Recognition of Object Presence and Material Type in a Water Container Using High Frequency Ultrasound

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Abstract

Detection and characterization of soluble, diffuse, and solid objects and their characteristics in water has important implications in various applications, including water quality assessment and incontinence monitoring for health applications. In particular in the latter task, it is essential to be able to non-intrusively detect the appearance, presence, and consistency of materials in the water without the need for special purpose instruments or a special purpose setting. To achieve this, this work investigates the potential use of high frequency sonar sensors retrofitted to an existing, water-filled container to detect and characterize events where materials are added to the water, and to classify characteristics of the materials in terms of solubility, granularity, and density.

Introduction

Ultrasonic waves are used in various applications such as range finding (SONAR), medical imaging (Sonography), flaw detection in metals, fluid flow monitoring, non-contact sensing and non-destructive testing of objects. In an example, ultrasonic waves are propagated through metals to find anomalies. The high frequencies propagate largely unperturbed when passing through the metals but are reflected and modified at defects, thus helping to identify flaws (Silk 1982). This ability to differentiate materials as well as the fact that humans cannot perceive sound waves above 20000 Hz, make them interesting also for health monitoring applications. In this paper, we aim to study the extent to which high frequency ultrasound can be used to non-invasively detect and identify materials being introduced in water. In the experiments, neural networks are trained to classify the materials into 8 classes: Rock, Soap, Metal Wire Mesh, Milk semi-solids, Flour, Sand, Bread Crumbs and Water.

Background and Related Work

Ultrasound as a means of analyzing materials has been studied in a number of contexts. (Kim, Lee, and Lee 2006) performed material classification using the reflected signal's amplitude and time of flight on five objects: aluminium, concrete, wood, glass and steel. Similarly, (Ecemis and Gaudiano 1999) developed a system that uses ultrasound to enhance object recognition by adding material properties. We here focus on materials in water and try to implement an approach that uses propagated and reflected signals to extract frequency domain characteristics. Here continuous monitoring will generate large amounts of data and hence dimension reduction as in (Reddy et al. 2020) has to be explored.

Methodology

In the system developed here, multiple 300kHz ultrasonic transducers are used with a Teensy micro-controller (tee). The transmitting and receiving circuits are separate, but are controlled by the same microcontroller which initiates wave function generator and High speed Data Acquisition.

Ultrasonic transmitters and receivers are mounted to a water-filled ceramic container into which materials are introduced through a filter as shown in Fig. 1.

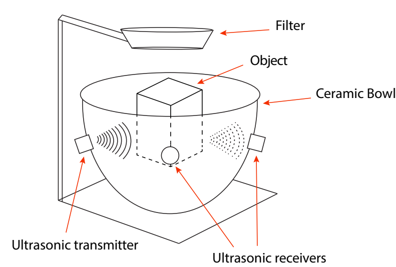

Figure 1: Experimental Setup

The system utilizes one transmitter and two receivers that are mounted on the opposite side and at 90 degrees to record different parts of the transmitted and reflected signal. The materials are introduced for some time and then settle in water and all ultrasonic wave patterns were recorded.

For the analysis we convert the signal to the frequency domain using Fast Fourier Transform (Mathuranathan 2021). We then attempt to automatically cluster our data into three main phases: Still state (No new object has entered the water), Entering state (Object being introduced into the water) and Stabilizing state (object settling underwater). The stabilizing state will have two sub-states: stabilizing and then being still. So, the original still state and the stabilizing still state can be harder to distinguish. Hence, we have to track state changes of a signal to differentiate these. Once the stage is identified, we use separate neural networks for each stage to classify the material. This process is shown in Fig. 2.

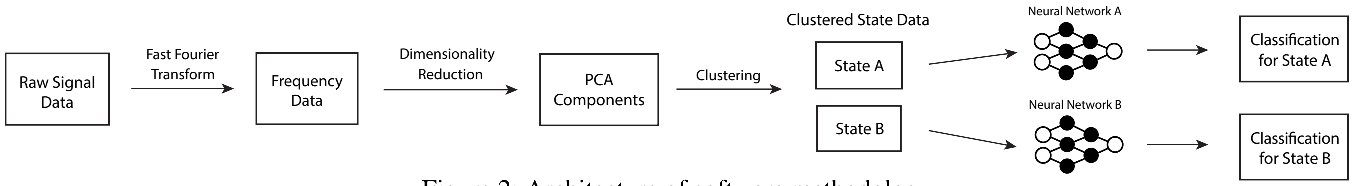

Figure 2: Architecture of software methodology

To address the high number of FFT components of the two 300kHz signals, we utilize Principal Component Analysis on the power spectrum to reduce the dimensions and extract features which represent significant frequency components. When segmenting the data, some events can initially be incorrectly clustered as illustrated in Fig. 3. Some of this can be corrected by observing that states will be in sequence.

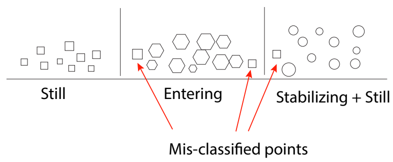

Figure 3: Misclassified Points for Temporal Stages

For material classification in each stage, we used the corresponding data to train separate neural networks. To effectively use these, we designed an input vector that contains the raw signals of both receivers and the PCA components of the FFT. The reason here is that more detailed signal shape information from the raw signal might be useful in addition to the frequency response information provided by the FFT spectrum. The vector is illustrated in Fig. 4.

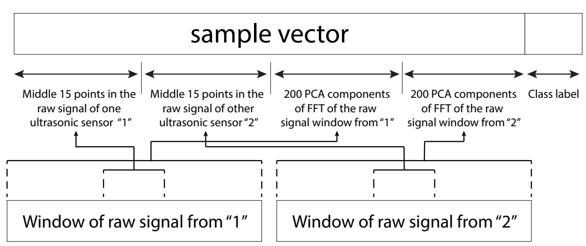

Figure 4: Sample Vector for Neural Network

Results

For validation we collected data, marking the state changes.

For the segmentation, we assumed three states: 'Still', 'Entering' and 'Stabilizing + Still'. We performed PCA on the FFT spectrum and selected PCA components with a 85% variance threshold, resulting in 200 components on which K-Means clustering was used to separate data into the 3 stages. Plotting cluster assignments over time, we can observe in Fig. 5 that initially many points that should be 'entering' are clustered as 'stabilizing'. To address this we enforce temporal consistency and add a 'still_after' stage to capture transitions from 'stabilizing' to 'still'. This results in cleaner stage assignments as shown in Fig. 5.

Now we built input vectors and train separate 8-class classifiers for the 'Entering' and 'Still_after' state. The network using 5 dense and 3 dropout layers is shown in Fig. 6 and was trained using Sparse Categorical Cross-entropy.

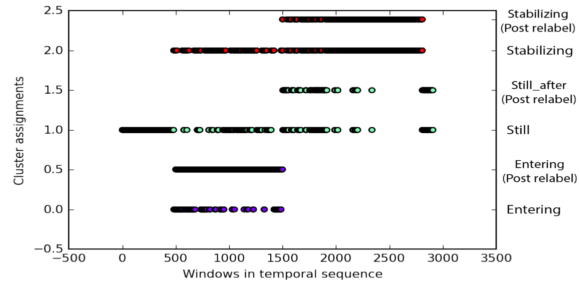

Figure 5: Cluster Assignments Before and After Relabelling

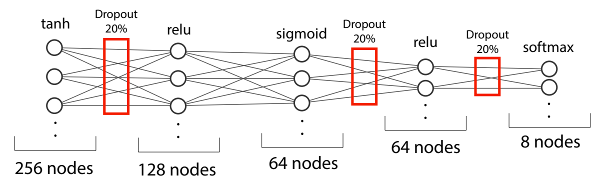

Figure 6: Neural Network Architecture

Training results in validation accuracies of 95.51% and 95.31% for the 'Entering' and 'Still_after' states, respectively, illustrating the soundness of the approach. Classification results for the 8 classes (water, rock, soap bar, metal mesh, bad milk solids, flour, bread crumbs and sand) are further illustrated through the confusion matrices in Fig. 7.

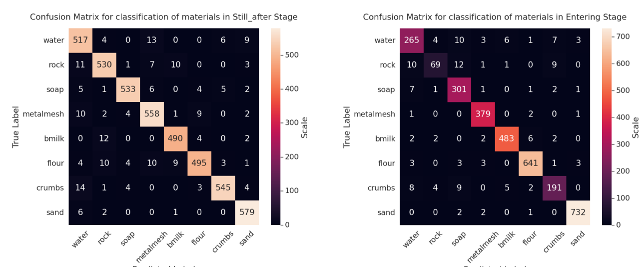

Figure 7: Confusion Matrix for 'Still_after' and 'Entering'

Results show high accuracy for all materials except rock in the 'Entering' state which also had the smallest number of samples as it exhibited a very short entering phase.

Conclusions

In this paper, we introduced a retrofittable ultrasonic material classification system. We explored its potential for segmenting the different stages when entering objects in a water-filled container and for classifying the materials based on ultrasonic data. Experiments using 8 different materials illustrated the approach's ability to successfully segment the stages using K-Means clustering and temporal consistency, and to classify both during the 'Entering' and the 'Still_after' stage using separate neural network classifiers, reaching accuracies for the 8 materials above 95% in both states.

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