SIMULTANEOUS DETECTION OF FLUID VISCOSITY AND DENSITY VIA PMUTS ASSISTED BY MACHINE LEARNING

Pei-Chi (Peggy) Tsao[1], Megan Teng[1], Yande Peng[1], Vivek K. Premanadhan[2], Ting Chen, Samantha Averrit[1], Wei Yue[1], Jong Ha Park[1], Huicong Deng[3], Fan Xia[1], Yuan Gao[1] and Liwei Lin[1]*

[1]University of California, Berkeley, USA, [2] Synergy Marine Group, Singapore, and [3] University of Chinese Academy of Sciences, Beijing, China

ABSTRACT

This work presents a new scheme to measure both fluidic viscosity and density simultaneously using PMUTs (piezoelectric micromachined ultrasonic transducers) with the assistance of machine learning. Advancements as compared to the state-of-art works include: (1) using PMUT pulse-echo signals to extract multiple fluid properties simultaneously with the assistance of machine learning; (2) differentiating viscosity and density successfully; and (3) sensing results with an error of 1.6 ± 1.57 % for viscosity and 0.20 ± 0.17 % for density for testing fluids in the viscosity range of 0.9 to 1.9 cp and density range of 1 to 1.05 g/mm^3. As such, this sensing technique could be applicable for continuous and precision monitoring of liquid property changes versus time such as engine oil degradations in oil and marine industry.

KEYWORDS

Viscosity, Density, ultrasound measurement, pulse-echo method, pMUTs, Machine Learning.

INTRODUCTION

Measurements of fluid density and viscosity are critical across various industrial sectors, impacting both product quality and process efficiency. In the automotive and marine industry, the precise quantification of these parameters is critical for optimal performance of lubricants and fuels [1]. In polymer manufacturing, the viscosity of molten plastics significantly influences the processing conditions and mechanical properties of the end products [2]. Furthermore, in the food sector, density and viscosity measurements are essential for controlling the consistency and textural attributes of consumables, which are crucial for both consumer acceptance and manufactural processes [3].

Despite its critical role, the traditional methodologies employed for viscosity and density measurements—such as capillary, U tube, falling ball, oscillatory, bubble, rotational viscometers, as well as ultrasonic and acoustic wave sensors—present multiple limitations. These include substantial production costs, considerable energy requirements, low sensitivity, and inadequate portability [4]. Moreover, such devices generally require large sample volumes and tedious calibration processes [5].

In response to these challenges, there are several recent works which leverage Micro-electromechanical Systems (MEMS) and microfluidic technologies [6][7]. This approach has several benefits including small form-factor, lower manufacturing cost, reduced power consumption, better sensitivity, and fast response [8]. Among various techniques, the application of ultrasonic methodologies provides a possible solution for the *in-situ* viscosity and density measurement in a variety of environments, such as within engine systems for the engine oil quality monitoring [9].

Piezoelectric Micromachined Ultrasonic Transducers (PMUTs) have been identified as promising tools to generate ultrasound waves required for the pulse-echo measurements for fluidic viscosity and density [10]. The pulse-echo technique has the potential for real-time and *in-situ* monitoring. However, the precise and simultaneous measurement of coupled fluid properties such as viscosity and density remains a significant challenge. Previously, micromachined ultrasonic transducers have been used to detect fluid viscosity/density [11] without accurately correlating experimental results to their physical properties due to the difficulty in separating the coupled density and viscosity effect.

In this work, a machine learning technique is employed to characterize liquid properties based on changes in acoustic signals from PMUTs such as time-of-flight, signal amplitude, and other parameters for improved measurement results as illustrated in **Figure 1**. Collected signals are analyzed by Neural Network techniques to characterize the fluid viscosity and density concurrently and accurately as the key sensing advancement for various applications.

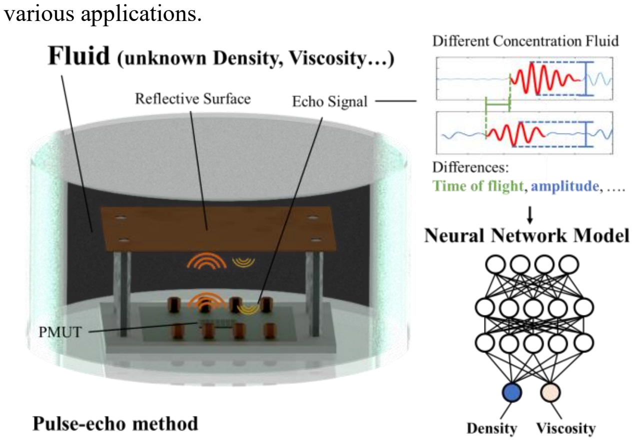

Figure 1: Pulse-echo signals collected by PMUT are analyzed by a neural network scheme for fluid viscosity and density measurements with a mean absolute error of 1.6% and 0.20%, respectively, for the testing fluids in the prototype system.

EXPERIMENT

Figure 1 presents the schematic diagram to measure fluidic properties using the pulse-echo method with a pMUTs array. The echo signals, affected by the fluid's characteristics, are collected and specific features in the signals are used to predict the fluid's density and viscosity by a neural network approach.

Figure 2a shows the experimental setup to collect signals. The ultrasonic waves are generated by the pMUTs array to travel through the fluid and reflect off the reflective surface. The echo signals are received by the same pMUTs array, amplified by a charge amplifier, and processed by a Pico 5444D-200 MHz, 4-Channel Oscilloscope. Both fluid viscosity and density will affect the receiving signals, such as velocity, attenuation, Time-of-Flight (ToF), and the pattern of ultrasonic waves. These complex and coupled effects can be analyzed using a multi-task neural network regression approach to characterize the viscosity and density of the testing fluid.

A 20x8 PMUT array is utilized in this work based on the bimorph dual electrodes design as shown in **Figure 2b** [12-15]. The piezoelectrical layer is made of AlN, and the material of the electrodes is Mo (indicated as a yellow area), which has good crystal structure matching with AlN [13]. The bimorph pinned dual-electrode design provides better performance and greater deformation amplitude compared to the conventional clamped boundary design, thereby generating higher elastic strain energy in the diaphragm. Electromechanical coupling, defined as the ratio of output mechanical energy to input electrical energy, is increased in the bimorph pinned dual-electrode PMUT design. Additionally, because sound pressure output is directly proportional to volumetric displacement—which is determined by the product of deformation amplitude and effective vibration area—the bimorph pinned dual-electrode design also yields improved sound pressure output [14,15]. In addition, the bimorph dual-electrode structure offers the advantage of independently controlling inner and outer electrodes.

During the experiment, the pMUTs device was immersed in the test fluid, shown in **Figure 2c**. A function generator is used to drive the pMUTs with a sine pulse signal of 10 Vpp and 3 different frequencies (1.3 MHz, 1.45MHz, 1.6 MHz, which is around the resonance frequency of the device in DI water). The pulse is generated in 3 successive sine wave and pause for 50 microseconds to wait for echo signal coming back. The signal is reflected by the top reflecting surface attached with a coper foil on a 3D printed frame, and the frame has 2 different heights (25 mm and 30 mm).

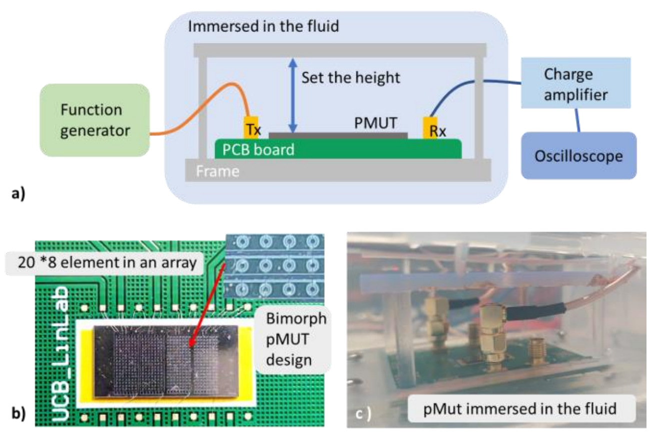

Figure 2: (a) Experimental setup for the fluid viscosity and density measurement. (b) A 20×8 pMUT array with the bimorph, dual-electrode design. (c) pMUT immersed in the testing fluid.

The main experiment principle is based on pulse-echo method. This method measures the viscosity and density of fluids by emitting ultrasonic pulses through a medium and analyzing the characteristics of the return echoes. The properties of this echo can reveal valuable information about the fluid. Density and viscosity primarily influence three critical aspects of receiving ultrasound: attenuation, sound velocity, and resonance frequency [16]. Higher viscosity increases the energy loss (attenuation) of the sound waves as they pass through the fluid to reduce the amplitude of returning echoes. The sound velocity varies directly with the medium's density and viscosity, such that the time-of-flight of echoes will change when the density and viscosity of working fluid may change. Also, the resonance frequency of the ultrasound waves is also changed due to the density and viscosity, which is crucial for identifying fluid characteristics. As the viscosity increases, the resonance frequency decreases if the density doesn't change. By analyzing all these variations, the pulse-echo method can be used to determine the viscosity and density of the fluid simultaneously.

In this project, we use the same PMUT elements to emit and receive the signal. The inner electrodes serve as emitters and the outer electrodes as receivers. **Figure 3a** displays the frequency response of the device in the air by sweeping the frequency. The resonance frequency response is measured by the PicoScope instrument from Pico Technology. The Gain is $20\log_{10}[v_{received}(f)/v_{emit}(f)]$, and this is negative because the amplitude of the received signal is smaller than the emitted signal. The gain has a local maximum at 1.49 MHz which is resonance frequency of the pMUTs in the air. The resonance frequency in the water is measured by a different method, pulse-echo method, and swept the frequency to find the frequency where echo signal has the maximum amplitude as shown in **Figure 3b** with a distance of 6 cm (3 cm *2).

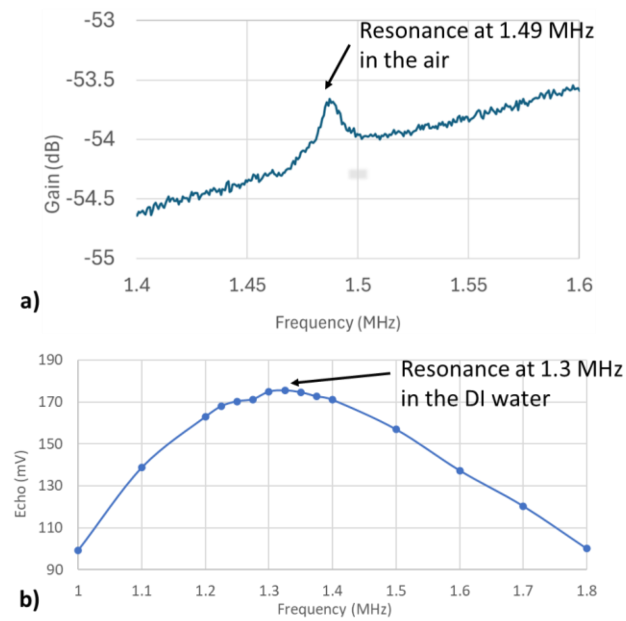

Figure 3: (a) The bode plot PMUT frequency responses in the air with a resonant frequency at 1.49 MHz. (b) Amplitude versus frequency measurement for a PMUT in the DI water with a resonant frequency at 1.3 MHz.

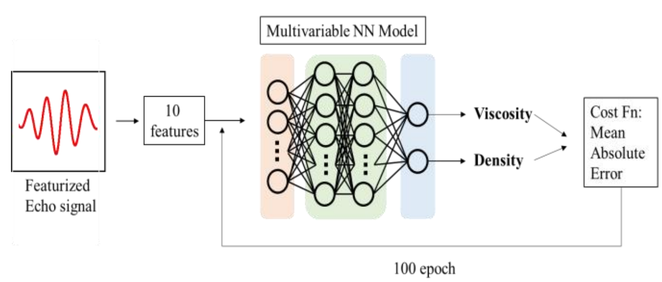

Figure 4: Data Processing steps: the echo signals from PMUTs are organized and characterized into 10 features for the multivariable Neural Network Model to predict the density and viscosity.

Since the effects on the ultrasound properties by the density and viscosity are coupled, machine learning method is introduced to characterize the viscosity and density in **Figure 4**. The multivariable Neural Network can build complex models with shared layers, multiple inputs, and multiple outputs. It can successfully work to predict 2 inputs which have been influenced relatedly by the features but not having identical influences from the features. This is suited for predicting viscosity and density in this case, as they both affect the echo signals relatedly but not identically. The cost function is the mean absolute error of the viscosity and density. After 100 epochs, the viscosity and density are predicted simultaneously.

Figure 5 explains the signal processing steps. It begins with the echo signal identification through a cross-correlation scheme using a standard pulse waveform. The standard echo signal, a selected piecewise signal that serves as a template, assists in extracting the echo signal, with the selected sample echo marked in red as shown in **Figure 5a**. Utilizing the echo template, the cross-correlation method is used to isolate the part that has the largest correlation factor from other received signals, as shown in Figure 2b. Then, eight features are derived: average peak amplitude, average valley amplitude, average peak time, average valley time, and four time-period values between peaks and valleys. The average amplitudes of peaks and valleys help to represent the attenuation. The time differences indicate the frequency shift effect, while the average times of peaks and valleys provide clues about the time-of-flight. A total of 10 features are acquired by adding two more features: frequency and fluidic height, which are incorporated into the machine learning model.

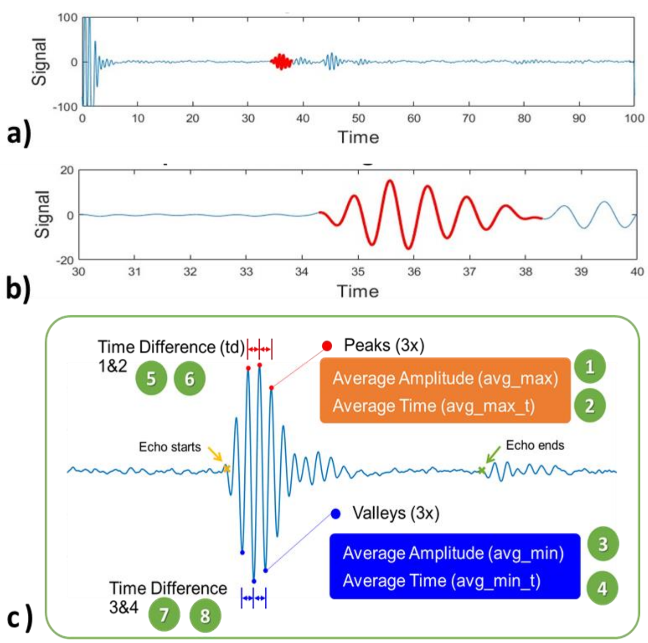

Figure 5: (a) The echo signal is highlighted in red. (b) The echo signal is analyzed via the cross-correlation scheme. (c) Eight features are extracted from the echo signal: the average peak amplitude and time, the valley amplitude and time, and 4 different time periods.

RESULT

Fluid classification

In preliminary tests, the 10 features are used for fluid classification to validate the ability of the features to represent the fluid properties. The 3 different testing fluids for classification are deionized water, ethylene glycol, and 80% glycerol/water mixtures (vol%) with the viscosity of 1 cp, 18.4 cp, and 91.45 cp at 20 °C, respectively. The experiment setup also includes 5 different heights and 3 different working frequencies to result in an overall of 45 combinations of experimental conditions. We randomly collect echo signals from these combinations to get 10,643 echo signals. After processing these data, the classification model with these 10 features results in 99.95% validation accuracy in identifying specific fluid types as shown in **Figure 6**. This shows 10 features can successfully identify the fluid type.

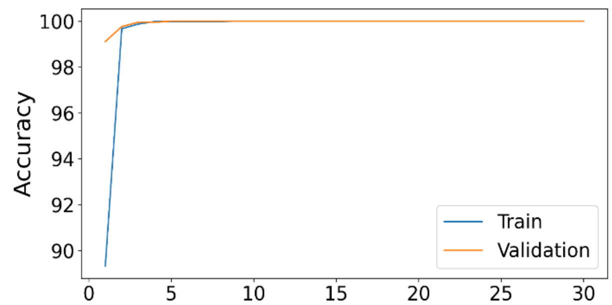

Figure 6: For fluid classification, it results in 99.95% accuracy in identifying 3 different fluid types.

Viscosity and Density measurement

To measure the viscosity and density and test the limitation of the measurement resolution, ethylene glycol-based fluids are prepared by mixing with water in 3% incremental concentrations from 0% to 30%, resulting in changes in both viscosity (0.9 to 1.9 cp) and density (1 to 1.05 g/cm^3), to mimic the minor variations in working fluids over time such as engine oils. **Figure 7** displays the theoretical density versus viscosity plot for the tested fluids with incremental ethylene glycol concentrations.

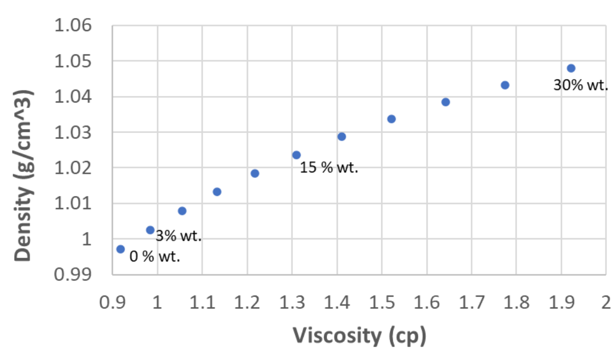

Figure 7: Density vs viscosity plot for the Ethylene glycol-water mixture of concentration from 0%-30% with 3% increments for each point.

The PMUT array, positioned at the bottom of a beaker filled with a testing fluid, collects pulse-echo signals under 66 different testing conditions with: 11 different incremental ethylene glycol concentrations, three PMUT operation frequencies, and two ultrasound wave traveling lengths (heights) for a total 8,839 data sets. Despite the small variations in viscosity and density among the testing fluids, **Figure 8a** shows the subsequent regression through a multivariable neural network with a reduced mean absolute error (MAE) over 100 epochs. By using this scheme, excellent sensing performances have been achieved with an error of 1.6 ± 1.57 % for the viscosity and 0.20 ± 0.17 % for the density in the testing dataset (1,750 data points), as shown in **Figures 8b & 8c**. These results validate this method for precise measurements of fluid viscosity and density simultaneously with great potential in various applications, including continuous monitoring of the engine oil.

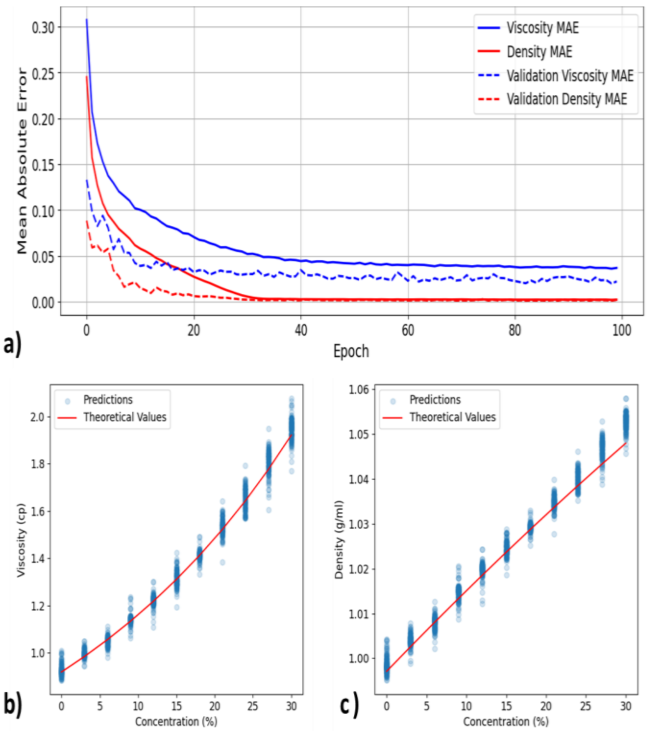

Figure 8: (a) The multi-tasking neural network regression with reduced mean absolute error (MAE) over 100 epochs for both the density and viscosity of the testing fluid. (b) Viscosity testing results with an error of 1.6 ± 1.57%, and (c) Density testing results with an error of 0.20 ± 0.17 % for the Ethylene glycol-water mixture of concentration from 0%-30%.

CONCLUSION

This paper presents the application of using Piezoelectric Micromachined Ultrasonic Transducers (PMUTs) to measure the viscosity and density of fluids concurrently and accurately with the assistance of machine learning. Results demonstrate that PMUTs can be effectively used in conjunction with a neural network to analyze the acoustic variations associated with changes in fluid properties. The preliminary tests show 99.95% accuracy in classifying three different types of fluids. Tests on Ethylene glycol-water mixture (concentration from 0%-30%), a resolution 0.1 cp and 0.01 g/cm^3 have been achieved for the fluid viscosity and density measurement, respectively. Furthermore, experimental results show simultaneous detection for viscosity and density for the testing fluids with precision to achieve an error margin of 1.6 ± 1.57 % for viscosity and 0.20 ± 0.17 % for density. These findings underscore the potential of integrating PMUTs with machine learning algorithms for industrial applications that require continuous and precise monitoring of fluid properties. This study aims to pave the way for further research in MEMS technology and acoustic signal processing, aimed to derive significant advancements in real-time and *in-situ* fluid monitoring across diverse sectors.

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CONTACT

*P.Tsao. Public, tel: +1-856-726-3722; pctsao@berkeley.edu