Poster: Liquid Level Detection Using Wireless Signals

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ABSTRACT

Sensing the liquid level in a container is critical to building many smart home and mobile healthcare applications. This paper presents a liquid level sensing system that is low-cost, high accuracy, widely applicable to different daily liquids and containers, and can be easily integrated with existing smart home networks. Our system uses an existing home WiFi network and a low-cost transducer that is attached to the container to sense the resonance of the container for liquid level detection. We evaluate our system in home environments with various containers and liquids. Preliminary results show that our system achieves an accuracy of 97% for continuous prediction and an F-score of 0.968 for discrete prediction.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing systems and tools**.

KEYWORDS

Liquid Sensing, Smart Home, Channel State Information (CSI)

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1 INTRODUCTION

In recent years, Internet-of-Things (IoT) is becoming more and more intergraded into our daily life and is revolutionizing the way we live. By connecting everyday objects together, it provides a variety of emerging services to improve the quality of our life, especially in a smart home environment [3–6, 8]. Among those emerging services, sensing the liquid level in the containers has gained increasing attention as it provides information on when and how much the liquid has been consumed each day. Such information is critical to building smart homes and mobile healthcare applications.

The challenge in liquid level sensing lies in finding low-cost and highly accurate solutions that are widely applicable and can be easily integrated with smart home networks. Existing commercial products are too expensive to be widely deployed. There are active research efforts in liquid level sensing. However, the capacitive sensor-based approach [7] requires the sensors to be immersed in the liquid. The camera-based approach [1] only works for transparent containers that are filled with opaque liquid.

In this paper, we introduce a new approach for sensing the liquid level that is low-cost, high accuracy, and widely applicable to different daily liquid containers. As shown in Figure 1, our system uses existing home WiFi networks and a low-cost transducer that is attached to the container to sense the inherent vibration characteristic (i.e., resonance) of the liquid in the container. The resonance of the liquid in the container is closely associated with the liquid level and can be applied to a wide range of liquids as well as containers of different materials. As the increase of liquid volume leads to the increase of mass, both the power and the value of the resonance frequency should decrease. Reusing existing home WiFi networks for sensing liquid levels allows the system to be integrated with existing smart home networks without additional communication hardware, which can directly support a variety of smart home applications.

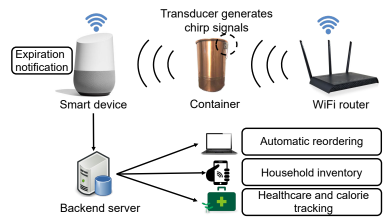

Figure 1: System overview.

2 SYSTEM DESIGN

The basic idea of our system is to use the home WiFi networks to sense the resonances of the container stimulated by the attached transducer for liquid level detection. The transducer generates an excitation from 0Hz to 1000Hz, which is one sweep. While the transducer sweeps the frequency, the wireless signals sense the vibration

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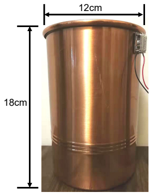

Figure 2: A transducer is mounted on a container.

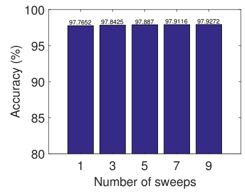

Figure 3: Overall accuracy for continuous prediction.

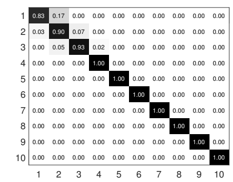

Figure 4: Overall confusion matrix for discrete prediction.

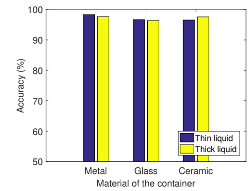

Figure 5: Performance for different containers and liquids.

of the container and our system extracts the Channel State Information (CSI) to detect resonance frequency for liquid level prediction. Specifically, we adopt Principal Component Analysis (PCA) to combine the 30 subcarriers' information of CSI to capture the subtle vibration of a container. Then, our system applies STFT to extract all the frequency components in the CSI and chooses the frequency with the strongest energy as the detected resonance frequency of the liquid container. Given the detected resonance frequency, we predict the liquid level based on the relationship between the liquid level and the resonance frequencies. Note that with an increase in liquid level, the resonance frequency will decrease.

To obtain the relationship between the liquid level and the resonance frequencies, we first collect the training data which includes different liquid levels in containers and the corresponding resonance frequencies. Then, we use both discrete and continuous manners to model the relationship. In particular, for discrete one, we adopt a Support Vector Machine (SVM) based approach to model the frequencies and the corresponding liquid levels. Moreover, we leverage the curve fitting to construct the model for the relationship between frequency and liquid level for continuous prediction.

3 PERFORMANCE EVALUATION

We conduct experiments with two laptops (i.e., one transmitter and one receiver) and both laptops are equipped with Intel 5300 WiFi NICs for extracting CSI [2]. As shown in Figure 2 the transducer is mounted on the container. To evaluate the performance, we choose three commonly used containers and they are made up of metal, glass, and ceramic. The experiments are conducted in a typical home environment with two categories of liquids: thin liquids (water, coke, vegetable oil) and thick liquids (milk, dishwashing liquid, laundry detergent). We collect 100 data samples for one container with one type of liquid. For continuous prediction, the training dataset contains 50% data samples and the other data are used for testing. The accuracy is the error to container capacity ratio. For discrete prediction, we label the liquid levels from low to high with 1 to 10 and randomly select half of the data for training. We use a confusion matrix and F-score to evaluate the performance.

Figure 3 shows that the accuracy of continuous prediction is great than 97% under different numbers of sweeps. This demonstrates our system can already achieve high accuracy with only one round of sweep. Figure 4 shows the confusion matrix of discrete liquid level prediction and the F-score is 0.968. The majority of the errors occur when the container has a lower liquid level. This is due to that with less liquid, the resonance frequency changes at a slower pace. On the other hand, when the container has a higher liquid level, our system can achieve better performance. We then evaluate the impact of different container materials. Both categories (i.e., thin and thick) of liquids are considered. As shown in Figure 5, our system achieves over 96.3% accuracy for three containers while filled with thin and thick liquids respectively. We train different models for containers of different materials and sizes. However, different liquids belonging to the same category can share the same model as we found that the liquids with similar densities have similar resonance frequencies.

4 CONCLUSION

This paper presents a low-cost, high accuracy, widely applicable liquid level sensing system. The proposed system leverages only one transducer and commodity WiFi devices to achieve liquid level sensing, which can be easily integrated with a smart home environment. Preliminary experiments under different types of liquids and containers of different materials demonstrate that the proposed system is effective in predicting a number of liquid levels.

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