Machine Learning for Transcranial Narrowband Ultrasound Signal Onset Delay Estimation

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I. ABSTRACT

Focused Ultrasound is an emerging medical technique which requires the precise modelling of ultrasound signal propagation through the skull. To verify models, onset time delay between two signals with varying parameters, but measured at the same spatial location, is used to benchmark accuracy. Common approaches, which calculate the delay using correlation or other means, suffer from signal distortion and poor signal to noise ratios, producing less than satisfactory results. We seek to use machine learning to predict, rather than calculate, the onset time delay for the purpose of accurately determining the propagation time delay of a signal. Data from Pichardo et al.[1] will be used as features for the machine learning algorithm, and its accuracy will be benchmarked against manually identified onset time delay.

II. INTRODUCTION & BACKGROUND

Focused Ultrasound (FUs) is a non-invasive treatment for various disorders that can concentrate mechanical energy on specific volumes within the body. This energy can have various effects based on ultrasound parameters, such as intensity and frequency. For example, it can allow larger-than-normal particles through the blood-brain barrier (BBB)[2], thermally ablate[3] tissue, or neurostimulate[4].

To ensure the accuracy of a target region within the brain, computer models[3,5] simulate the transcranial propagation of narrowband ultrasound pulses. Two simulations are performed, one with a skull in place and one without, to find the onset time delay between them at a specific location. The comparison of the simulated signal's onset delay to that of the experimental signal is an important benchmark to validate a computer model.

Time delay estimation techniques are often used in literature[5,6] to identify onset time delay, yet they are not ideal for this situation. The onset of multi-pulse signals in the presence of strong aberrations, such as the skull, is difficult to identify due to echoes which distort and delay the rest of the signal. Cross-correlation is a robust choice for time delay estimation, but often miss-identifies the delay and requires human adjustment for the best results[1,7].

As signal generation techniques become more advanced, and therefore signals more complex, a new onset time delay estimator is required. The goal of my project is to implement a reliable algorithm to predict the onset time delay between two signals and validate it against current methods. In this document, I will summarize previous work investigating how to determine onset time delay and our proposed solution using machine learning (ML).

III. PREVIOUS WORK

In the past, authors have studied the effectiveness of correlation algorithms, time delay estimators, as well as onset detection methods[1,6]. Time delay estimators can be split into four different classes[8]: time-delay approximation model, explicit time-delay parameter, area and moment, and higher-order statistics methods. Unfortunately, none of these techniques have shown the ability to accurately detect the onset of a signal – most find the best fit overall, even if there is significant distortion after the signal's onset[5,7].

Previous research conducted by N. Meulenbroek[6] concerned the merging of onset detection methods, which use transient detection techniques to determine the onset of a sinusoid, with correlation methods. The study compared the effectiveness of seven new variants at identifying the time delay in signals. The best algorithm, a Hilbert transform with cross-correlation, was shown to be 37% more accurate than regular cross-correlation in the best case. However, this is still not accurate enough to be used independently and without manual adjustment except in the ideal case. Therefore, we wish to pursue ML to reduce the number of signals which need to be manually identified.

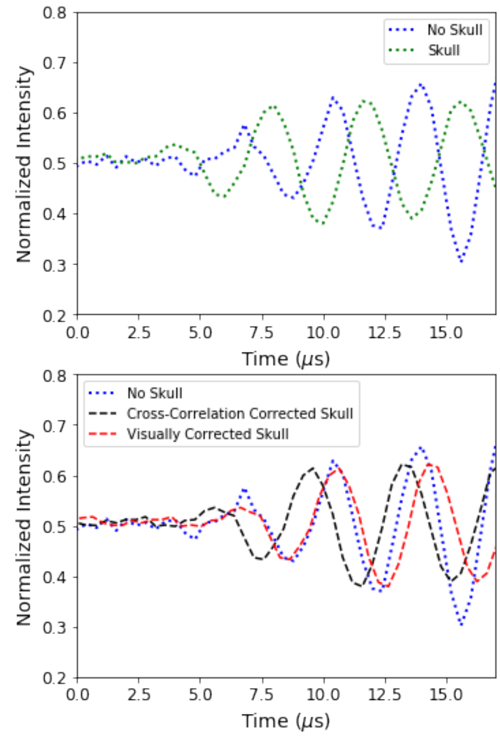

FIG. 1. A 270 KHz ultrasonic signal pair measured underwater[1]. **Top:** Ultrasound signal measured from the same location, with and without a skull between the hydrophone and the transducer. **Bottom:** Comparison of cross-correlation and visual correction for time delay estimation.

IV. METHODS

Many signal processing techniques are unable to determine the time delay due to excessive noise and distortion[7] and, therefore, we intend to use ML to predict onset time delay instead of calculating it. Our goal is to find a relationship between features of the experiment (information about the skull, hydrophone location, and ultrasound signal) and the onset time delay between two signals. The specific ML algorithm to be used for this study will be determined by a literature review prior to implementation.

Implementation will be done in Python using Jupyter notebooks. Third party libraries will be used to improve run-time and robustness. Potential libraries will be evaluated as needed during the implementation of our solution.

To train and test the chosen algorithm, we will be using data from a previous study by Pichardo et al.[1]. This study used a focused ultrasonic transducer to create a signal underwater, which then recorded using a hydrophone. The hydrophone was precisely positioned across an evenly spaced grid and two signals are recorded at every point: one with only the hydrophone and transducer, and one with a skull between the hydrophone and transducer (FIG. 1). Parameters about the experiment, such as skull density and incidence angle, were were recorded for each signal pair and will make up the features for our ML algorithm.

A random sample of at least 300 signal pairs will be chosen to have the delay identified manually. A portion of these pairs will be used as a training data set for supervised learning. The ML algorithm will then be compared to traditional algorithms (cross-correlation, a Hilbert transform with cross-correlation, and spectral energy with cross-correlation) across the remaining signal pairs.

To account for common confounding factors (signal to noise ratio (SNR) and frequency) results will be grouped into two frequency bins of 270 KHz and 836 KHz, as well as three SNR bins (low, medium and high SNR). The primary metric for determining the effectiveness of the algorithms will be the mean difference between the actual time delay and the determined time delay.

V. TIMELINE

Researching and identifying ML techniques well suited to regression through a literature review will be the first step of this project. During this step, I will be learning about and experimenting with machine learning. This will be completed within three weeks, or by mid February.

The second step will be the implementation of the chosen algorithm. Should the algorithm not be sufficient to establish a relationship, alternative algorithms will be explored given enough time. Time delay will be manually identified for the 300 signal pairs during this portion of the project as well. Time and resources permitting, this sample may be expanded with the help of a high school student over spring break. We expect that the implementation and validation of the algorithms will be completed within four weeks, and would therefore finish mid March.

Barring any significant setbacks, performance comparison and data analysis would take approximately two weeks. Finally, this will leave two weeks to write the final report and create the final presentation.

VI. CONCLUSION

In summary, we seek to improve the identification of onset time delay between direct and transcranial narrowband ultrasound signals. Throughout this project, I will be learning about machine learning to apply supervised learning to a set of signal pairs from previous experiments. At least 300 signal pairs will be used and will, therefore, have their time delay manually identified. Finally, the results of the algorithm will be compared with traditional algorithms across a variety of SNRs and frequencies.

** Project website can be found at https://nathanmeulen.github.io/index.html.*

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