An Investigation of Machine Learning Capabilities for Cavitation Detection

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Abstract: *Due to environmental concerns, there is a growing need to reduce the radiated noise of marine traffic. The noise from marine vessels comprises multiple sources, with propeller cavitation typically being the dominant source when present. Cavitation can be avoided by operating the vessel at lower speeds. However, the speed at which cavitation occurs may not be explicit and may change over the life of the vessel. Therefore, in order to ensure noise levels are minimised, there is a need to detect when cavitation occurs and take the necessary corrective action. In this contribution, the capability of machine learning in the detection of propeller cavitation is evaluated. Using time series signals as the input feature, the performance of two models is evaluated. Special attention is given to the signal to noise ratio to more fully understand the capabilities of the models and to determine if any signal conditioning is required to increase performance. A number of signal statistics are also evaluated to identify additional features that may accurately characterise the presence of cavitation. The present work enables a rapid detection of cavitation and may allow for vessels to avoid this noisy operating state and hence reduce the impact on the marine environment.*

Keywords: *Propeller Cavitation, Classification, Detection.*

1. INTRODUCTION

With the increasing awareness of the impact of noise from shipping on marine life, there is a growing need to reduce the noise from ships. The noise radiated from ships is comprised of multiple complex sources with propeller cavitation typically being the dominant source. Whilst efforts can be made to reduce cavitation at the design stage, its control is more difficult for in-service ships. It is typically suggested to operate at lower speeds to avoid cavitation. However, the speed at which cavitation occurs is not always evident due to its dependence on local conditions at the propeller blade. Further, for variable pitch propellers, cavitation can occur, even at low rotational speeds. Therefore, in order to mitigate the effects of ship noise, there exists a need to detect the presence of cavitation during ship operations.

Cavitation can be detected following analysis of measured vibration or acoustic pressure in a location near the propeller. Whilst cavitation manifests as an increase in measured level, advanced signal processing methods are usually applied to distinguish cavitation from other sources of increased noise. Traditionally, DEMON processing has been used for identifying cavitation, requiring operator knowledge in order select appropriate frequency bandwidths [1]. More recently, Cyclostationarity has been proposed [2, 3], whilst removing the operator input, tuning is still required to select the appropriate signal overlap and peak-picking parameters.

To overcome the need for an operator to analyse measured signals, we investigate the use of Machine Learning (ML) for detecting the presence of cavitation. In particular, we investigate the utility of time-series classification methods in order to overcome the need for advanced signal processing of the measured data. Previous work [4] highlighted the challenges of time-series classification for cavitation detection using readily available ML models. One of the challenges identified was the effect of Signal to Noise Ratio (SNR) in the data. In this contribution, we build on the previous work with an investigation on ML approaches more suited for time series classification, evaluating their performance across a range of SNRs.

2. METHODOLOGY

2.1. DATA

For the present work, synthetic data has been used in the evaluation of the ML methods. Synthetic data has been used as it allows close control of specific properties of the data. In particular, synthetic data has been generated covering a range of SNRs. Six data sets were generated. For five of these data sets, the data within each was constructed with a fixed SNR. Namely, data sets were generated for SNRs of -30, -20, -10, 0, and +10 dB. The final data set was constructed from a range of SNRs between -30 and +10 dB.

Hull vibration or hydrophone measurements made in the proximity of a cavitating propeller are characterised by an increased level across a broad frequency range, modulated by the propeller blade rate and its harmonics. To avoid a model simply training on an increased level and not the underlying features of a cavitating signal, there was not an overall increase in levels between non-cavitating and cavitating signals.

The synthetic data is generated by the summation of continuous and broadband components. Where cavitation is present, the broadband component is modulated. The continuous component is modelled as Gaussian white noise and controlled the SNR in the overall signal. The broadband component is filtered Gaussian white noise and the modulated component is produced by a summation of harmonics at multiples of the blade rate. To increase the variability, the modulating component was scaled according to a cavitation index, randomly generated in the range zero to one. For signals where no cavitation is required, the modulating component is excluded.

Across the analysis, 500 samples were nominally used, split 80/20 for training/testing. Further, an equal split of cavitating/non-cavitating signals was used throughout.

2.2. MACHINE LEARNING METHODS

To avoid the need for data preprocessing, the present work investigated the capabilities of time series classification methods. To this end, the Time Series Forest (TSF) [5] was first evaluated. The TSF is a relatively simple approach to extend the Random Forest algorithm to support time series classification. The TSF is based on identifying a number of random intervals of the time series signal and using the properties of the signal in these intervals as the input features for the random forest model [6]. In particular, the mean, standard deviation and slope of each interval is computed and used as input features. Fig. 1 shows a schematic of the model feature generation. The number of input features is therefore $3N$, with N the number of segments.

The kurtosis and skewness have been investigated to understand if they can better characterise the presence of cavitation within a signal. These measures have previously been used within time series classification [8, 9]. The TSF classifier is therefore modified, with additional segment features of kurtosis and skewness. Thus, increasing the number of features to $5N$.

In the subsequent analysis, the TSF model hyperparameters were tuned for each evaluation. In particular, the minimum number of windows and minimum window length were tuned. The default hyperparameters for the underlying random forest model were not modified as they had a minimal impact on model performance.

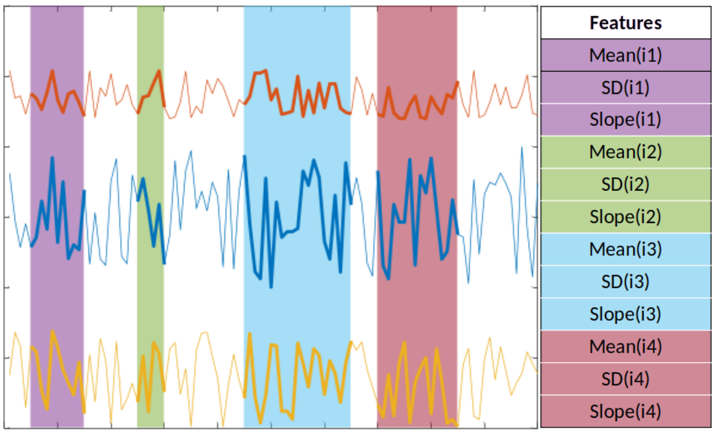


Figure 1: Schematic of the Time Series Forest

A Feed Forward Convolutional Neural Network was adopted to compare with the TSF approach utilising more training parameters and a larger input dimension of the full time series signal. The Fully Convolutional Network (FCN) architecture from [10] was adopted as a simple test bed to analyse full time waveform binary classification. The structure of this network allows for a progressive feature learning order; basic, complex and refined. This ordering aims to prevent early compression or loss of features. Global Average pooling is used to compress features into predictions and helps to avoid over-fitting.

3. RESULTS & DISCUSSION

Fig. 2 compares the F1-score for the unmodified TSF and the TSF with kurtosis and skewness as additional segment features. The performance of both models is seen to increase as the SNR increases. In the case of the lowest SNR data, the unmodified TSF outperforms the modified model. At increasing SNR, the modified TSF shows improved performance, indicating the utility of the kurtosis and skewness as input features. This aligns to the findings of a separate feature importance analysis carried out using a Random Forest Classifier.

For the data set comprised of data across a range of SNRs, a relatively poor performance is observed, particularly for the unmodified TSF. Inclusion of the kurtosis and skewness shows a significant improvement in model performance. The results for the case are expanded in the confusion matrices shown in Fig. 3. The unmodified TSF generally shows the model has not been able to learn well, essentially guessing the classification. On the other hand, modified TSF shows an improved performance in predicting both classes. Given the increased variability of this data, increasing the data size is suggested to improve the overall performance for this case.

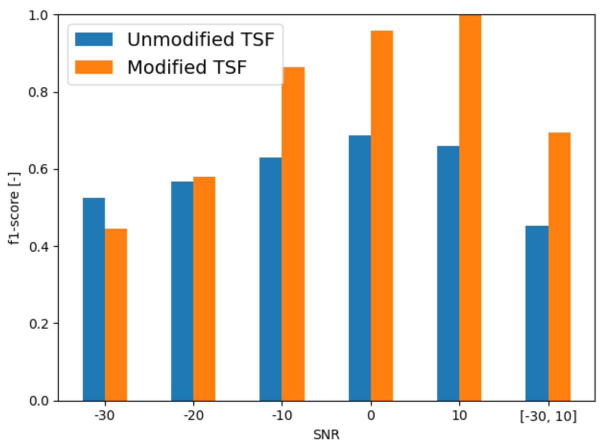
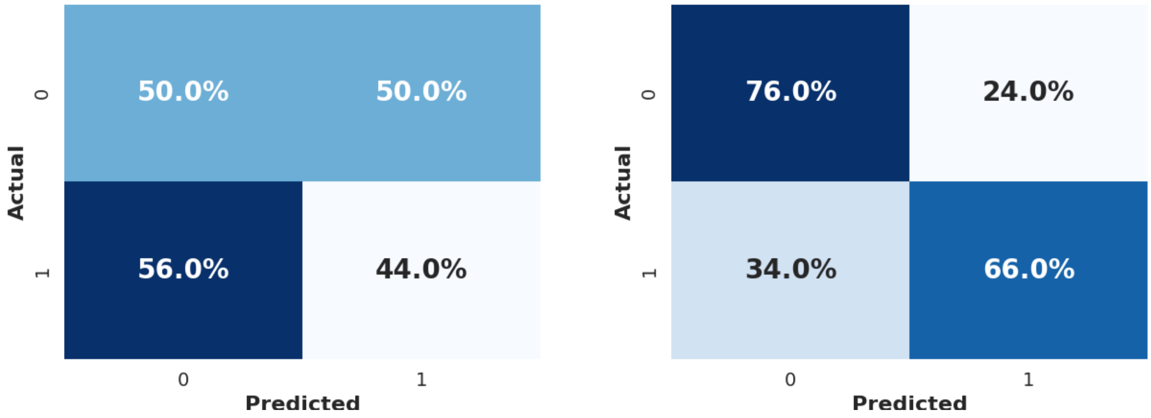


Figure 2: TSF performance across SNR range.

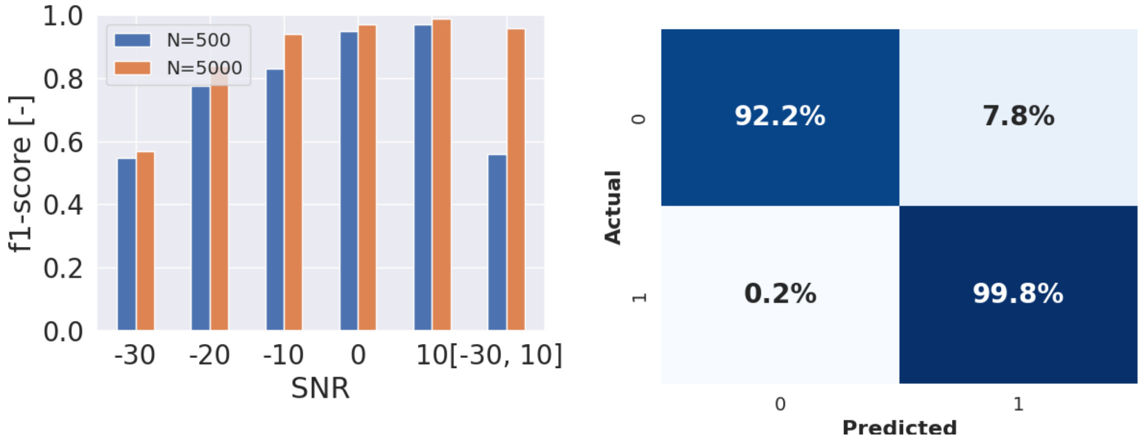
Fig. 4 shows the F1-score for the FCN and the corresponding confusion matrix for the data across a SNR range. The FCN performance shows a similar trend to that observed for the TSF, with increasing performance as the SNR increases. However, the FCN shows a greater performance at lower SNR.

Using the nominal sample size of 500, the performance of the FCN for the data comprising a range of SNR was relatively poor. It was found that by increasing the sample size, it was possible to drastically improve this, with the corresponding confusion matrix showing the ability to accurately classify both cases. For the data with fixed SNR, the nominal sample size was found suitable. This difference in performance, as identified for the TSF is suggested to be due to the increased variability within this data. The precise sample count required to increase the performance for this case has not yet been determined, with the larger value used to demonstrate the capabilities. The precise data requirements will be the focus of future work.



(a) Unmodified TSF *(b) Modified TSF*

Figure 3: Confusion matrices for the unmodified and modified TSF.



(a) F1 score for different sample sizes. *(b) Confusion matrix, [-30,10] dB range with N = 5000.*

Figure 4: FCN performance across SNR range for varying sample sizes.

4. CONCLUSIONS

The capability of two Machine Learning methods for detecting cavitation has been demonstrated in the present work. Using synthetic data to control the noise level, the capability of a Time Series Forest and a Fully Convolutional Network has been explored.

The TSF showed increasing performance as the SNR increased, indicating that some level of signal conditioning may be required for very low values of SNR. The utility of kurtosis and skewness in aiding in the detection of classification was explored. Modifying the TSF, the kurtosis and skewness were found not to be beneficial in circumstances of very low SNR. However, as the SNR increased, they demonstrated significant improvements in the TSF classification capability.

The FCN generally showed improved performance when compared to the TSF. However, when evaluating the data whose signals were constructed from a range of SNRs, the performance was comparable to the TSF. FCN performance increased dramatically when the number of samples was increased which may not always be a feasible option in practice. However, the precise data requirements should be studied further.

Further work will apply the developed models to a measured data set to evaluate their capabilities to real data. Further work will also focus on comparing the two explored models and identifying the most suitable approach for transitioning to a deployable service as a cavitation detection system.

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