Sound Analysis of Drop Characteristics by Evaluation of Impact on Water Pool

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***Abstract*—The goal of this research is to study and characterize the effects of water drop impact on a deep water pool using sound recordings. In this paper, we present the experimental setup and the analysis of two sets of droplet sizes. The recordings provide significant temporal and spectral information that may be useful tools in the classification of drop characteristics. A general SVM was trained to classify droplets into the two size categories. The resulting accuracy for the classification is 94.4%.**

I. Introduction

The goal of this research is to study and characterize the effects of water drop impact on a deep water pool using acoustic signals. Analysis is demonstrated by examining some of the temporal and spectral characteristics. Machine learning is applied to automatically classify droplet size given the audio recordings of the individual droplets.

When a drop impacts a water pool, its behavior varies with speed and liquid characteristics. The interplay of capillary, surface tension, and viscous forces influences droplet formation and fragmentation [1]. Ray [2] categorizes these phenomena into seven regimes, characterized by unique patterns such as coalescence, jet formation, and bubble entrapment. Common stages across these regimes include crater and wave swell expansion, wave swell retraction and crater retraction.

High-speed image analysis, including X-ray imaging [3], [4], and laser Doppler velocimetry [5], [6], are common in drop impact studies.

Audio recording provides an accessible alternative. Studies have used audio recordings to document hydrodynamic and acoustic processes [7], [8]. In other fields of research, audio recordings have been shown to be practical in various applications, including meteorology and water leak detection [9]–[11].

The effectiveness of machine learning models has been demonstrated in different studies, such as those involving the analysis of high-speed image sequences of drop impacts on liquid pools [12].

Utilizing acoustic signatures to classify hydrodynamic phenomena, as shown in [13], could significantly enhance the learning base for identifying signals.

The specific objective of the study presented in this paper is to derive the physical characteristics of droplets from their acoustic recordings. Through the application of machine learning, the study aims to analyze the temporal and spectral data captured in audio recordings of droplet impact, thereby offering dependable insights into the dynamics of droplet interactions. The workflow related to this objective is depicted in Fig. 1.

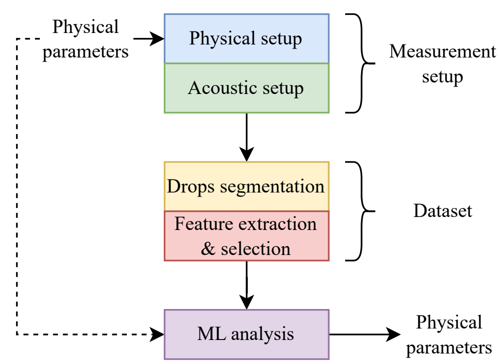

Fig. 1. Illustration of the research workflow designed to derive physical characteristics of droplets from acoustic recordings using machine learning.

II. Experimental Design

A. Technical Design

A water pool filled with tap water is placed beneath a distilled water drop generator (Fig 2). The measured distilled water density was 987.3 kg/m^3. The experiment consisted of two sets of drops released from a height of 220mm. Multiple drops were weighted and then the average volume value was derived. The documented dataset consisted of 124 drops, 49 of which were at an average volume of 55 μL and 75 of which were at an average volume of 76 μL. Table I presents the drop-volume measurement.

B. Acoustic Setup

In previous studies, varying microphone setups were used, for example, in [8], acoustic data was recorded using a high-quality multi-purpose audio interface. In [13], acoustic measurement-standard equipment was used for recording microphone and hydrophone signals.

Several microphones were tested for our setup, including several multi-purpose dynamic and condenser microphones. A high-sensitivity directional condenser microphone provided favorable results (Audio Technica AT2031 condenser microphone with low pass filter). Further research may compare experiment results using acoustic measurement-standard equipment. Signals

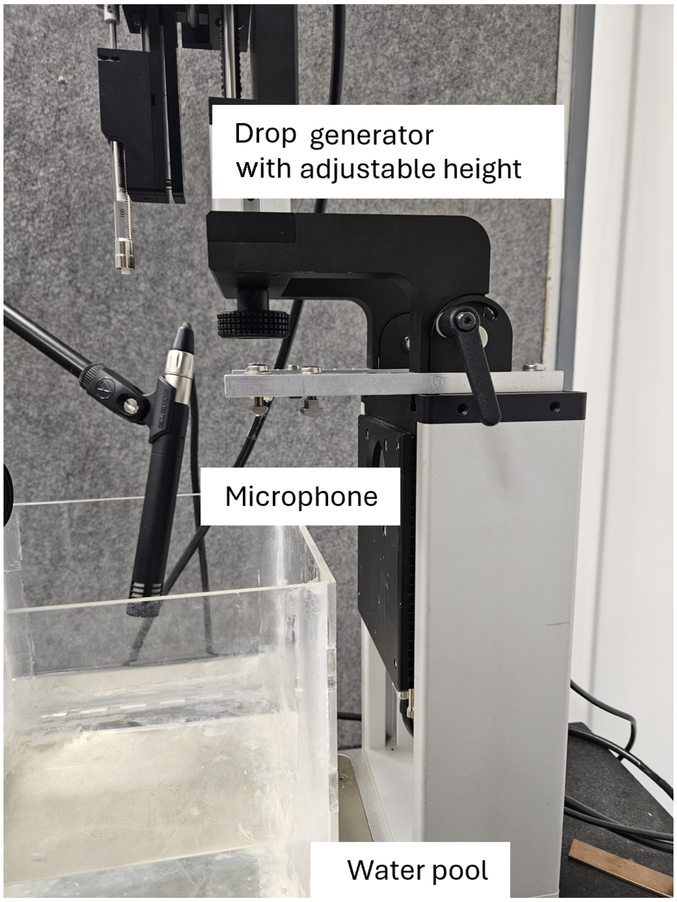

Fig. 2. The experimental setup photo.

were sampled at $44,100$ samples per second using a FocusRite 2-channel sound card.

The dataset consisted of 124 drops, 49 of which were 55 μL and 75 of which were 76 μL. Each droplet recording was separated into a 25,000 sample signal.

An example of two different recordings of the 76μL-sized drops is presented in Fig. 3. Note the significant difference

TABLE I
AVERAGE DROP VOLUME EVALUATION.

Number of drops	Weight [gr]	Average weight [gr]	Volume [μL]	**Average**
15	0.7053	0.047	47.6	**55.1**
15	0.837	0.056	56.5	
10	0.5422	0.054	54.9	
10	0.605	0.061	61.3	
15	1.1437	0.076	77.2	**76.48**
15	1.1841	0.079	80.0	
10	0.7171	0.072	72.6	
10	0.7515	0.075	76.1	

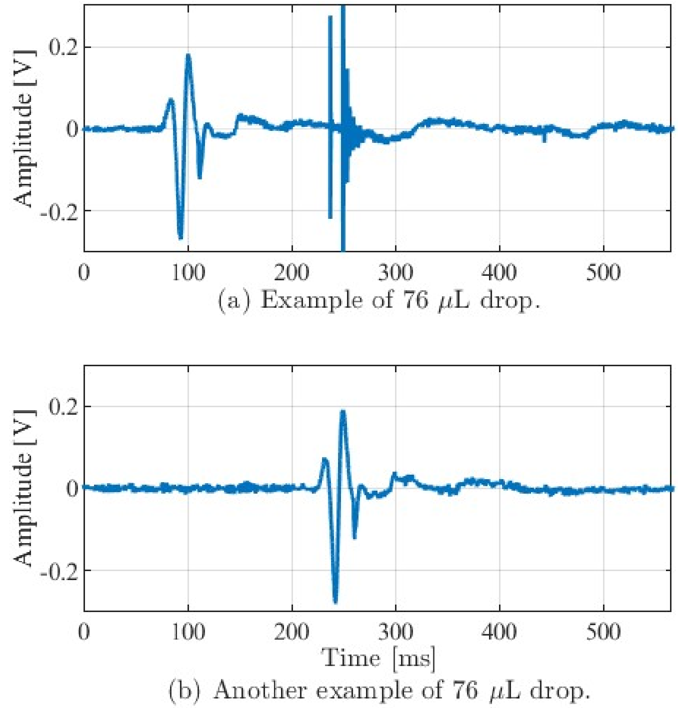

Fig. 3. An example of a tagged drop impact sound recording. The difference between recordings follows the different droplet regimes.

between the recordings. These differences indicate the regimes described in [2].

III. Preliminary Analysis

Previous studies of drop impact characteristics examine both temporal and spectral characteristics of the data. This indicates spectrograms may be used to as a suitable tool for studying the droplets. The spectrograms in the following figures were created using a 512 sample window, an overlap of 511 samples and an FFT size of 2048 samples. Within each size group, several types of behavior were noticed. Within the 55μL group, the drops typically displayed either a single event or a dominant event followed by a slightly weaker event at a lower frequency value. Figure 4 shows the spectrogram for two single event droplets. In these examples, the energy is centered at around $5.75k$Hz.

Figure 5 shows the spectrogram for two 55μL 'multiple event' drops. In both drops, the energy of the first, dominant, event is around $10k$Hz, and the energy of the second event is between $7-8k$Hz. The second event occurs approximately $20ms$ after the first.

The drops within the 76μL group displayed varying behavior. Figures 6 and 7 show the spectrograms of four drops. Due to the larger drop size, the duration of each drop was longer than that of the 55μL drop. Therefore, in the spectrograms of the 55μL droplets, the time scale is 30 msec, and for the 76μL droplets, the time scale is 200 msec.

The graphs in 7 show a multiple event behavior, in which a second event appears approximately $120ms$ after the first. The

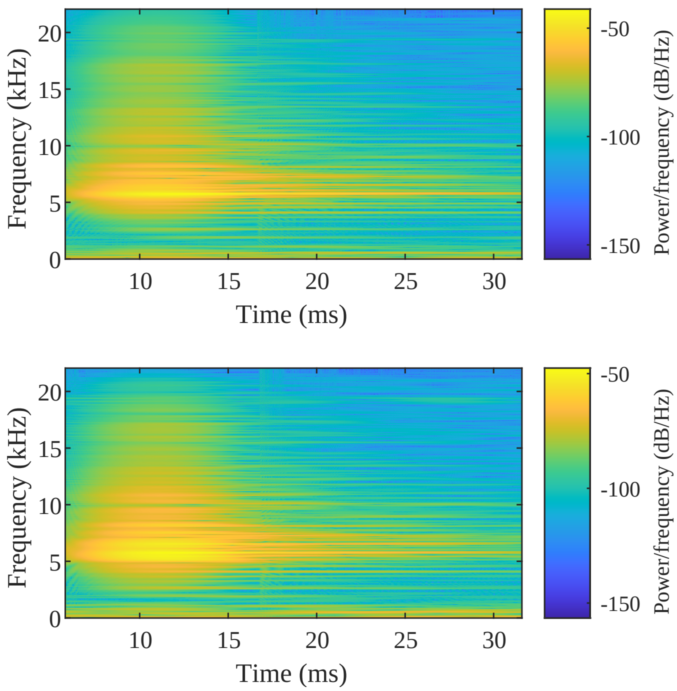

Fig. 4. Spectrograms of two 55μL single event drops. Energy is centered around 5.75 kHz

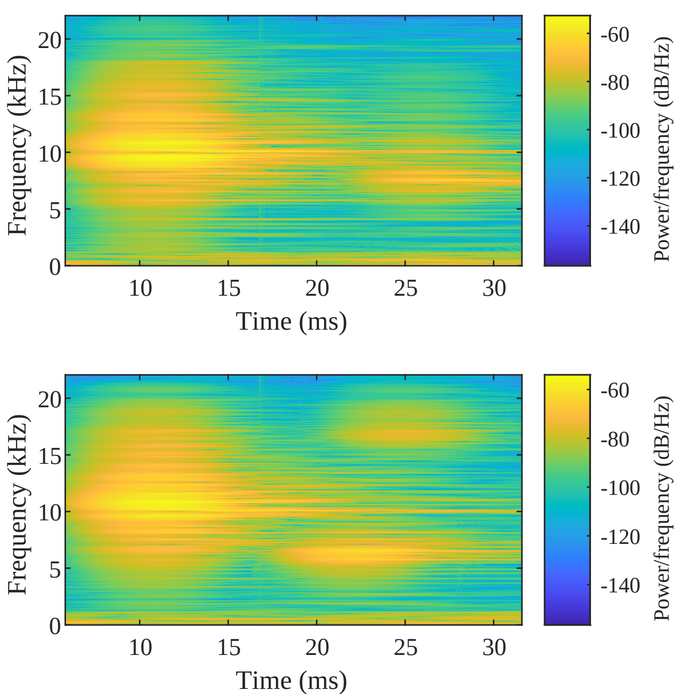

Fig. 5. Spectrograms of two 55μL drops with multiple events. The energy of the dominant event is centered around $10k$Hz. The second event occurs approximately 20 msec after the first.

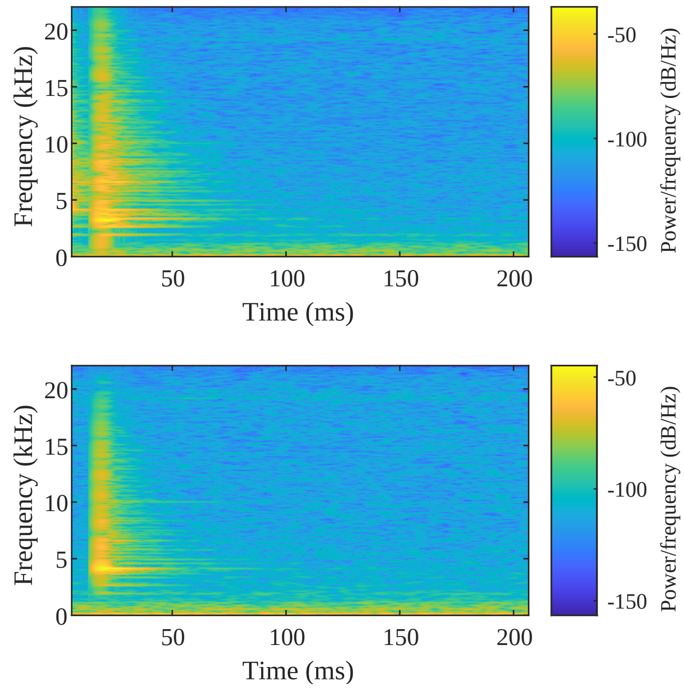

Fig. 6. Spectrograms of two 76μL drops with single events. The energy of the two drops is below $5k$Hz.

energy of the first event in these drops is between $5-6k$Hz. Figure 6 shows two examples of drops with a single, dominant event. The energy of the two drops is below $5k$Hz.

Figure 8 presents a comparison between the normalized fast Fourier transforms of the two full sets of drops. The signals were down-sampled to $16k$Hz in order to examine the signal content below $8k$Hz. In the heavier (76μL) drop set a greater degree of signal content can be noticed below $5k$Hz. In the 76μL set the signal content below $5k$Hz was 44% while in the 55μL set it was only 18%.

The above analysis demonstrates that using audio to record drop impact can provide significant temporal and spectral information and may be useful in the analysis of drops. Other methods to this effect also appear in [13].

IV. Feature Extraction & Classification

The dataset consists of 10 sound recordings, each approximately 1 minute in duration. Five recordings are with 55 μL droplets, and the other five with 76 μL droplets. These recordings were processed using a peak location algorithm to identify the location of each sound event. The resulting dataset includes 124 events, each 25,000 samples long.

The feature extraction performed by `catch22` library, which encompasses 22 different methods selected for their robustness across varied datasets [14]. For each event, the library returns a 22-dimensional feature vector. Finally, all the events were organized in the 22×124 feature matrix that was used for classification.

Model performance was evaluated using an extended 5-fold cross-validation approach to ensure robustness and reduce

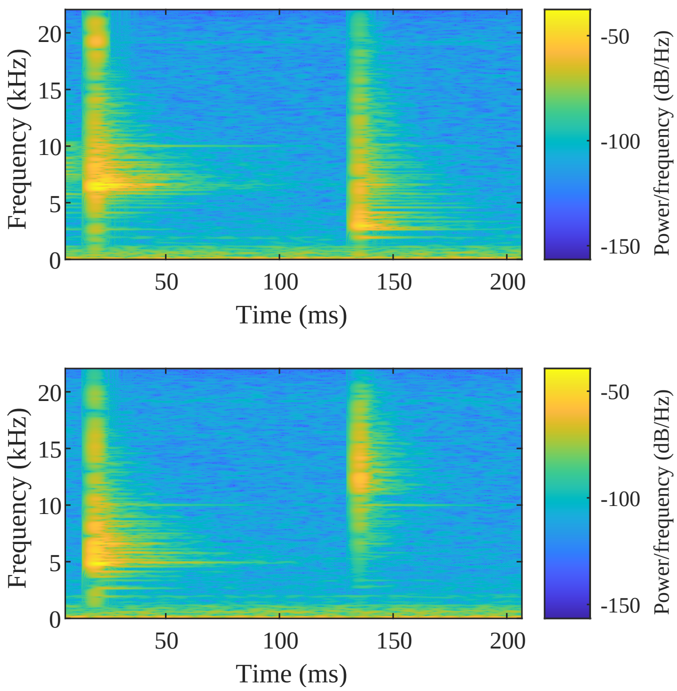

Fig. 7. Spectrograms of two 76μL drops with multiple events. The energy of the first event in these drops is between $5-6k$Hz. A second event appears approximately $120ms$ after the first.

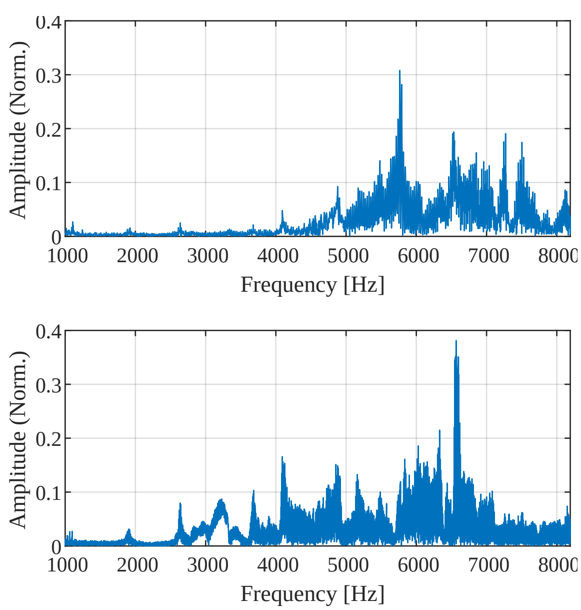

Fig. 8. Normalized FFTs of the two sets of drops, top 55μL, bottom 76μL

TABLE II
CONFUSION MATRIX

		Predicted	
		55μL	76μL
Actual	55μL	46	3
	76μL	4	71

overfitting. The SVM classifier has the resulting classification accuracy of 94.4%. The corresponding confusion matrix is presented in Table II.

V. Summary & Future Work

This study explores the feasibility of characterizing drop properties through the recording of impact sounds. An experimental setup was introduced, and two sets of data were analyzed.

A further goal is to refine the characterization process, ultimately enabling the classification of impact regimes. This sound analysis leverages machine learning (ML) techniques to achieve these objectives. In subsequent studies, the impact of individual droplet events will be investigated, analyzing how various parameters, such as drop characteristics and initial conditions, contribute to the resulting acoustic signature. This research aims to refine event classification based on these findings. For signal processing, additional feature extraction methods using `hctsa` [15] or `tsfresh` [16] software packages may be examined. The next stages would involve reducing irrelevant features by an appropriate feature selection algorithm and hyper-parameter optimization of the SVM classifier.

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