Appliance Fingerprinting Using Sound from Power Supply

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ABSTRACT

Recognizing the working appliances is of great importance for smart environment to provide services including energy conservation, user activity recognition, fire hazard prevention, etc. There have been many methods proposed to recognize appliances by analyzing the power voltage, current, electromagnetic emissions, vibration, light, and sound from appliances. Among these methods, measuring the power voltage and current requires installing intrusive sensors to each appliance. Measuring the electromagnetic emissions and vibration requires sensors to be attached or close (e.g., $< 15cm$) to the appliances. Methods relying on light are not universally applicable since only part of appliances generate light. Similarly, methods using sound relying on the sound from motor vibration or mechanical collision so are not applicable for many appliances. As a result, existing methods for appliance fingerprinting are intrusive, have high deployment cost, or only work for part of appliances. In this work, we proposed to use the inaudible high-frequency sound generated by the switching-mode power supply (SMPS) of the appliances as fingerprints to recognize appliances. Since SMPS is widely adopted in home appliances, the proposed method can work for most appliances. Our preliminary experiments on 18 household appliances (where 10 are of the same models) showed that the recognition accuracy achieves 97.6%.

CCS CONCEPTS

• Human-centered computing → Ubiquitous and mobile computing systems and tools; **• Security and privacy → Domain-specific security and privacy architectures**.

KEYWORDS

Appliance Fingerprinting; SMPS; Acoustic Signals

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1 INTRODUCTION

Home appliances, such as the refrigerator, TVs, air conditioners, and mobile devices, have become an indispensable part of people's lives. According to statistics [5], the overall appliances market is predicted to be more than 450 billion dollars by 2023. Recognizing the working appliances is of great importance for smart environment to provide services including energy conservation, user activity recognition, fire hazard prevention, etc.

There have been many existing traditional methods for distinguish -ing home appliances, including: i) fingerprinting using power related sensors. By using power related sensors such as the voltage, current, and energy consumption, and attaching sensors to appliances, and analyzing each appliance's power data, this method can directly fingerprint them; however, this method is invasive, making it hard to deploy. ii) Fingerprinting using other sensors. By applying magnetic, vibration, lighting sensors, or a combination of these sensors, this method can cover different appliances and identify which appliance is working. However, the sensors are required to be quite close to appliances, and often many sensors are required for identifying appliances, which also making it hard to deploy. iii) Fingerprinting using acoustic sensors. By using microphones to get audible sound like the sound of motor vibration and mechanical collision, this method can infer which appliance is being used by the characteristics of these sounds. However, this method is not universal for the appliance type it can identify is limited.

Different from them, in this paper, we proposed a novel method based on the switching-mode power supply (SMPS) to identify domestic appliances. SMPS is widely adopted by electronic devices due to its small size, light weight, and high efficiency. When SMPS is working, it generates high frequency noises. By analyzing these high-frequency sound signals, we can distinguish different electrical equipment.

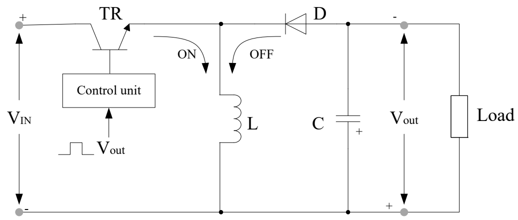

Figure 1: Circuit of a typical SMPS.

The contributions of this article are summarized as follows: 1) To the best of our knowledge, we are the first to propose to use the sound from SMPS to fingerprint appliances. 2) The proposed method is non-invasive, can be applied to recognize most appliances, and use a COTS microphone for detection. 3) Our preliminary experiments show that the method can successfully classify 18 appliances with the accuracy of 97.6%.

2 BACKGROUND

2.1 Principles of SMPS

SMPS (switching-mode power supply) has replaced in most cases the traditional linear ac-to-dc power supplies because of its satisfactory size and weight, high energy efficiency, and little heat dissipation.

SMPS uses a switching element to transform the incoming power supply into a pulsed voltage, which is then smoothed using capacitors, inductors, and other elements. The typical buck-boost switching regulator procedure can be described in Fig. 1. In the basic circuit configuration, it contains a drive circuit that keeps the output voltage as close to the desired level as possible, a diode, D, an inductor, L and a smoothing capacitor, C. The switching transistor TR can be turned "ON" or "OFF". When TR is closed, the voltage across the inductor is equal to the supply voltage and the diode D is reverse biased. In this stage, the inductor accumulates energy from the input supply and the capacitor supplies energy to the load. When the transistor switch is open, the diode becomes forward biased and the energy previously stored in the inductor is transferred to the capacitor and the load. The result is that the magnitude of the inverted output voltage can be greater than or smaller than (or equal to) the input voltage magnitude based on the duty cycle. The buck-boost switching regulators steady state output voltage, V_{OUT} is given as:

$$V_{OUT} = V_{IN}\frac{-D}{1-D}, \qquad D = \frac{t_{ON}}{t_{ON}+t_{OFF}}$$

Repeating the ON-and-OFF operation at high speeds makes it possible to supply voltage efficiently and with less heat generation.

2.2 Source of high-frequency sounds of SMPS

SMPS works by continuously turning on and off a switch to output steady and higher voltage. The steady output is confirmed by the smoothing capacitor sufficiently large enough; the higher voltage is achieved by setting $t_{ON} > t_{OFF}$ in a duty cycle. And the switching frequency of the switching power supply is generally in the range of $100kHz \sim 6MHz$ [2]. Generally speaking, besides the elements illustrated in Fig. 1, the physical SMPS often consists of a transformer. When the SMPS is working, the transformer and capacitors in SMPS

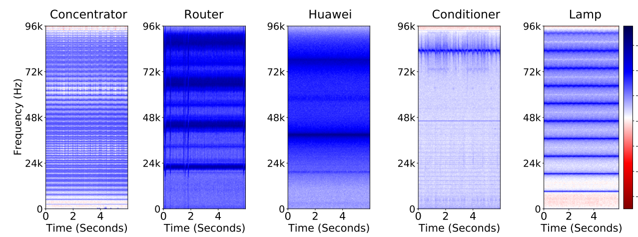

Figure 2: Spectrum of acoustics of 5 common appliances. The y-axis is the frequency of sounds, while the x-axis is collecting time. The 5 appliances are concentrator, router, Huawei mobile phone, air conditionerlamp and OPPO.

can both generate high frequency sound. Also, for rare cases without transformers, inductance in SMPS serves as the main source of high frequency sound. The sound generated by transformer is mainly caused by the magnetic phenomena. The high frequency switching of SMPS results in high frequency alternating current, which finally results in a strong alternating magnetic field. The magnetic core and coil is seriously affected by the magnetic field. Under the influence of magnetic force, if periodic vibration, friction, material deformation, etc. happen to those magnetic materials, then high-frequency sound is produced. The similar phenomena is with the capacitor and the inductor. As all insulating materials will deform under the pressure of electric field brought by high frequency switching of SMPS, cheap small ceramic capacitors usually produce piezoelectric effects even at normal operating temperatures. The mechanical structure of the circuit where the inductance is located is more complicated, and it is easier to emit high-frequency sound under the drive of high-frequency switching current.

3 METHOD

In order to collect the sound signals to analyze which appliance is running, we put a microphone near the SMPS of appliance and used a sound card with high sampling frequency of $192k$Hz to sample the collected analog signals. The collected traces are labeled with the corresponding appliance's name.

For each trace, we split the data into many tiny windows, each window contain part of collected traces with length of 1 second. For each window of data, we used FFT to extract their frequency distributions.

We employed a Random Forest classifier to classify the feature extracted traces. The overall classification accuracy of all kinds of appliances were employed as the metric to evaluate the performance of the classifier, and the average accuracy of 5 cross validation was reported as the final accuracy.

4 EVALUATION

4.1 Preliminary study

In this part, we research 3 questions: i) Whether common appliances can generate high-frequency sounds? ii) If so, whether the sounds are from adapters or the devices themselves? iii) Whether the sounds from the same devices are stable over time and space?

As for question 1, we visualized the sounds of 5 common appliances. As seen in Fig. 3, the 5 appliances can all generate detectable

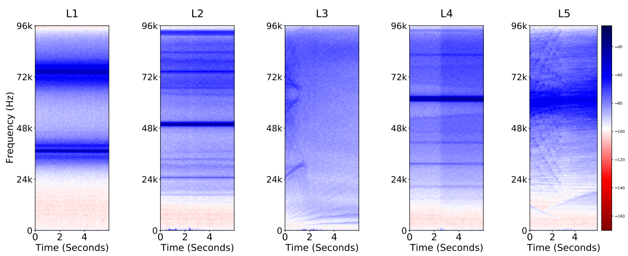

Figure 3: Spectrum of acoustics of different lamps (L1-L5) with the same adapter. The 5 lamps are all of the same brand from the same company.

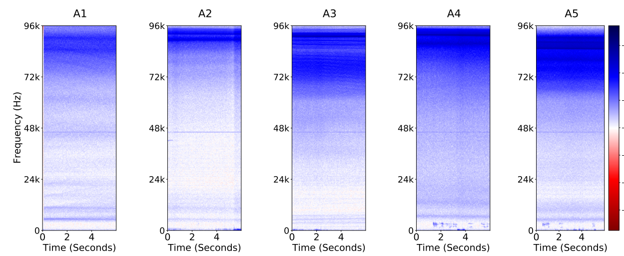

Figure 4: Spectrum of acoustics of the same lamp using 5 different adapters (A1-A5). The adapters are of same brand from the same company.

high-frequency sounds, which are very different. It's because that, different appliances have different requiring voltages and currents, since resulting in different frequency of adapters, and finally leading to the imparity of sounds.

As for question 2, we then experimented on 5 same lamps and their corresponding adapters to find out the reason of the difference. As shown in Fig. 3 and Fig. 4, we found that difference in devices themselves can result in quite different sounds, while difference in adapters produces less different results. This is because that, for the same brand and same model of devices, the charging voltage and current are similar; while different devices may differ in the structure and the way they are built, for example, there are so many electronic components inside, these components may generate different sound when influenced by the continually On-and-OFF currents, so the high-frequency sounds of these devices may be somehow different.

As for question 3, we collected the sound signals of one device (for example,air conditioner) over 5 weeks. Results in Fig. 5 show that the sounds are temporally consistent. It's because that the frequency is mainly the feature of the adapter and the device themselves.

The 3 questions suggest that: different appliances can generate quite unique high-frequency sounds when being charged; the sounds are closely related to the devices themselves; the sounds of the same appliances are temporally and spatially consistent. So we can conclude the high-frequency sounds from SMPS are suitable for fingerprinting appliances.

4.2 Classification result

Fig. 6 shows the confusion matrix of 18 appliances' classification results using Random Forest classifier. Results show that using SMPS method for fingerprinting can achieve an average accuracy of 99% when classifying different appliances, 98% for different brand of the same appliance, and 95.4% for different devices of the same company's appliance.

5 RELATED WORK

Appliance fingerprinting: For appliance fingerprinting, many approaches have been presented, which could be divided into three types according to the signals they exploit. Some works employ power related signals, such as the voltage and current [4] passing through the appliance, to directly detect the energy consumption. For example, products like Plogg, Kill-a-Watt, and Watts Up [6]

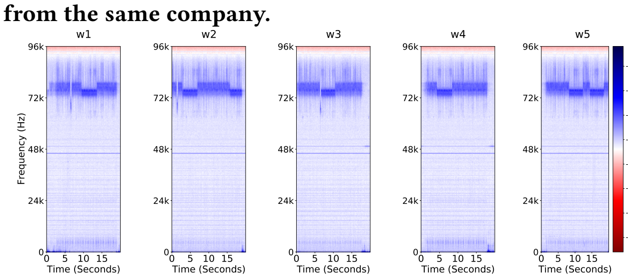

Figure 5: Spectrum of acoustics from appliance at 5 different weeks. Acoustics of the same air conditioner were collected 5 times at 5 week from W1 to W5.

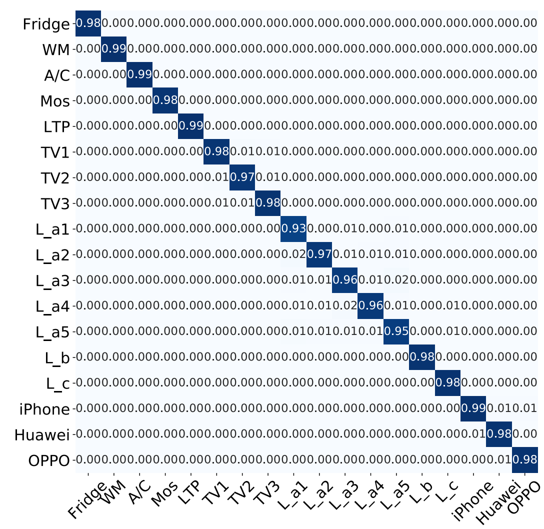

Figure 6: Confusion matrix of 18 **appliances classification results. Fridge for refrigerator,WM for washing machine, A/C for air conditioner, Mos for mosquito killer bat, LTP for laptop, TV1-TV3 are 3 TVs of different brands, L_{a1}-L_{a5} are 5 lamps of the same brand of same company, while L_a-L_c are lamps of different type. iPhone,Huawei,OPPO are 3 mobile phones.**

are commercially available products. However, some appliances such as heating and ventilation systems (HVAC) , and ceiling lights can not be easily instrumented. Other work uses other signals such as the magnetic signals, the light, and the acoustic signals of motor vibration, or their combination [1]. However, the sensors are required to be quite close to appliances. Compared with these methods, our ultrasonic signal based solution is non-invasive, can be applied to all appliances with SMPS, and uses only one sensor for appliance fingerprint, making it more convenient for deployment. There have also been prior researches on detecting appliance using audible sound like the sound of motor vibration [3] and mechanical collision. However, the fact that there are many appliances(i.e., the lamps) without these structures limits its wide application. Audible sound based methods may also endanger user's privacy. By comparison, our method can only use ultrasonic signal, and can detect more appliances without causing privacy issues.

6 CONCLUSION

In this paper, we researched the source and stability of high-frequency sound signal from SMPS, and proposed a novel method for home appliance identification using acoustic signals. Compared with traditional appliance identification methods, our method uses the acoustic signal that already exists in life, which saves cost and is easy to deploy. Our method can also be employed in many fields like privacy protection, power consumption reducing, and the intelligent enhancement of home appliances.

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