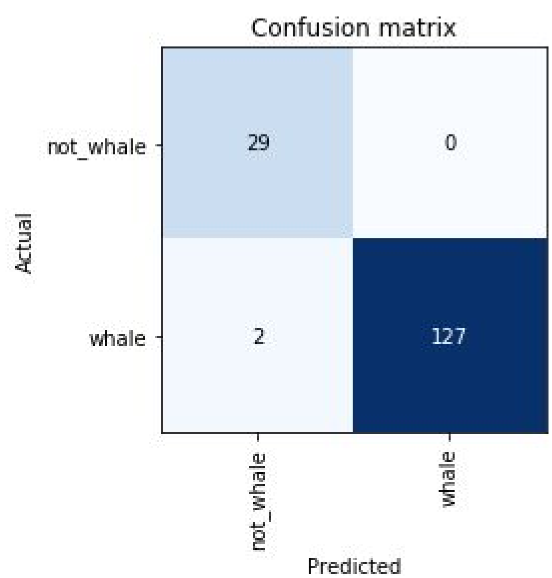
This process has been separately tested and validated by the source that produced it (Gende et al., 2019). This project focuses on the detection process piece and the other pieces will be filled in with advice from this process.

2.5 Validation Process

The validation plan is to test each component individually before their eventual assembly into a single unit. This project focuses on the AI system. The AI has a built in validation system involving a set of images secluded from the training data that are used to discern data on how well the system performs. However in addition to this, it will be fed sonograms in five categories: whale, not whale, whale with quiet background, whale with level background, whale with loud background. Most of the images fed to the sonogram were of whale with loud background because these were the images that the system had a difficult time classifying. The style of sonograms for the whale with background categories will be different from the other sonograms because of the use of a different software. The original software that was used could not give clear images when paired with background noise at a higher frequency.

3.0 Results

The AI system was trained using the set of 416 images described in 2.1. The AI withholds a small portion of the training set for validation. In this case, the validation set was 158 images. As seen in the Confusion Matrix to the right. The AI



system effectively sorts sounds into whale and not-whale categories. It confused two pictures the last time it was trained with files in all five categories. As a part of the training of the AI, the software created a confusion matrix automatically. The confusion matrix to the right shows the actual images on the y-axis vs the predicted images on the x-axis of an AI generated validation set.

When manually validating the system, 20 images of all five categories were loaded into the system and the AI predicted all of the images from four of the five categories correctly. It could not predict correctly when the background noise was louder than the whale sound.

The triangulation system is able to output the slope of a single line. It has not been validated. From a single input channel (the microphone built into the computer) peaks can be detected and the difference between the peaks can be translated into a distance and the slope of that line can be found.

4.0 Discussion

While the AI is unable to achieve 100% recognition rate of whale sounds, frequent sampling (one image per second) will allow false positive and false negative detections to be removed. The limitations with this AI software involve the creation of sonograms. That process is manual. In phase two if the sonograms could be created automatically, that would greatly speed up the process. However, with technology limitations, this process feels very far off. The images that the software produces are sometimes not clear and that can make the sorting of images very difficult.

As of right now, the system is completely manual. From the sound source into the mics, the sound is manually converted into a sonogram and manually loaded into the AI. Phase Two of this project will automate those systems so they work as a unit with no manual steps.

Phase Two will include the finishing of the triangulation hardware (the construction of three microphones) and the separation of the microphone channels to differentiate which microphone received the signal first. The problem of not knowing which microphone received sound first allows for too much uncertainty in which quadrant the sound is coming from. Separating the channels and being able to differentiate them will allow for a more accurate location of a sound source.

The coding will also need to be updated to find the slope of a second line and intersection of those two lines and the AI will need to be mobilized.

The triangulation system will be validated using a superimposed grid over a source of water. The microphones as well as the sound source will have X and Y values. The more accurate the X and Y values of the sound source are, the more accurate this system is. This validation has not happened yet, but the plan is in place.

The system needs to be tested on a vessel to determine how loud the background noise will be and if the software can handle it.

Phase One allows for detection of a whale in a system where the background noise is less loud than the target whale sound. In a system similar to the SailDrones mentioned earlier in the report, this software can successfully classify whale and not-whale sounds in a relatively closed system. The system can detect the presence of the whale and in future work a large ocean vessel will be able to use this information to avoid hitting whales.

5.0 Conclusion

Lack of whale detection and avoidance has been detrimental to both whales and vessels. This project attempts to alleviate the detection piece of this system. Using a series of microphones as well as an image processing software, the distance and direction of a whale can be measured in relation to the boat. Phase one of this project allows the system to detect a whale with an underwater microphone through the image processing software and the prototyped hydrophone. In the future, the triangulation process needs to be completed and the microphones need to be built.

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7.0 Appendices

1. Final Documentation Folder
2. AI User Manual
3. Commented Code
    - 3.1 AI
    - 3.2 Triangulation

4. Project Journal
5. Original Proposal