Detection of snapping shrimp using machine learning.

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SUMMARY

The marine environment consists of many different sound sources covering a wide frequency range. Accurately identifying and analysing these sound sources is difficult and time consuming. This is compounded by effects such as variable ambient noise, multi-pathing and multiple sources. One promising technique for analysing such complex data sets is machine learning. This has been successfully used in many other applications. In this work we will use it to detect snapping shrimp impulses. These are a dominant noise source in shallow tropical waters and ideal for testing new algorithms. The logistic regression method is used as the main algorithm. A snapping shrimp acoustics matrix (SSAM) is constructed from features such as the band energy ratio, frequency centroid, spectrum flatness, etc. It has been ensured that the extraction speed of the SSAM is sufficiently fast such that it is suitable for real time processing. A number of data sets for different locations covering a range of conditions will be analysed and compared.

INTRODUCTION

The field of machine learning has been around since the 1950s. Recently however, due to developments in neural networks and increased computational power, there has been a dramatic increase in its use. Applications can be found everywhere from speech and facial recognition to medical diagnosis. In the area of underwater acoustics however its popularity is not quite as prevalent although over the last twelve months there has been an increase in the research in this area. For example, Malfante et al (Malfante et al. 2016) reported on its use for automatically classifying fish sounds with reasonable success both for post-processed data and for continuous underwater recordings. Wang et al (Wang and Peng 2018) reported on its use for underwater acoustic source localisation and Hu et al (Hu et al. 2018) reported on its use for underwater target feature extraction and recognition.

In this work, we investigate the usefulness of machine learning for detecting underwater transients. As in any machine learning application the abundance of good data is vital. In addition, the ability to have large amounts of data from different locations would allow the robustness of the model to be tested. Fortunately, there is one underwater sound source that can help provide such data. This is the snapping shrimp. It can be found in littoral Australian waters ranging from temperate all the way to tropical. Despite their small size the source level of individual snaps is extremely high and covers a very large frequency range (Cato and Bell, 1992.). Due to their large numbers the accumulative effect of their "snapping" can produce large increases in the overall ambient sound field that varies on a daily basis and from place to place. Acoustic data was recorded in three shallow water locations in Western Australia and a features based Machine Learning algorithm used to detect individual shrimp snaps.

METHOD

The machine learning algorithm is based on logistic regression and was written in python. It is a classification method based on the sigmoid function commonly used in features based machine learning.
Acoustic data was collected in three different shallow water locations in Western Australia. In two of these locations (Shoawater and Monkey Mia) the shrimps were located on the seabed. The third location was off the Navy Pier in Exmouth and as a result the shrimp could reside at any depth along the pylons. Each location had different ambient noise conditions and experimental setup. 78 well defined shrimp signatures were selected from the Monkey Mia data set. From these snaps 18 features were extracted and used to train the model. Many of these features are commonly used to create accurate predictive models and are listed in Table 1. To test the model, 60 seconds of data was manually analysed to identify all the shrimp snaps above a certain level. These were then compared with those detected using the machine learning algorithm.

Table 1: Features used for identification of the shrimp pulse

Dynamic range	Frequency centroid	Rate attack
Standard Deviation	Mel-Frequency Width	Rate decay
Standard Deviation/Mean Value	Higher order cross	Thresh max cross
Max/Mean	Flatness	Thresh min cross
Energy (dB)	Spectral Bandwidth	Max(Abs)
Envelop crest factor	Shannon entropy	Band energy ratio

RESULTS

Figure 1 shows a comparison of the shrimp detection using the manual (Black▼) and machine learning (Red▲) for the three data sets. Each set consists of 60 seconds of data and has been split into three blocks of 20 seconds as shown in Figure 1. For the Monkey Mia data set (middle plot) 100 % of the manually detected shrimp snaps (20 in total) were detected by the ML algorithm. The ML algorithm also detected a further 42 snaps which corresponded to snaps below the threshold value used for the manual detection. For the Shoalwater data both methods detected approximately the same amount of shrimp snaps with a 94% accuracy whereas for the Exmouth data the ML algorithm detected significantly more shrimp than the manual method but had 100% agreement with the manual detection results.

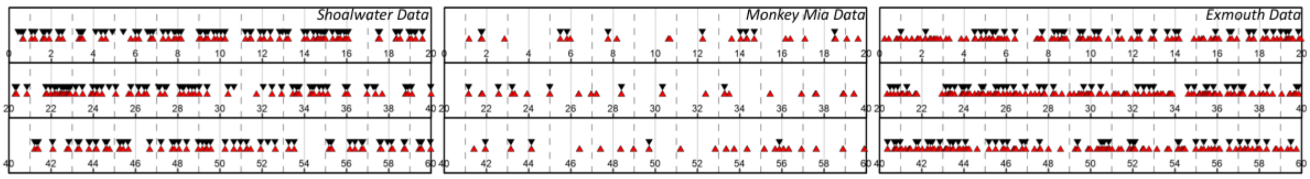

Figure 1. Comparison of the manually detected and feature based machine learning detected shrimp snaps for the three data sets

These differences can be attributed to variations in the ambient noise, shrimp distance from the hydrophone and the hydrophone location and orientation.

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