Detecting Underwater Objects using Ultrasound

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Within waste-water treatment plants it is mandated that the level of harmful pollutants be reduced to a safe level before the treated water is released to the environment. An effective method to approach this processes begins with initial measurements of the concentration of objects within the water. Although a variety of sensors and instruments exist to measure this concentration, this work demonstrates a waterproof instrument that can examine objects through ultrasonic wave technology within a reservoir, not through samples. This instrument will allow workers to examine the presence of objects within a size range that are exiting the plant. A hydrophone receiver was used to measure the signal, and digital signal processing algorithms were applied to classify the frequency response and identify what the materials were composed of. The results demonstrate that the instrument can accurately detect and identify the presence of objects in a water environment, and are promising for the future application of this method to detecting contaminants in wastewater.

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Introduction

In the industry, there are many different ways in which wastewater is sampled. According to EPA guidelines sampling is completed four different ways: flow-proportioned sampling, time-composite sampling, grab sampling, and sludge sampling [1]. Flow-proportioned sampling is the process by which an automatic sampler pulls a sample from a flow of water during a set flow interval. While time-composite sampling is the process by which an automatic sampler creates a constant volume sample at regular time intervals at the source of the waste water. Grab sampling is the process by which samples are manually sampled for a total of fifteen minutes. This sampling technique requires at least four samples to be taken, however, twelve samples are preferred. Sludge sampling is the process by which a series of samples of sludge/mud are taken from a randomly selected target area and combined into one, total sample and tested to ensure regulations are adhered to.

This paper presents a proposed alternative to the water sampling technique, and demonstrates a proof of concept for detecting submerged objects using ultrasonic waves. Ultrasonic waves are defined as acoustic pressure signals that have frequencies higher than 20 kHz [2]. They are known to have many different purposes in industry which include but are not limited to the detection and display of images that people cannot easily see in real life. Some examples of these imaging techniques include sonography, and navigation systems [3].

The method proposed in the paper would allow regular, information to be collected that would not require the use of physical water sampling. In order for this to be completed, ultrasound is used to create as acoustic pressure wave, and the change in the pressure wave due to an object is observed. In this work, the technique was employed to detect submerged objects in water is a proof of concept that could potentially be used in the future to detect contaminant objects in wastewater.

One potential application of ultrasonic signals is the identification of particulate matter in a water system. To do this, an instrument that used an algorithm to classify materials based off their ultrasonic impact was created. It was used to determine the peak amplitudes at each implemented frequency. By knowing the amplitudes of the frequency waves, this instrument would be able to demonstrate the response of the different materials in a water tank given an input ultrasonic pressure wave.

Theory

The fundamental concept behind this project is the response of different materials at different sizes and positions to a driven acoustic wave in water [4]. A sensor is used to measure the response of materials to an ultrasonic wave, and this data is used to build a database for classification. Once the classifier is constructed in software, a new signal can be classified into one of the object classes from the database.

There were a total of four tools that were used for this project: an ultrasonic wave actuator, an ultrasonic wave sensor, a fish tank, and digital signal processing software. The ultrasonic wave actuator consists of a function generator and an ultrasonic transducer. The function generator was used to generate an ultrasonic wave that was transmitted to the ultrasonic transducer. The ultrasonic transducer is a hydro-piezoelectric component that has the same frequency bandwidth of the function generator. The ultrasonic wave sensor is a hydrophone that picks up the ultrasonic signal and amplifies it in order to be useful. The fish tank was used as the environment where multiple experiments took place. Each experiment was completed with different materials submerged in water. The materials included: plastic, sand, rubber, rocks, and even plain water. After receiving an amplified signal, digital signal processing software was used to obtain only needed data out of a set of data. To do this, unwanted data that was obtained by many peripheral sources due to environmental noise needed to be accounted for and reduced. The targeted data was obtained by converting signals from time domain to the frequency domain and processing the clear reliable frequency made by each material.

The same experiment was done three times and averaged together to decrease outliers of the frequency responses. Also, the same experiment was done at three frequencies: 41KHz, 61KHz, and 81KHz.

The natural frequency of the rectangular enclosure was calculated using the following equation [5].

$$f = c\sqrt{\left[\left(\frac{n_x}{l_x}\right)^2 + \left(\frac{n_y}{l_y}\right)^2 + \left(\frac{n_z}{l_z}\right)^2\right]} \quad Eq. 1$$

Where c is the speed of sound in water (1482 m/s), n are the natural modes of the enclosure and l is the length in the x, y and z directions. The dimensions of the tank are 0.254 m in the x-axis, 0.127 m in the y-axis and 0.4064 m in the z-axis. The tank had a width of 0.254 m and a length of 0.4064m.

Methods

To examine whether pressure waves would be able to differentiate materials in water, a function generator (BK Precision, 4005DDS), transducer, hydrophone (RESON, TC4013), and oscilloscope were used.

Tests were conducted using a 5-gallon rectangular fish tank filled with water, an 18in wooden dowel, a function generator, voltage source, and hydrophone. The experimental setup is visualized below in Figure 2 and Figure 2.

The fish tank was filled so that there was 4-6 inches of water within. Then the wooden dowel was placed over the fish tank lengthwise so that the hydrophone

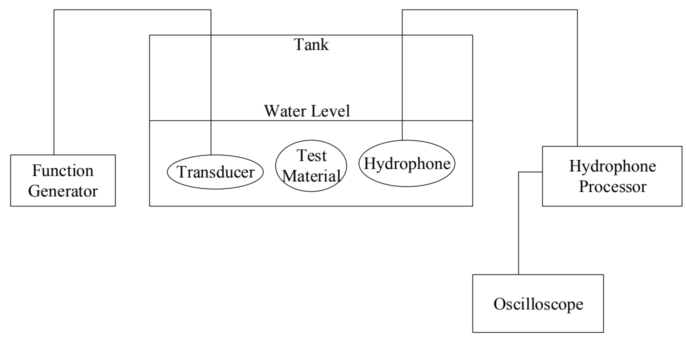

Figure 1: Visio sketch of the complete apparatus

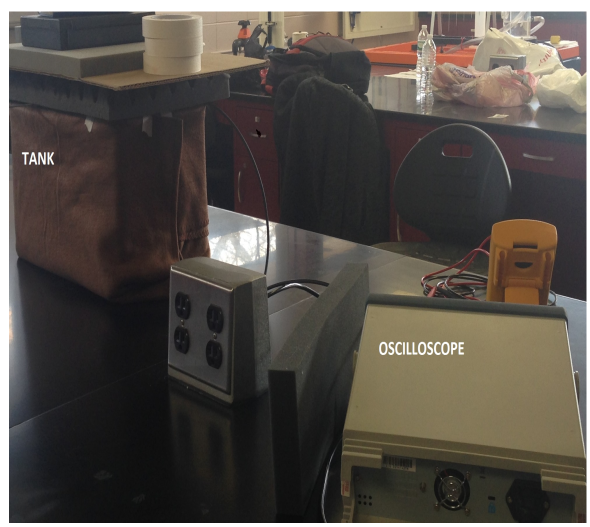

Figure 2: Picture showing the experimental test site with the tank covered in a shroud. The tank was covered in order to reduce environmental noise interference with the data.

could be placed in the water in such a way that it would not touch any of the glass of the tank. The transducer was placed on the opposite side of the tank and connected to the function generator.

The bottom and sides of the apparatus were wrapped in a blanket, while the top was covered with a noise reduction foam pad that was about 1-2 inches thick. These dampening techniques were used in order to minimize environmental noise to the system. Both the blanket and foam pad reduced the vibrations that the system was affected by outside of the system. In early tests, neither the blanket nor the foam pad were used and no results were accumulated. The system acoustics were drowned out by the noise from the surrounding area.

A total of forty-five different tests were conducted, testing five different materials: plastic, rubber, rock, sand, and water, pictured in Figure 3, Figure 4, Figure 5, and Figure 6. Each material was tested at different frequency levels (41 kHz, 61 kHz, 81 kHz), three separate times in order to account for any variations between tests. Once the tests were completed, all the data from each of the tests was imported into MATLAB and the Fast Fourier Transform was performed. The resulting data was graphed on three separate plots: one for each frequency. Through the analysis of these plots, a set of key points was found corresponding to the frequency response of the different objects.

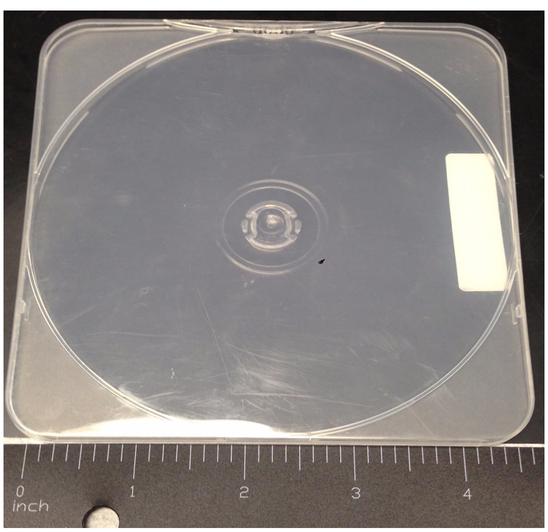

Figure 3: Picture of the plastic specimen used for tests

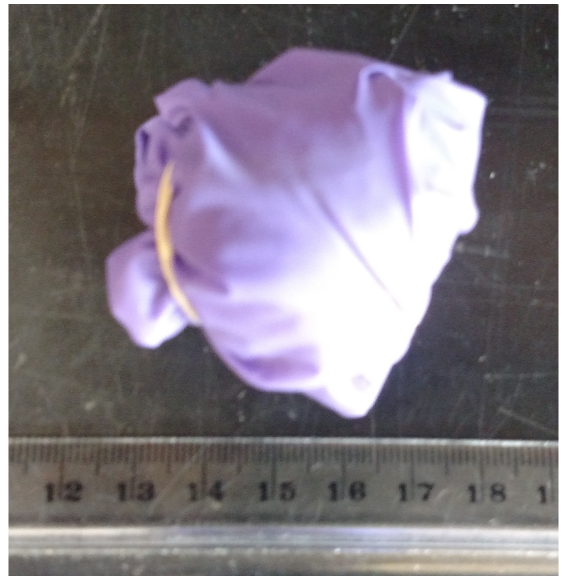

Figure 4: Picture of the rubber specimen used for tests.


Figure 5: Picture of the rock specimen used for tests.


Figure 6: Picture of the sand specimen used for tests.

For the three frequencies, the frequency content of the highest unique magnitude were used as the key points within the classification algorithm. Each plot used for the calculations can be seen in Figure 7, Figure 8, and Figure 9. In each of these plots there are distinct peaks for each material. The classification process used these to determine what type of material an unknown substance was.

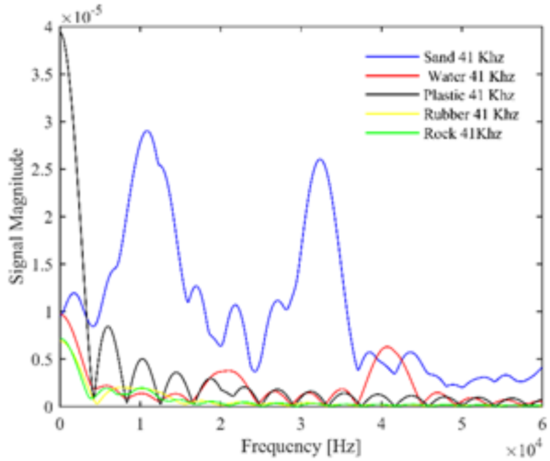

Figure 7: Frequency response of average of classifier data at 41 kHz

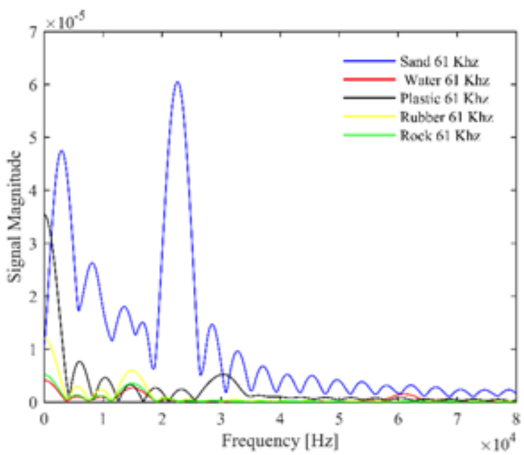

Figure 8: Frequency response of average of classifier data at 61 kHz

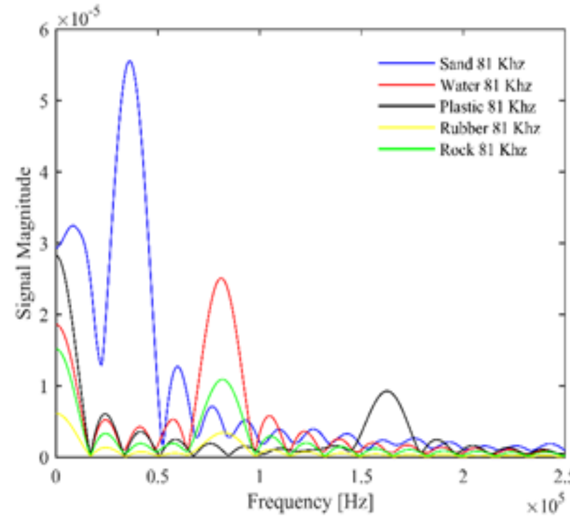

Figure 9: Frequency response of average of classifier data at 81 kHz

A set of key points was extracted by observing the data that make up the classifier. Each material possessed a different frequency response at each input frequency. These key points were chosen as the highest peaks within the frequency response for each class. The set of classes was defined as the parameter vector V, which is $V = \{water, rubber, sand, plastic, rock\}$.

An algorithm for material identification was developed which identifies a new data measurement as belonging to one the classes in V. This algorithm evaluates the differences between the key point locations for each class to form the cost function Eq2.

$$J(n_k, c_k, k, m) = \left|\sum_{k=1}^{nm} n_k - c_k\right|, \qquad Eq. 2$$

Where k is a specific key point, n_k is the new data at point k, c_k is the value of the classifier at point k, and m is the number of key points.

Once the cost function is produced, the goal of the classification algorithm is to minimize the cost function with respect to object class, as in Eq. 3.

$$\min_{v} J(n_k, c_k, k, m)\,, \qquad Eq. 3$$

The class, which minimizes the cost function, is then chosen as the unknown material [6]. This classifier was used to to classify objects for 10 measurements that were not used to construct the classifier to perform a very basic test of classification accuracy.

Results and Discussion

The simple test of classification accuracy for 10 measurements of materials resulted in a classification accuracy of 100%. While 10 samples is not to make a conclusive statement of the method's efficacy, this result is promising for further extension of this method to detecting particles in wastewater.

Even though the classifier correctly classified the objects, there are some possible sources of of mechanical or procedural errors that could interfere with the data given a larger test pool. A source of error that was previously mentioned was that of environmental noise. A noise reduction foam pad was used to dampen the effects of this noise, however, it might not have been enough. The foam padding that was used could have been thinner than what was needed, thus allowing environmental noise to interfere with the test apparatus. Even though the noise witnessed during testing was reduced enough to produce data, there were still variations in frequencies that could have been attributed to small amounts of environmental noise.

Another possible issue is random noise, in which the data is significantly different from one trial to the next. In this experiment, random error was reduced by taking the averages of the FFTs. Upon completion, the random noise associated with each dataset was significantly reduced, however, not all random error sources could be accounted for.

Another source of error that could interfere with the data collected is the natural frequency of the tank. These frequencies were calculated using Eq.1. Table 1 shows the dependence of different frequencies based on the modes. The mode described in the natural frequency equation (Eq.1) corresponds to the minimal pressure locations present in the coordinate axis. The natural frequency of the rectangular tank depends on the modes in this axis. Depending on the combination of modes, the natural frequency of the tank will change. In this experiment the combination of modes where all three axes were equal to one was taken into account. This infers that the natural frequency of the tank would be around 6.8 kHz. This natural frequency could have caused the data collected to be larger than what it actually was because the hydrophone would gather both the natural frequency of the tank and the frequency response of the object.

Table 1: This shows the natural response of the rectangular tank, due to different modes.

Modes			Frequency
Nx	**Ny**	**Nz**	(Hertz)
0	0	0	0
0	0	1	1823.3268
0	0	2	3646.6535
0	0	3	5469.9803
0	1	0	5834.6457
0	2	0	11669.291
0	3	0	17503.937
1	0	0	2917.3228
2	0	0	5834.6457
3	0	0	8751.9685
0	1	1	6112.9053
0	2	2	12225.811
0	3	3	18338.716
1	0	1	3440.2461
2	0	2	6880.4921
3	0	3	10320.738
1	1	0	6523.3322
2	2	0	13046.664
3	3	0	19569.997
1	1	1	6773.3583
2	2	2	13546.717
3	3	3	20320.075

Conclusion

Overall, the results obtained from this experiment demonstrate that this method may be used to accurately classify the materials tested. As previously mentioned, each object had a unique frequency response to the applied ultrasonic waves. The frequency response from each object was used to build a classifier for identifying materials.

There are a few areas of improvement to take this project from a proof of concept to a realizable product. The most valuable improvement would be to add more materials to the classification system, and to include a large number of trials for each material. These trials would be used to build a large database for use with pattern recognition techniques. A large number of trials would reduce any statistical error associated with the data in each classification group. In addition, more complicated classification schemes could be employed, and detailed statistical analysis can be used to find the classification rate, sensitivity, and specificity of the classifier. By implementing these improvements there would be sufficient data to verify the classification process that was created in this project.

If given the opportunity, a future goal would be to provide a larger database for future classification trials. It would be best to have numerous materials tested so as to broaden the baseline. This would demonstrate that the algorithms created are accurate in classifying the materials based upon their frequency response. Another future goal would be to develop a better understanding of the physical system dynamics and the response of different materials to applied ultrasonic waves. This understanding could lead to a compelling explanation of the differences in the frequency content of the signal for each material.

Overall, the results shown in this work demonstrate an approach for detecting submerged objects through the application of ultrasonic waves. The results are promising for extending this work to identify objects in wastewater treatment. While further work is required, this method could provide a feasible alternative to water sampling.

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