Appliance Detection System Based on Sound from Power Supply

Honglu Li

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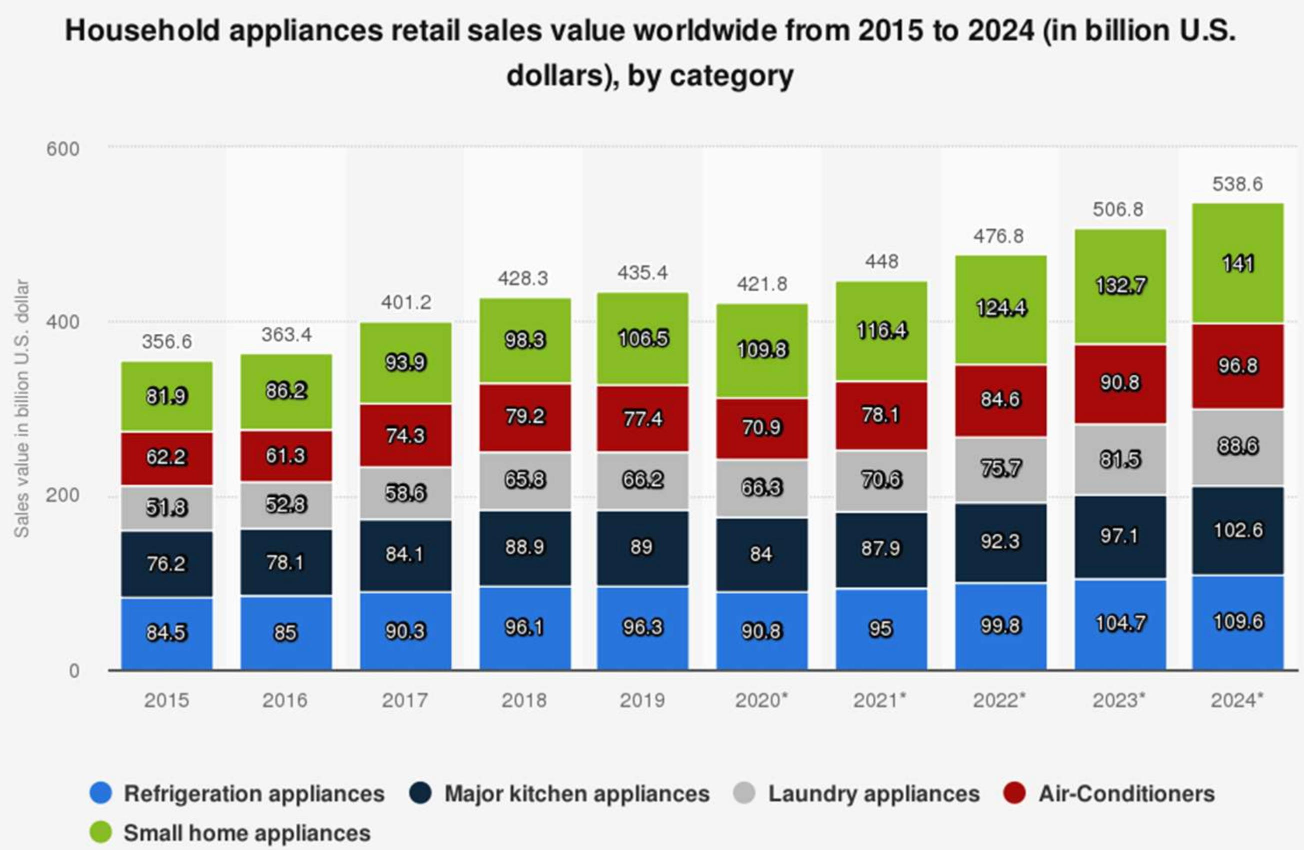
Introduction

- The Internet of Things (IoT) is a huge network that combines various information
- With the development of the Internet of things, smart home is bound to drive the further rapid development of household appliance

Introduction

- According to relevant data [1], the total sales of household appliance in the world will reach 538 billion dollars in 2024
- The huge appliance market and development prospects have attracted a lot of attention of researchers

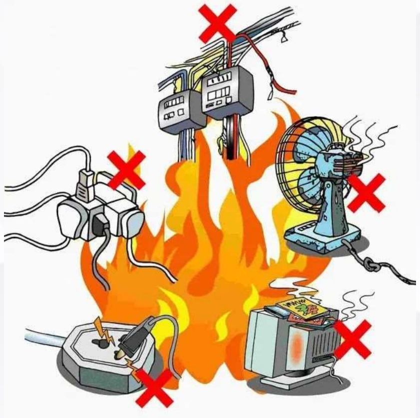


[1]https://www.statista.com/statistics/1033516/worldwide-household-appliance-retail-sales-value-by-category/

Introduction

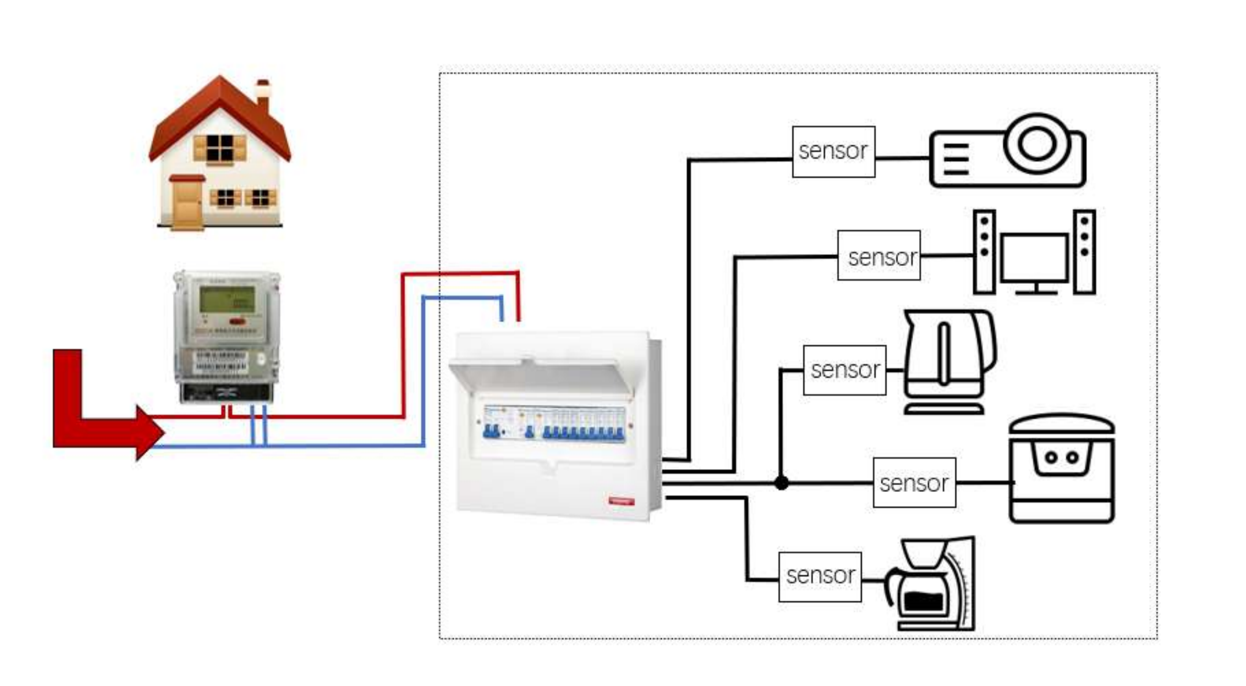
- A method of user behavior recognition is to use the working state of surrounding appliance

- Recognizing the working appliances is also of great importance for smart environment to provide services including energy conservation, fire hazard prevention, etc



Related Work

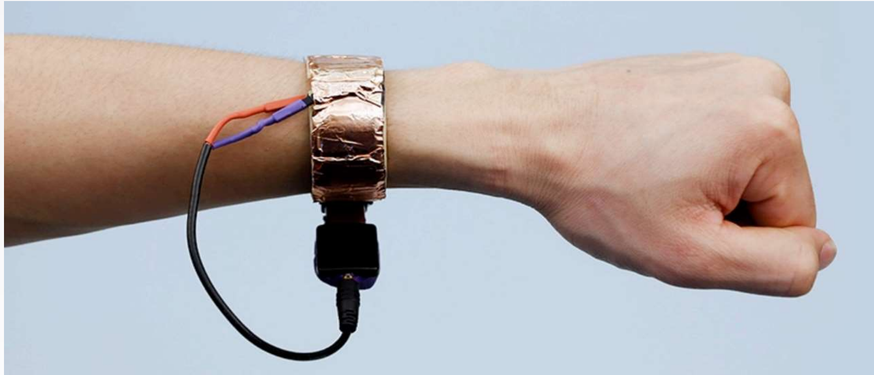
- Intrusive load monitoring method
  - Power related sensors
  - Monitoring energy consumption
  - Bulky and large quantity devices
  - High cost
  - Based on complex system (HAVC)



Related Work

- Method based on electromagnetic signal

MagnifiSense[1]



EM-Sense[2]

- Mobile phones have a low sampling rate for EM signals
- Additional wearable devices
- Close to the surface of appliance
- High cost

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[1] UbiComp ’ 15: 15-26. https://doi.org/10.1145/2750858.2804271. DOI: 10.1145/2750858.2804271.

[2] UIST ’ 15: 157-166. https://doi.org/10.1145/2807442.2807481. DOI:10.1145/2807442.2807481.

Related Work

- Acoustic signal based method
    - Audible sound
    - Special structures
    - Poor universality
    - Privacy information

[1] UbiComp ’ 15: 15-26. https://doi.org/10.1145/2750858.2804271. DOI: 10.1145/2750858.2804271.
[2] UIST ’ 15: 157-166. https://doi.org/10.1145/2807442.2807481. DOI:10.1145/2807442.2807481.

Contribution

- A novel method to identify appliances using sounds generated by switch-mode power supplies (SMPS)
- Contribution:
  - The first to use the sounds from power supplies to fingerprint appliances and working states
  - Can be implemented using a smartphone microphone
  - No additional hardware needs to be installed on the appliance or data collection device
  - Strong universality: according to the relevant research [1] ,the proportion of SMPS will reach 72.3% in 2024
  - Low cost, no need for expensive devices
  - Contactless identification
  - High accuracy: the classification f1-score can reach 0.95

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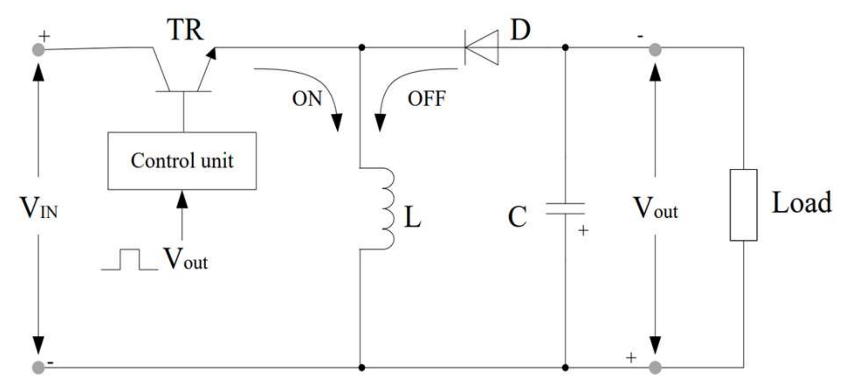
[1] MarketIntellica. World Switching Mode Power Supply Market Research Report 2024 [Z]. https://www.marketintellica.com/report/MI62006-world-switching-mode-power-supply-market. 2019.

Background

- Principles of SMPS

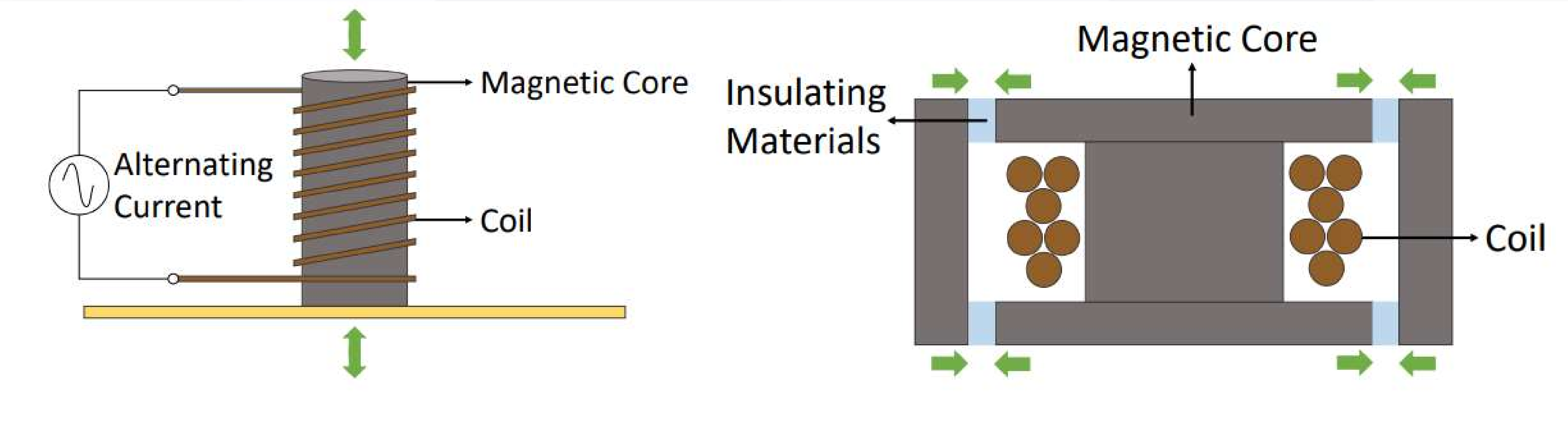


$$V_{OUT} = V_{IN}\frac{-D}{1-D},$$

$$D = \frac{t_{ON}}{t_{ON}+t_{OFF}}.$$

Background

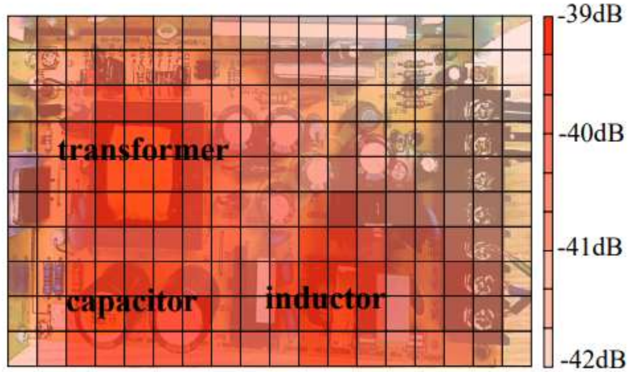
- Source of sounds of SMPS

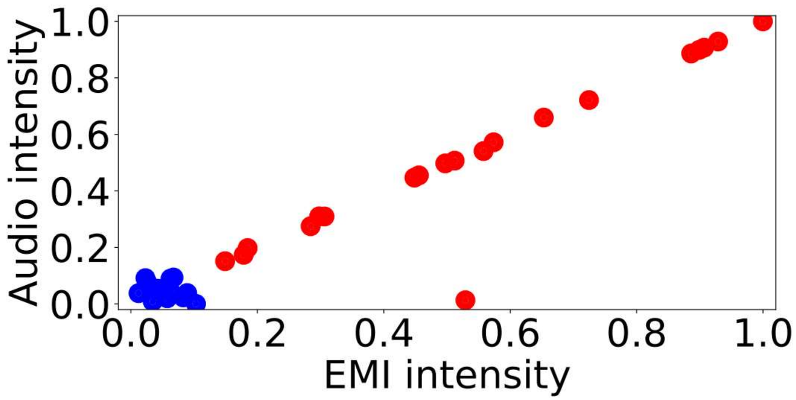


- The shape of the magnetic core changes slightly
- Different magnetic cores attract each other

Background

- Verification

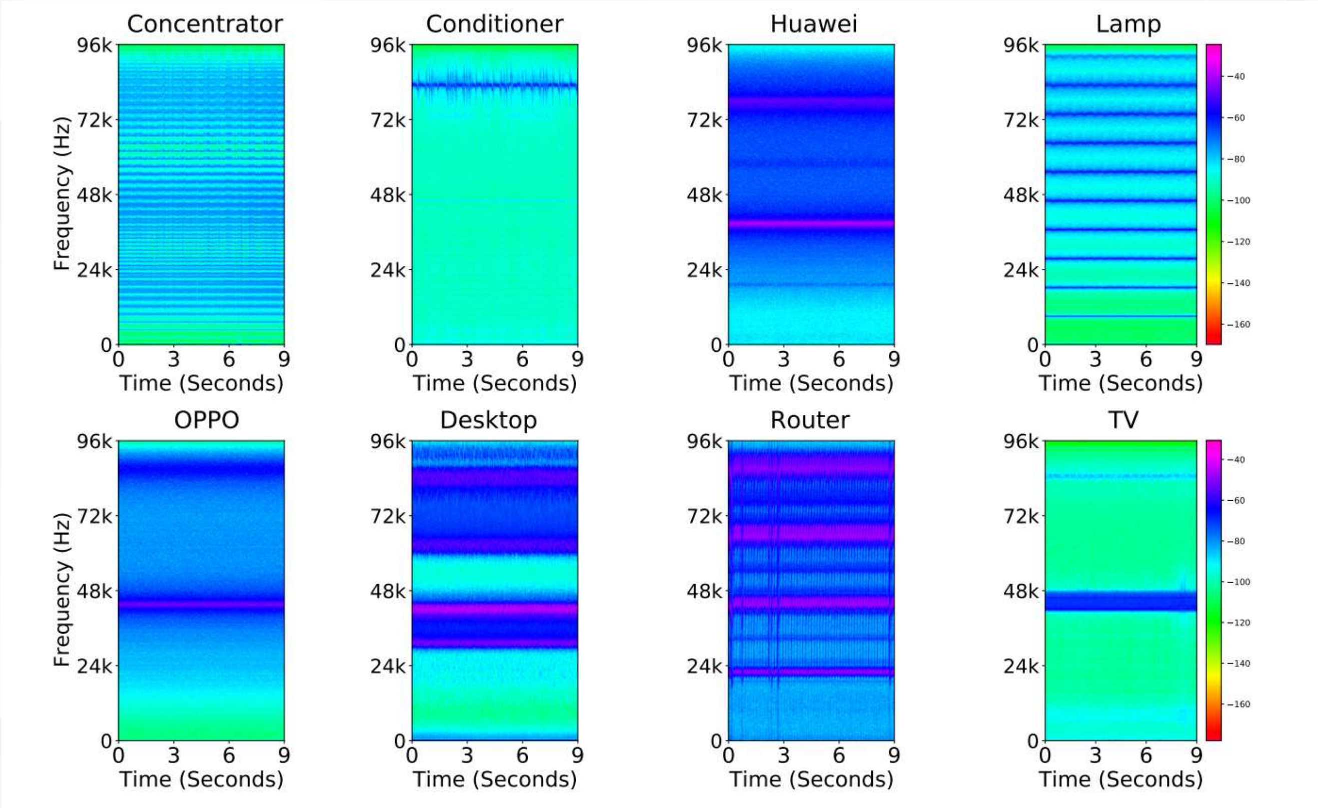




- Sound sources include capacitors, inductors and transformers
- The sound strength near the SMPS is proportional to the EMI
- EMI from other parts of appliances is usually weak

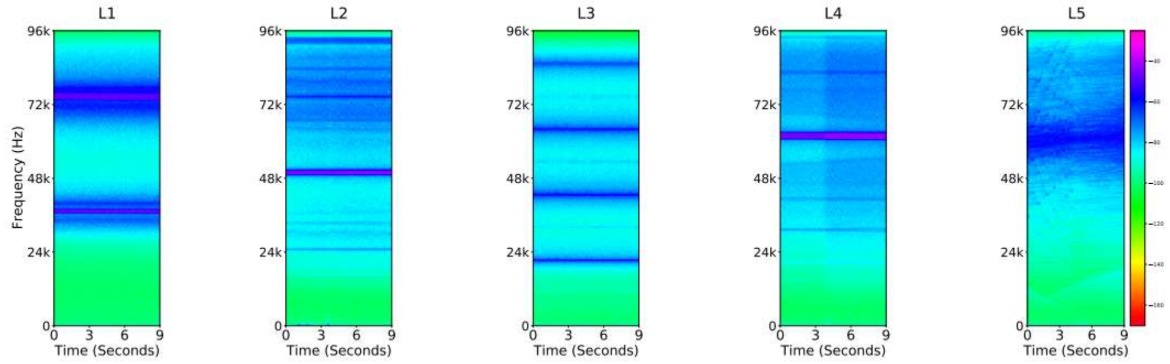
Preliminary Study

- The high-frequency sounds generated by common appliances

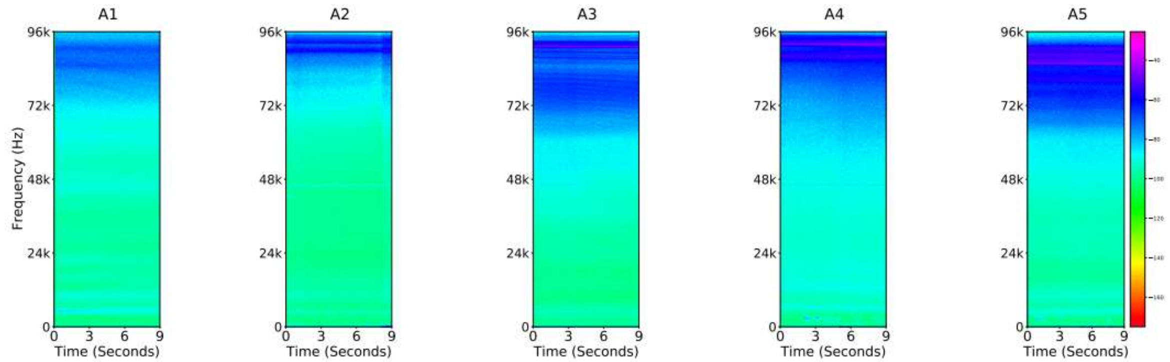


Preliminary Study

- Effect of appliances and SMPS types on high frequency sound signals
  - Appliances type:

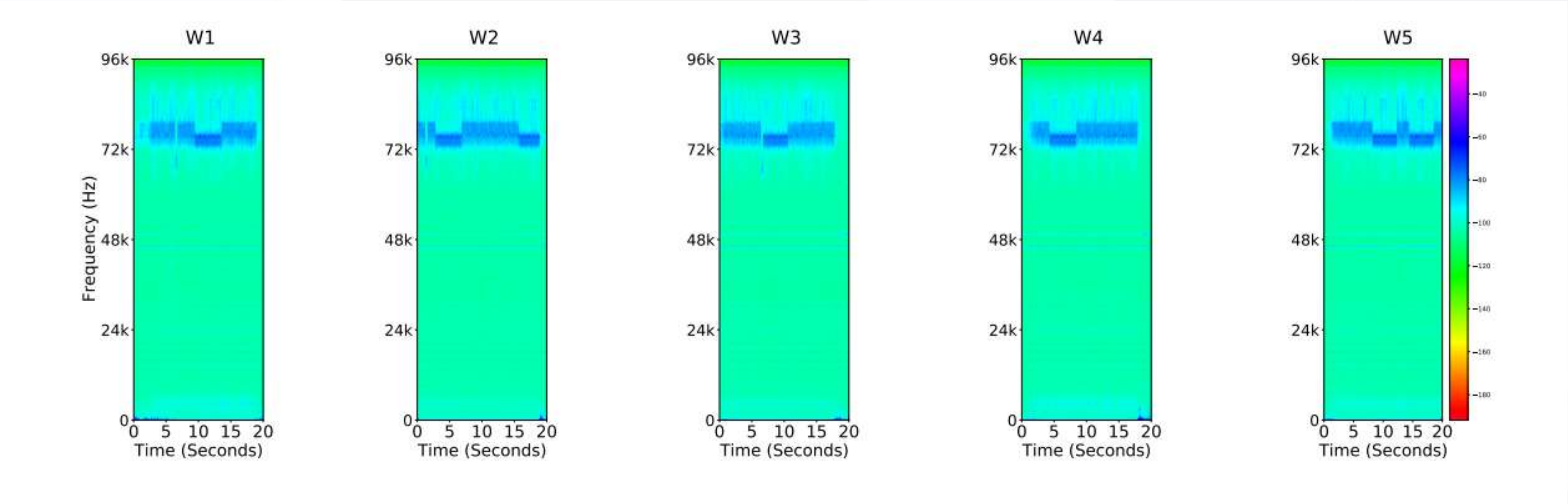


  - SMPS type:



Preliminary Study

- Whether the sounds from the same devices are stable over time and space



Methodology

Issue 1:

The sound strength degrades quickly over distance

SNR-Boosting Scheme

Issue 2:

many appliances work concurrently and the sounds linearly superpose

Multi-label Classification Scheme

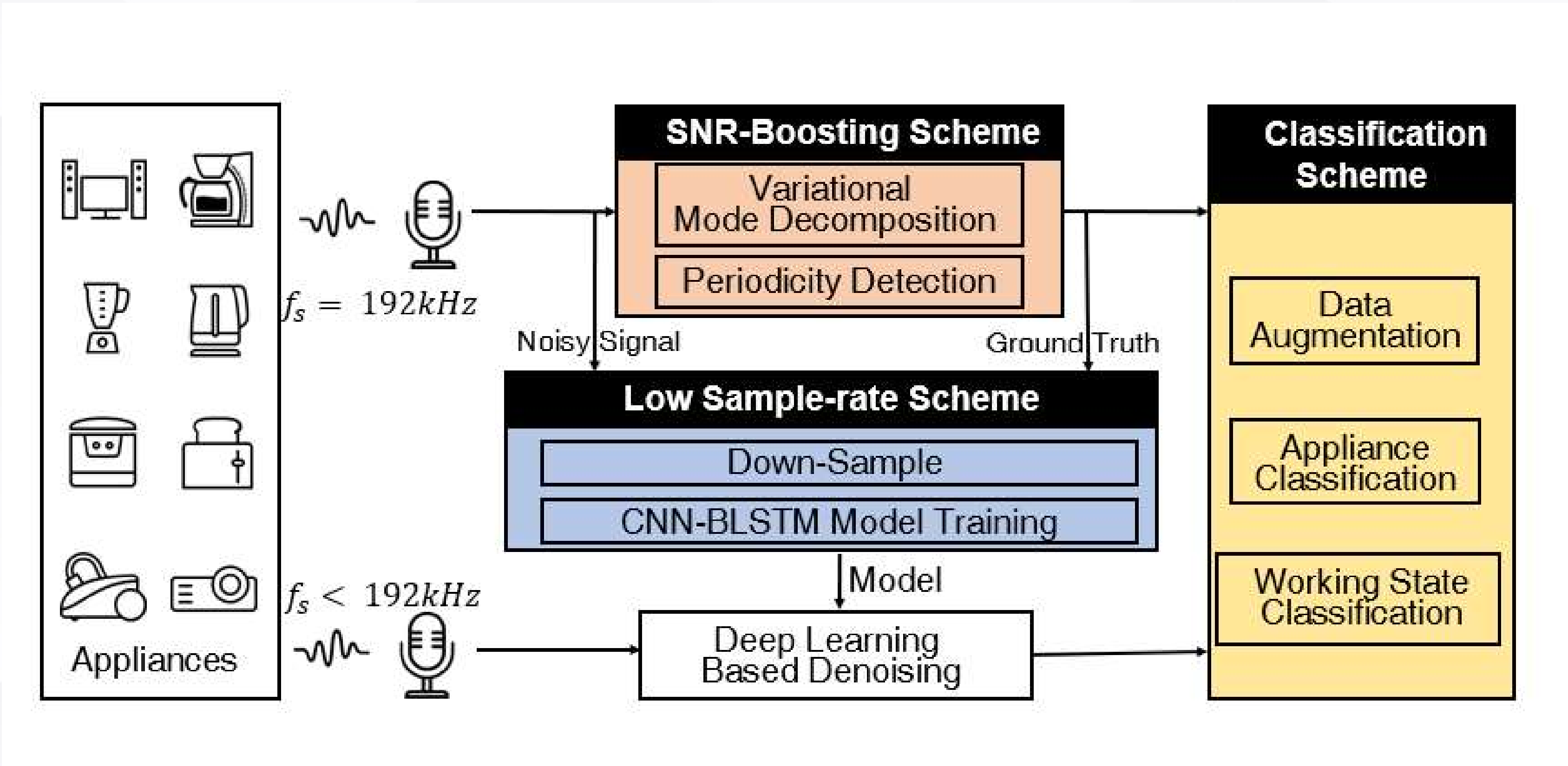
Issue 3:

Mobile devices have low sampling rates and sound signals are aliasing

Low Sampling-Rate Scheme

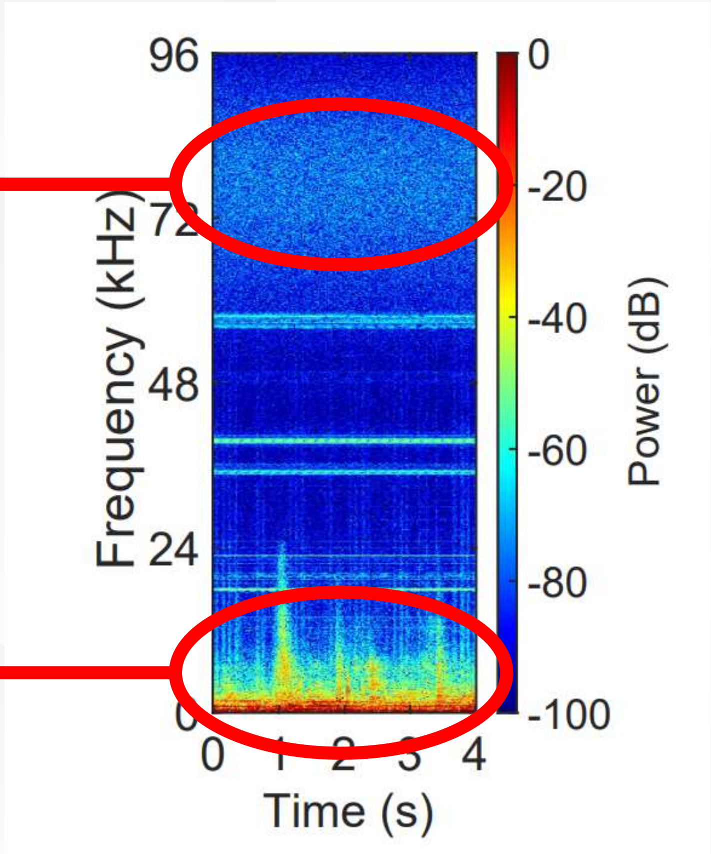
framework

- Framework of the whole system



SNR-Boosting Scheme

- Sources of noise
  - noise floor from hardware circuit of the sound card
    60kHz to 90kHz
    removed using spectral subtraction
  - environment noise
    time variant
    below 20kHz
    High strength
    a great impact on the performance



SNR-Boosting Scheme

- Variational Mode Decomposition (VMD)

VMD is an adaptive, variational signal processing method, the principle is as follows:
Assume the received signal f_0 is mixed with additive Gaussian noise $\epsilon(t)$:

$$f_0 = f + \epsilon(t) \tag{1}$$

The objective of Wiener filter is to find an optimal solution which minimize the following equation 2:

$$\min_{f} \quad \{\|f - f_0\|_2^2 \; + \alpha\|\partial_t f\|_2^2\} \tag{2}$$

Because the total energy of a time series is equal to that of its Fourier transform.
Therefore, this optimization problem can be solved in frequency domain, which can be written as:

$$\min_{f(\omega)} \quad \{\|f(\omega) - f_0(\omega)\|_2^2 \; + \alpha\|j\omega f(\omega)\|_2^2\} \tag{3}$$

The solution can be obtained by assigning its first derivative to zero, which is:

$$\hat{f}(\omega) = \frac{f_0(\omega)}{1 + \alpha\omega^2} \tag{4}$$

SNR-Boosting Scheme

- Variational Mode Decomposition (VMD)

Wiener filters cannot be directly applied to high frequency sound signals. we borrow the idea from VMD to separate our signal into k narrow band signals, and compute the penalty term after converting them from pass band to base band, then the optimization objective in frequency domain becomes:

$$\min_{u_k(\omega)} \quad \{\|\sum_k u_k(\omega) - f_0(\omega)\|_2^2 + \alpha \sum_k \|j\omega u_k(\omega - \omega_{ck})\|_2^2\} \tag{5}$$

To improve the fidelity of reconstructed signal, a restriction is added. Hence, the final optimization model becomes:

$$\min_{u_k(\omega)} \quad \{\|\sum_k u_k(\omega) - f_0(\omega)\|_2^2 + \alpha \sum_k \|j(\omega - \omega_{ck}) u_k(\omega)\|_2^2\} \tag{6}$$

$$\text{s.t.} \quad \sum_k u_k(\omega) = f_0(\omega)$$

The optimal solution can be achieved by using Lagrange multiplier, followed by ADMM algorithm to find the saddle point.

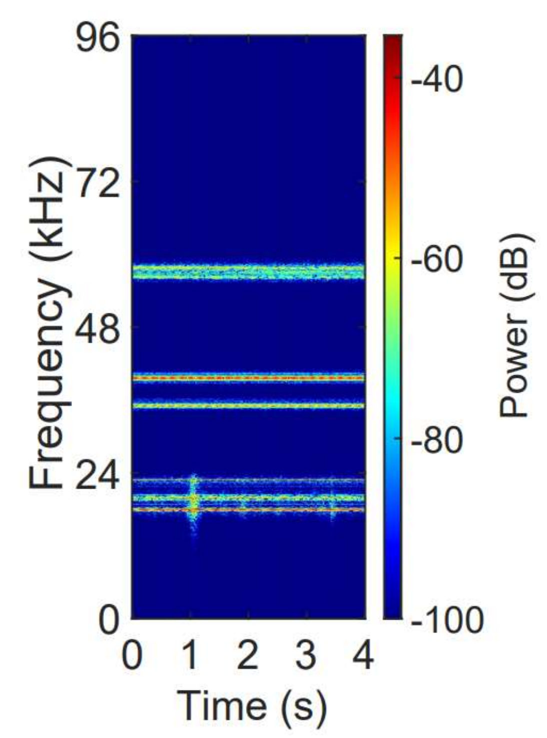
SNR-Boosting Scheme

- Variational Mode Decomposition (VMD)
  - Conclusion:

    (1) k and α should be jointly tuned to achieve the best decomposition performance

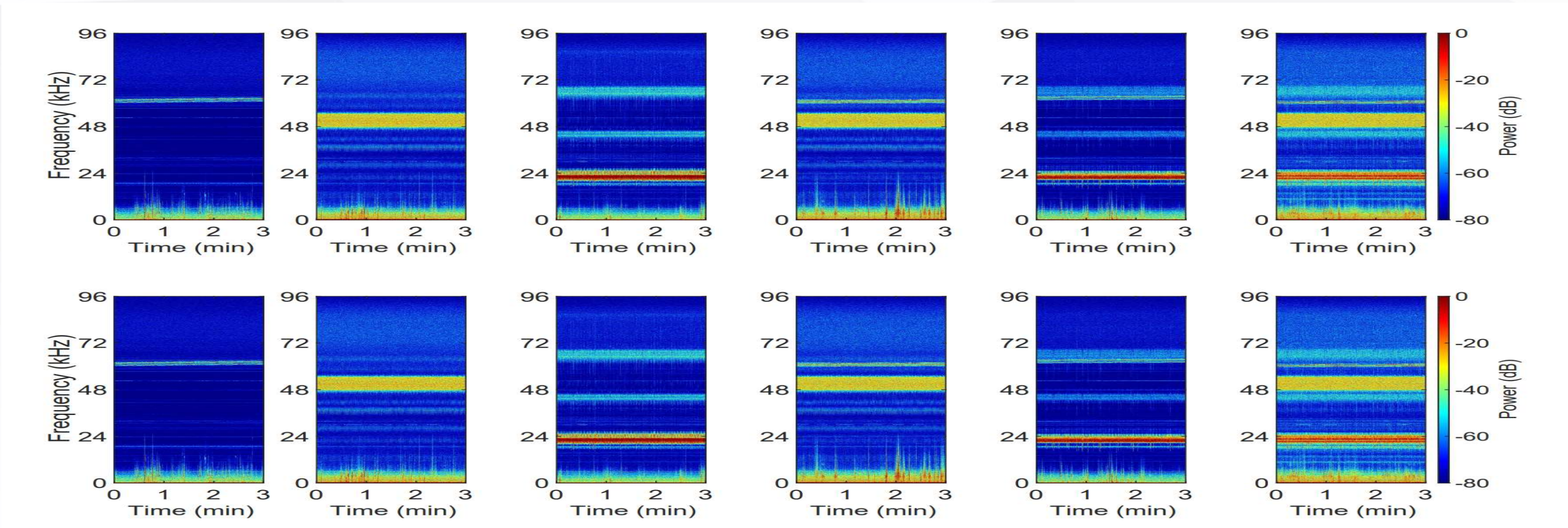
    (2) the larger the α is, the narrower the bandwidth of each IMF should be

We set k = 40 and ωck is uniformly initialized, so that the central frequency difference between each two initial modes is 2.4kHz which ensures the capability of extracting weak periodic signal. Moreover, we set α to a large value to impose a strict restriction on the bandwidth of each mode.



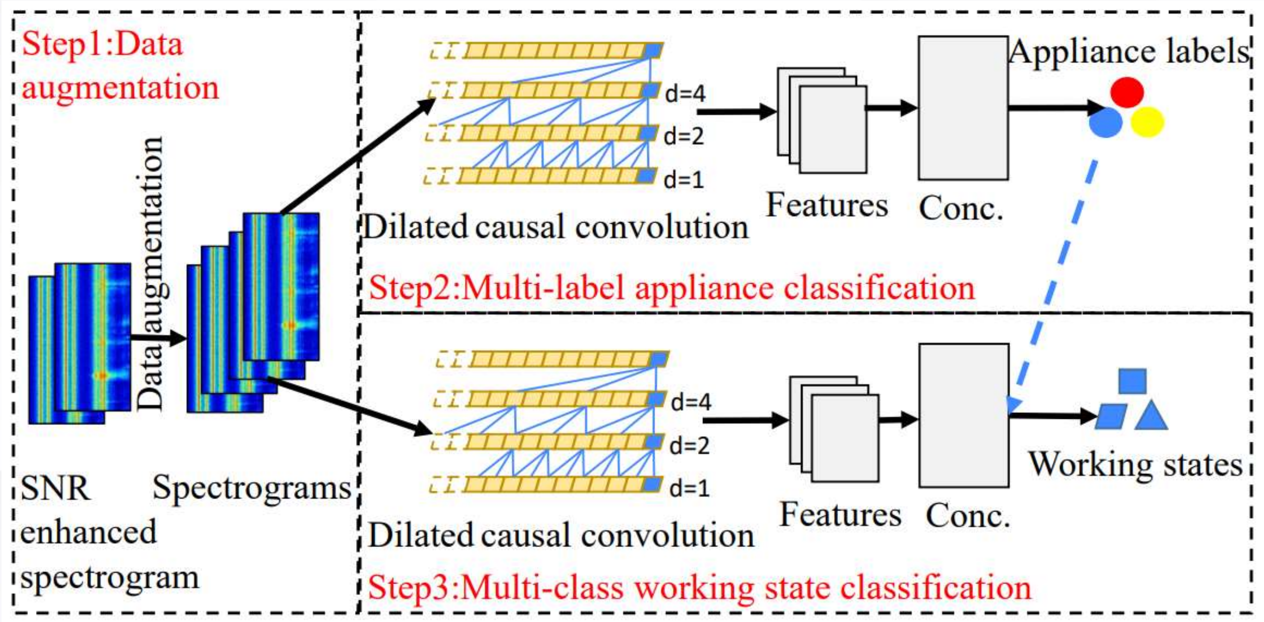
Multi-label Classification Scheme

- Linear superposition of high frequency sound signals in the frequency domain



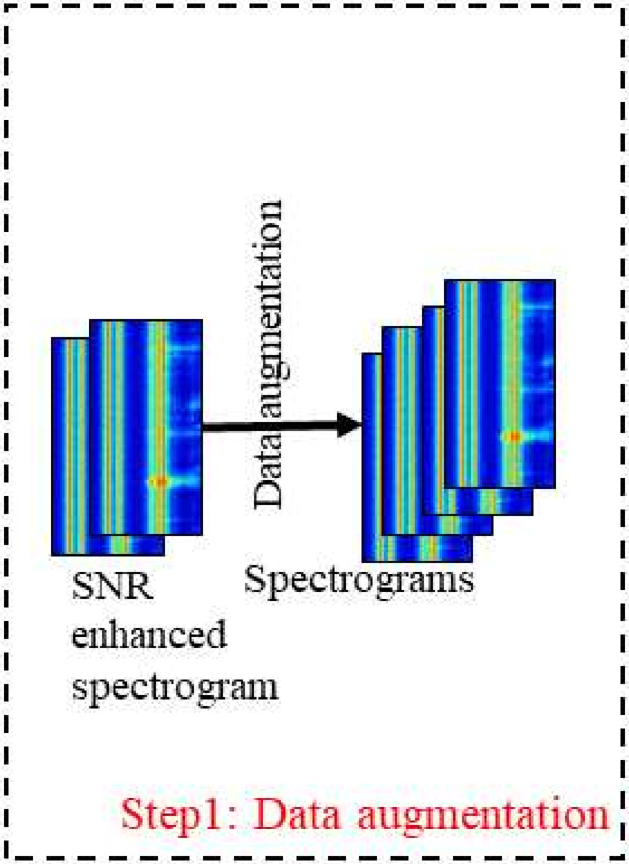
Multi-label Classification Scheme

- Multi-label Classification Scheme based on cascaded 2D TCN
  - Data Augmentation
  - Multi-label Appliance Classification
  - Multi-class Working State Classification



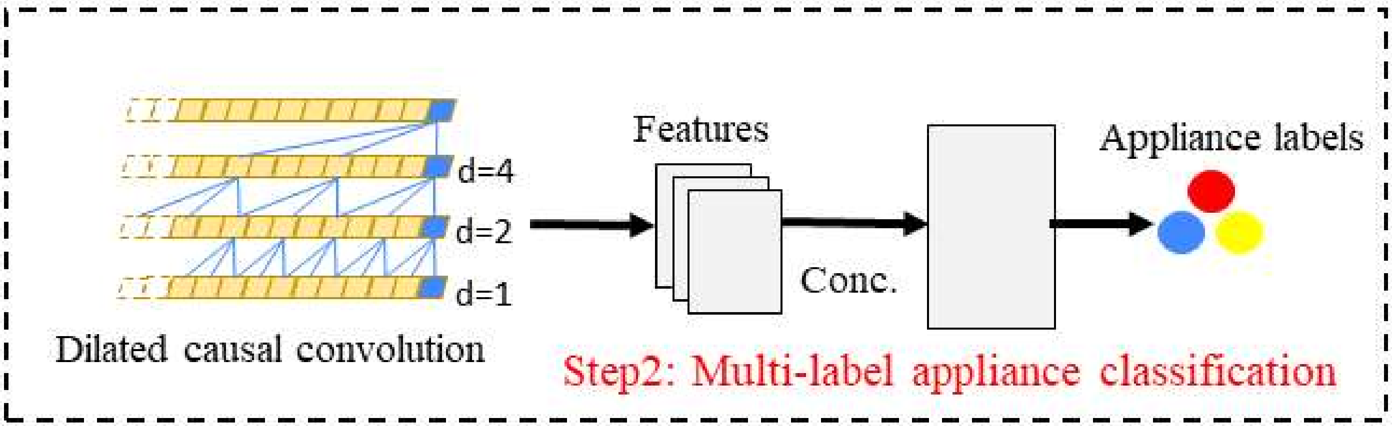
Multi-label Classification Scheme

- Data Augmentation
  - Too many combinations of overlapping appliances
  - High-frequency sound is linearly superimposed



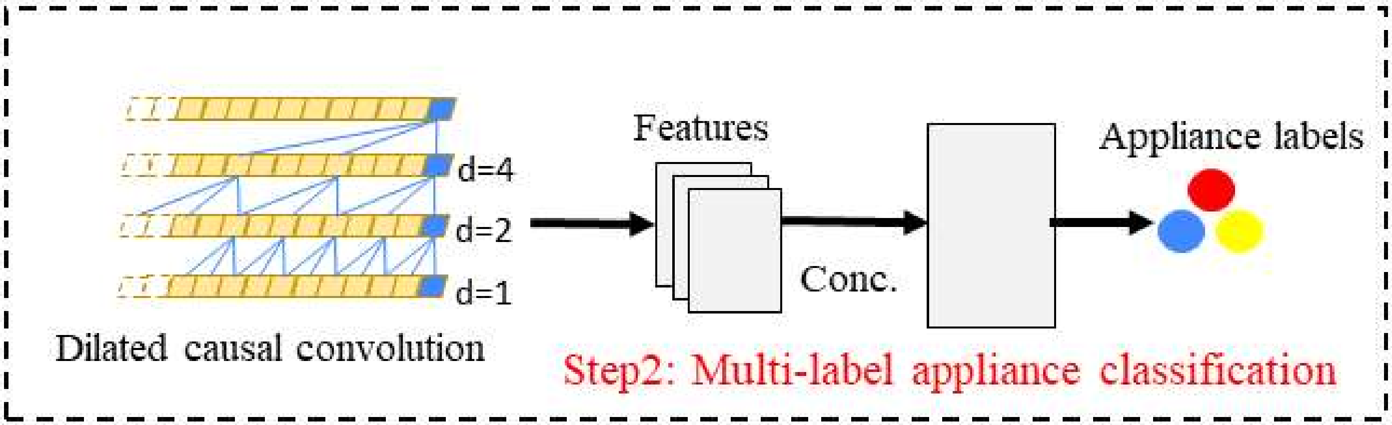
Multi-label Classification Scheme

- Multi-label Appliance Classification-------TCN
  - Cascade 2D temporal convolution network
  - TCN uses exponentially increasing convolution kernel sizes to greatly improve the computational efficiency without losing the accuracy
  - The bandwidths of the humming sounds are usually narrow and stable and the TCN kernels can effectively use the locality in the sound spectrogram and learn the desired features



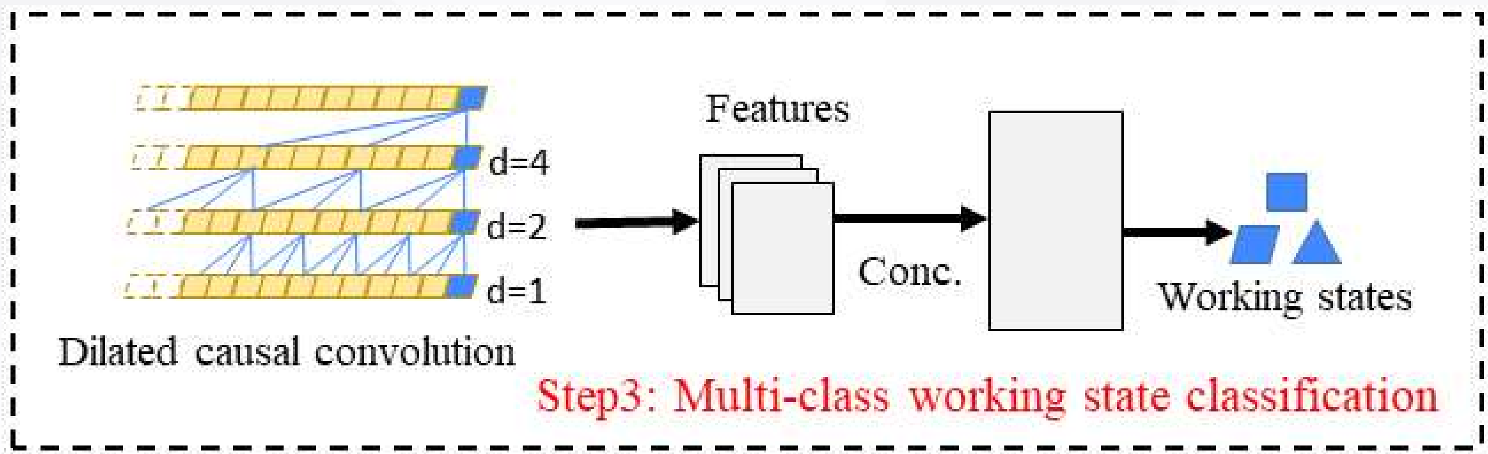
Multi-label Classification Scheme

- Multi-label Appliance Classification-------Multi-label Classification
  - Reduce the training data scale
  - Increase the overall accuracy
  - Enables the classifier to deal with untrained appliances



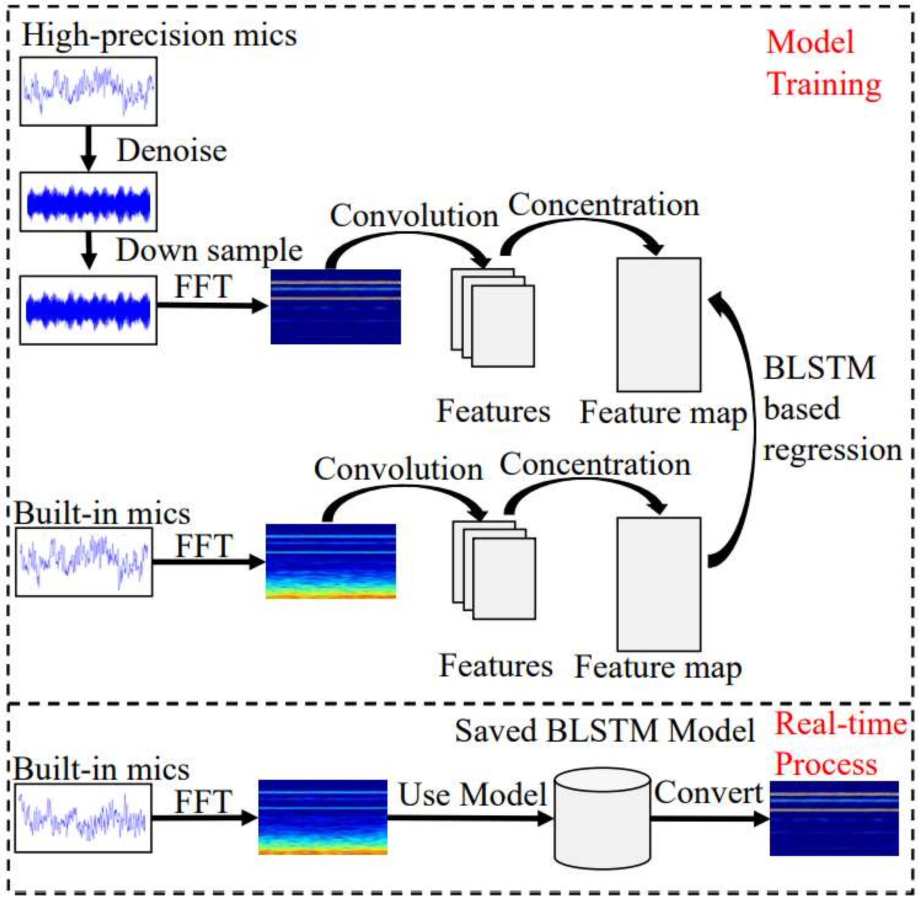
Multi-label Classification Scheme

- Multi-class Working State Classification
  - Each appliance has an individual classifier to identify its working states
  - The classifier structure of the multi-label appliance classification and multiclass working state classification models are the same so the feature maps can be reused



Low-Sampling-Rate Scheme

- Low sampling rate mobile devices
  - Mobile devices at a low sampling rates of 44.1khz or 48khz
- drawbacks to use the aliasing sounds
  - The aliased frequencies are likely to be interfered by environmental noise
  - Sounds at various frequencies may be folded to the same frequency



Low-Sampling-Rate Scheme

- CNN-BLSTM Model

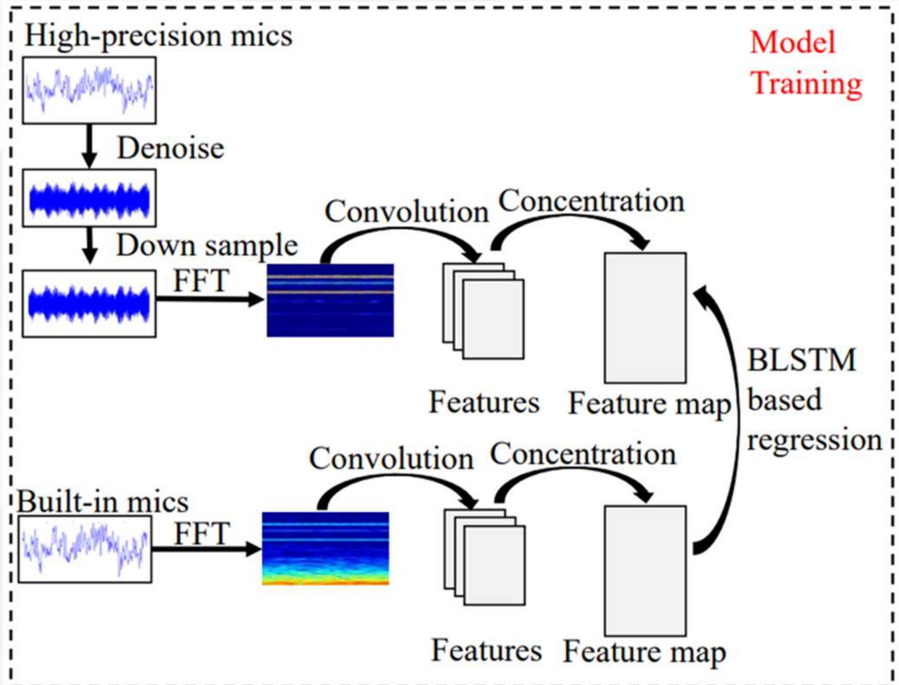
As for the collected sounds, let x be the noisy raw spectrogram, and y is its corresponding target spectrogram, where t is the time of the spectrogram, and d is the frequency bins in each frame. Assume that there are N pair of raw and target spectrograms, the problem can be formulated as

$$\underset{\theta}{min} \frac{1}{2} \sum_{i=1}^{N} ||f_\theta(x_i - y_i)||_F^2$$

where $f\theta$ is the mapping function from raw to target

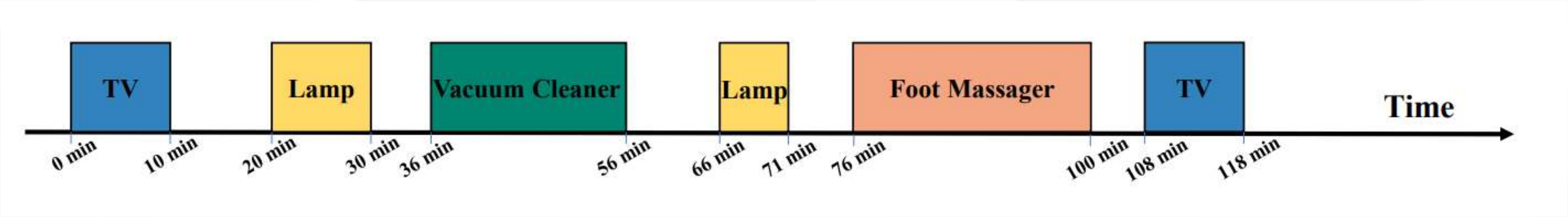
Low-Sampling-Rate Scheme

- CNN-BLSTM Model
  - CNN —— Single spectrogram
    - Local similarity
    - All feature maps learned by CNN block are vertically concatenated along the feature dimension to form a 2D feature map $H(x)$.
  - BLSTM —— contiguous spectrograms
    - Input $H(x)$ and split it into several time steps and learn the long-term dependence
    - Using a many-to-many training strategy, the BLSTM block finally outputs $H'(x)$
    - Choose the mean squared error between $H'(x)$ and target y as the regression loss.

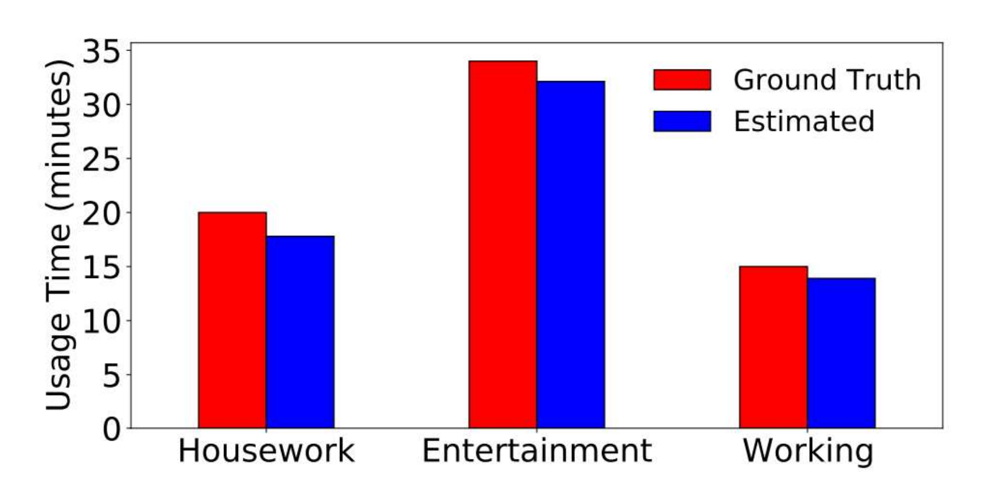


Application

- Human activity recognition
  - Script:

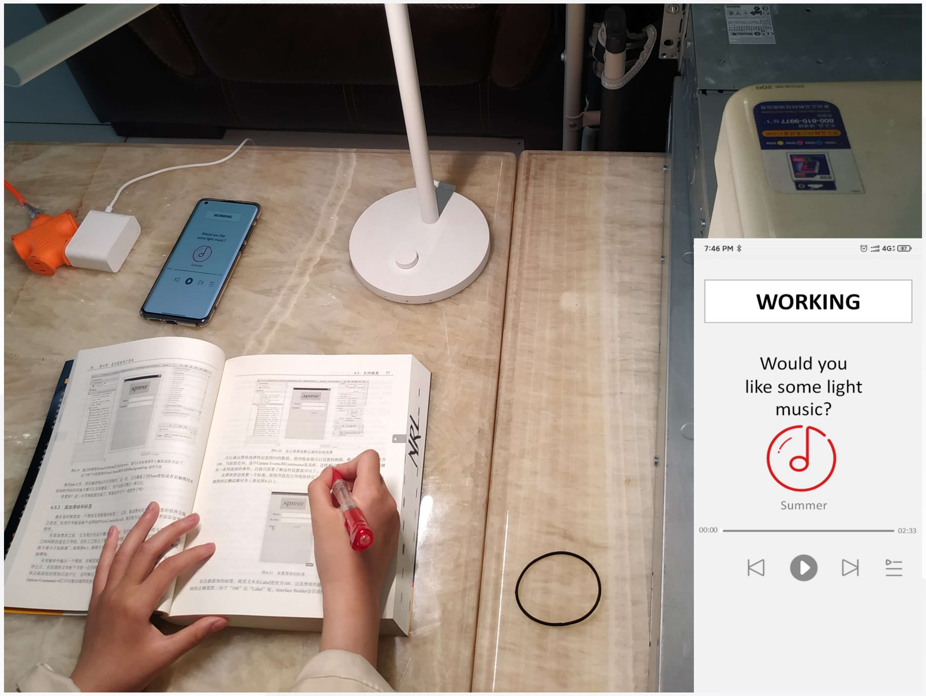


  - Performance:



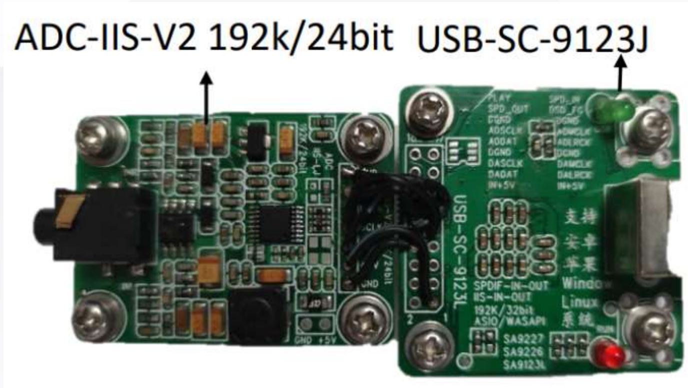
Application

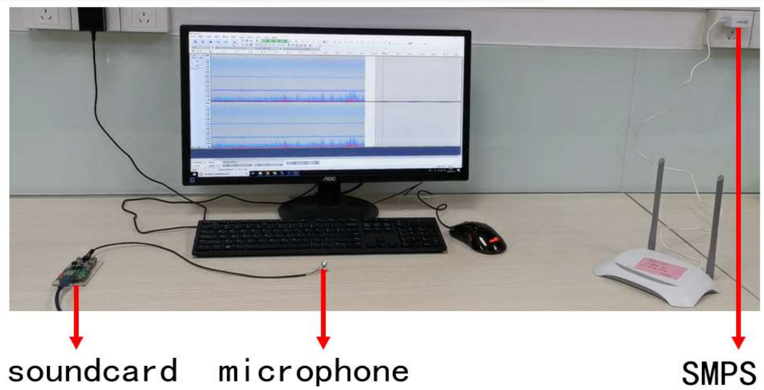
- Human activity recognition



Experiment Setup

- Data Collection
  - Device
  - Scenario





Experiment Setup

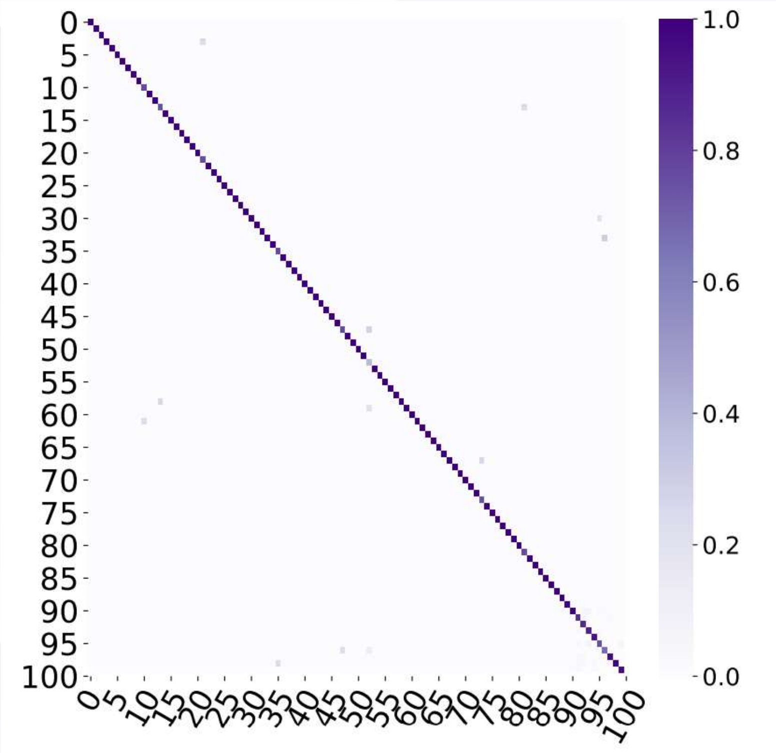
- Dataset
  - 100 appliances
  - 2-minute

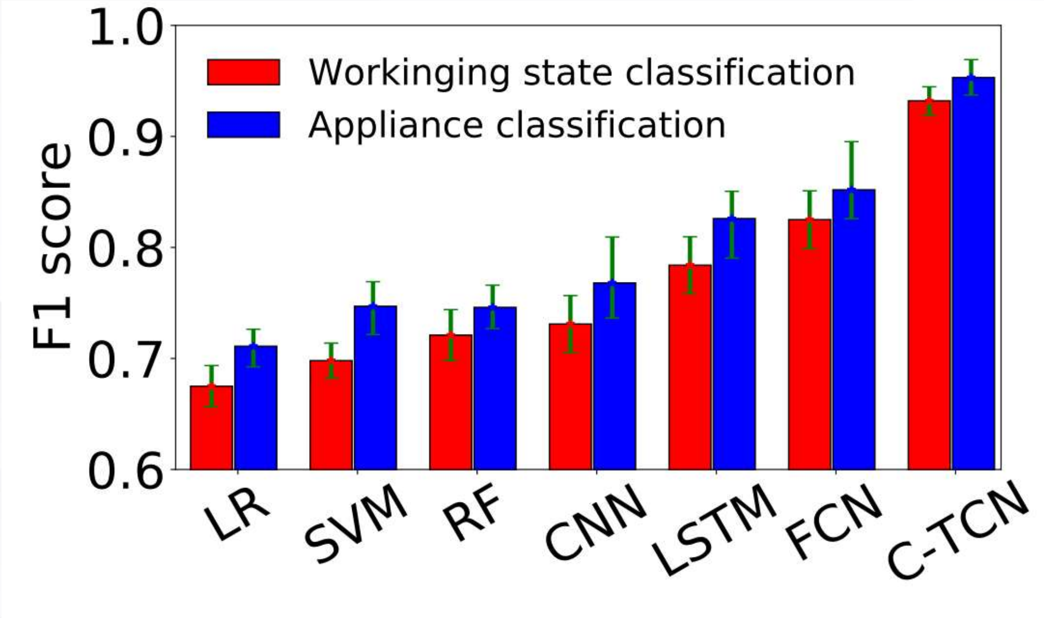
Appliance	Company	#Same	#Different	#Total
Lamp	OPPLE,PHILIPS,etc.	10	20	30
Washing machine	BEKO,Swan,SANYO,CUCIE	0	5	5
Air conditioner	Midea,Gree,MELING,etc.	0	11	11
Refrigerator	Electrolux,MELING,SMEG	0	4	4
Range hood	Midea	0	1	1
Fan	Midea,Haier	0	3	3
Electric water heater	Midea,Gemake	0	3	3
Gas water heater	Midea	0	3	3
Hair drier	Panasonic,PHILIPS,FlyGo	0	4	4
Coffee machine	DeLonghi,Donlim	0	3	3
Router	TPLINK,Tenda	0	3	3
Rice cooker	Supor,Bear,TATUNG	0	3	3
Kettle	LINKYU,Midea,Joyoung	0	3	3
Microwave	Galanz	0	1	1
Shaver	Flygo,PHILIPS	0	2	2
Massager	BlackLeaf,JuKang	0	2	2
Air cleaner	Xiaomi,PHILIPS	0	2	2
Bath heater	Leishiding	0	1	1
TV box	Skyworth	0	1	1
Dehumidifier	PHILIPS	0	1	1
TV	SkyWorth	0	1	1
Milk Frother	HadinEEon	0	1	1
Dishwasher	AIMABA	0	1	1
Waterpik	Panasonic	0	1	1
Steamer	Supor	0	1	1
Heating pad	MingZhen	0	1	1
Mosquito swatter	KangMing	0	1	1
Mosquito killing lamp	YaXin	0	1	1
Desktop screen	HP	0	1	1
Smart speaker	TmallGenie	0	1	1
Projector	Canno	0	1	1
Electric toothbrush	PHILIPS	0	1	1
Weighing machine	Xiaomi	0	1	1
Printer	HP	0	1	1
Water dispenser	AUX	0	1	1
Monitor	AOC	0	1	1

Method Evaluation

- Overall Performance

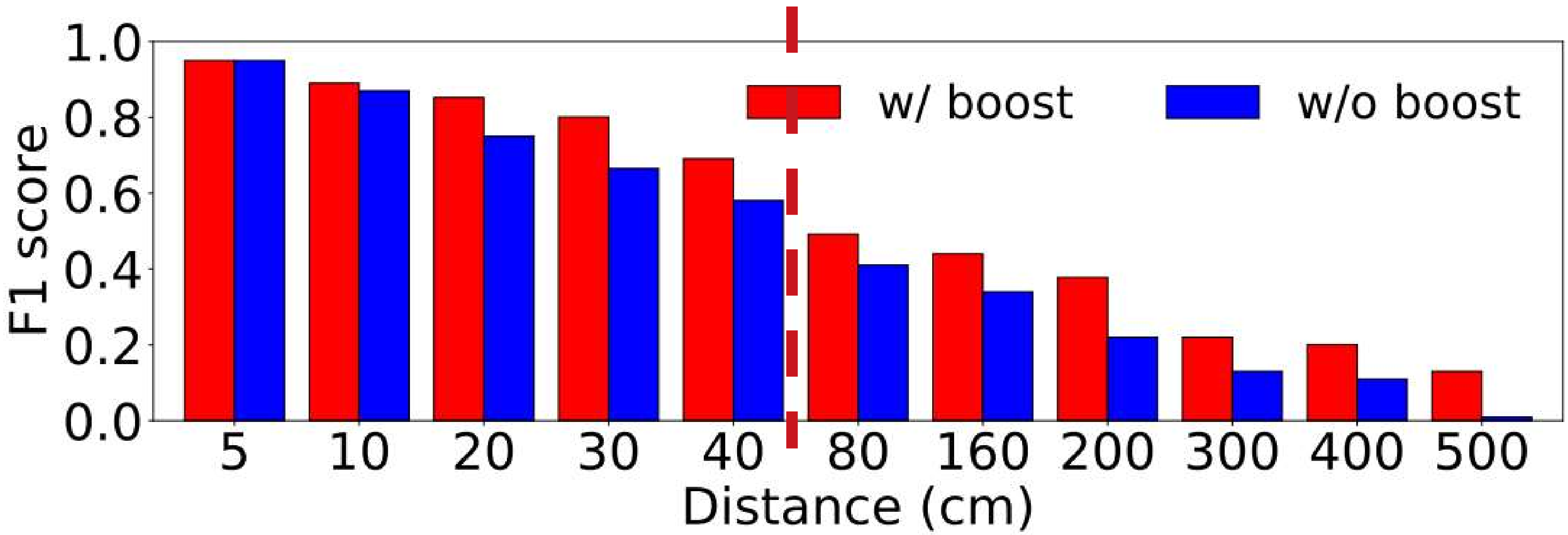
Average classification F1 score of 100 appliances is 0.95





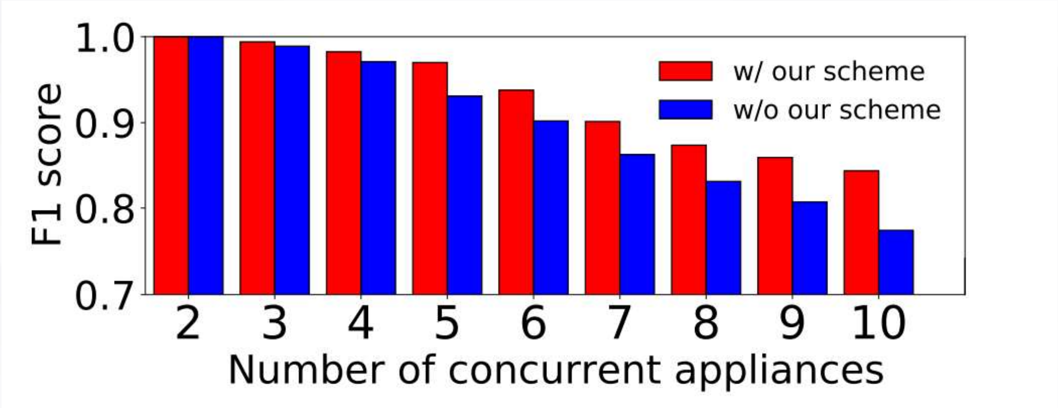
Method Evaluation

- Performance of SNR-Boosting Scheme

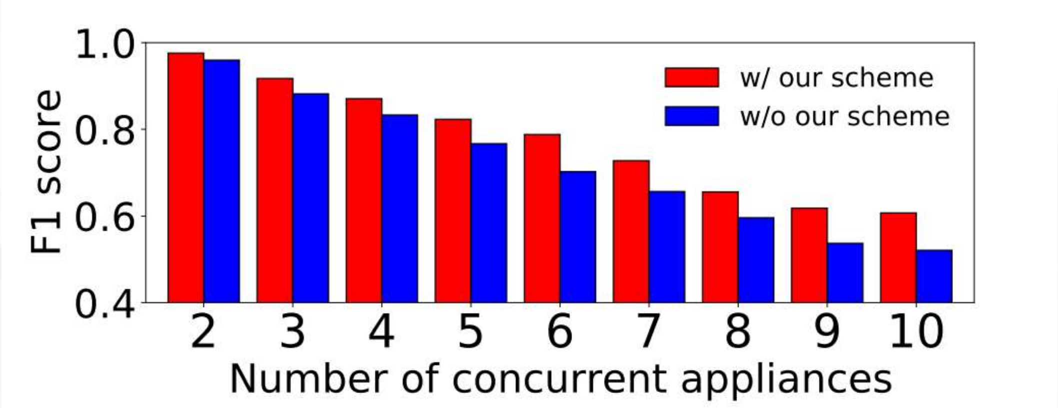


Method Evaluation

- Performance of Multi-label Classification Scheme
  - Different models :



  - The same model:



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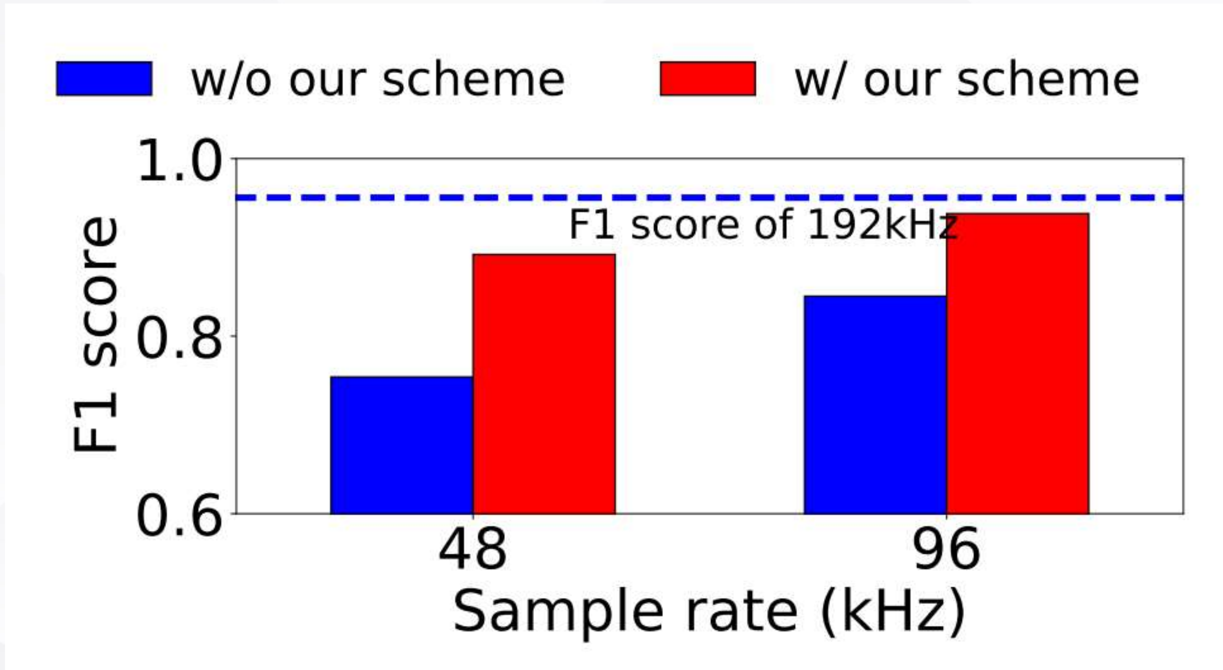
Method Evaluation

- Performance of Low-Sampling-Rate Scheme
  - Data collection devices:

    192kHz： Desktop

    96kHz ： Desktop

    48kHz： Mobile phone



Method Evaluation

- Impact of Environmental Interference
  - Scenario:

    Playing music

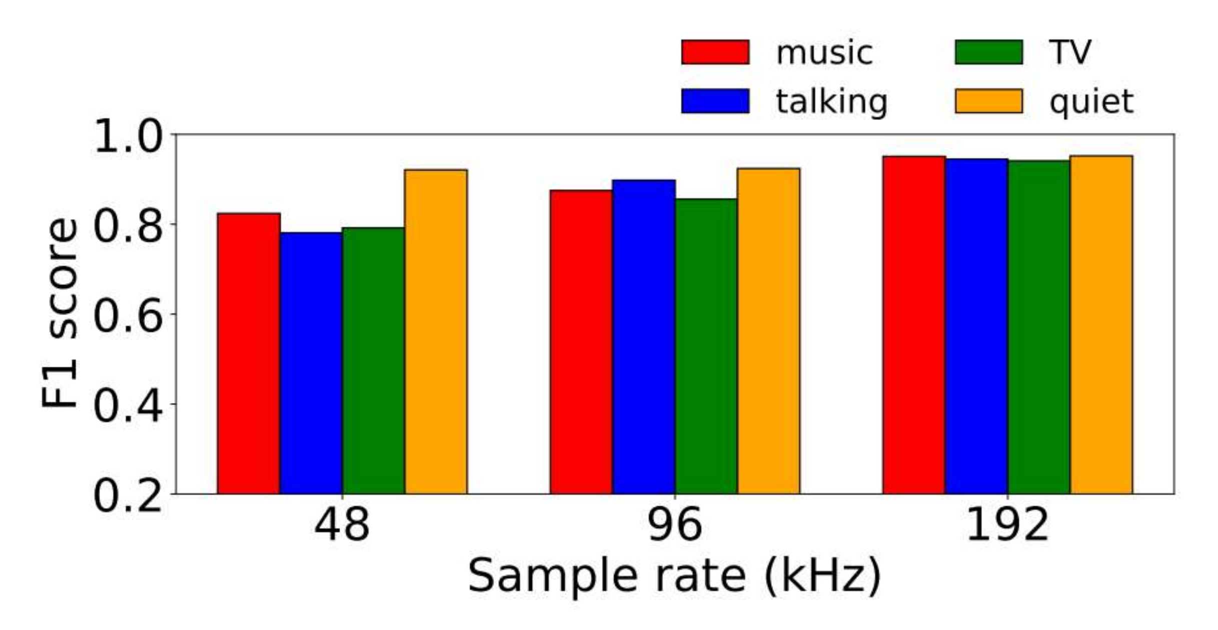
    Talking

    Turning on the TV
  - Sampling rate

    $192kHz$

    $96kHz$

    $48kHz$



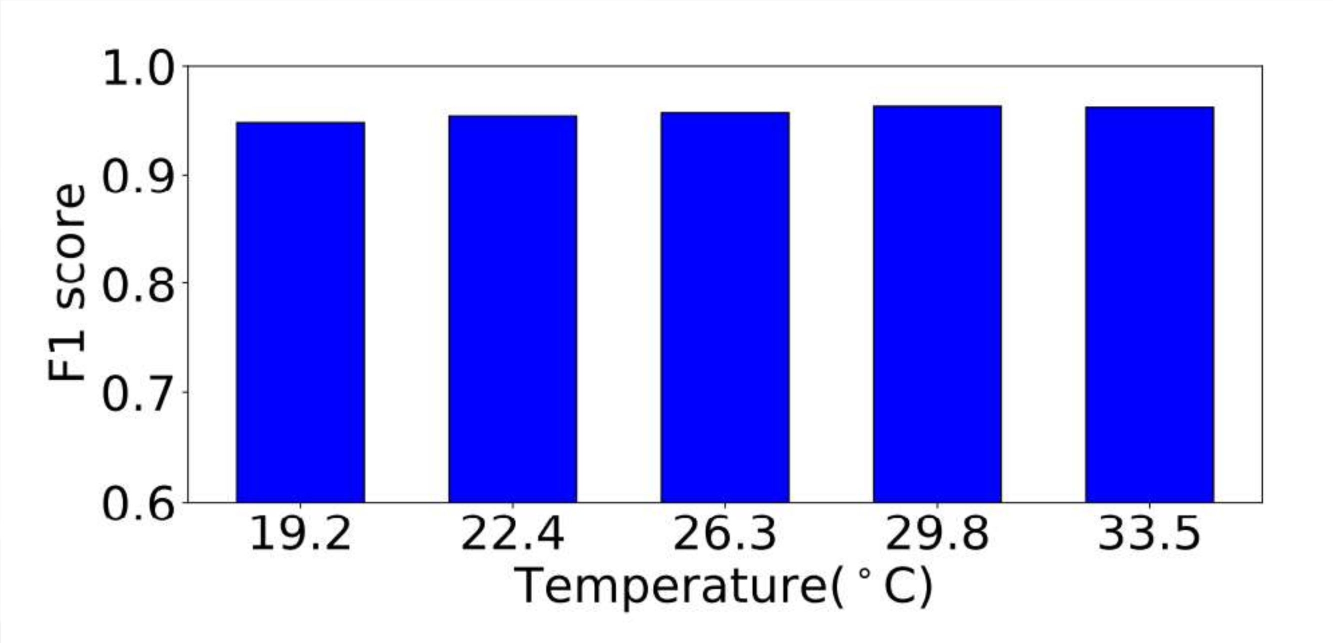
Method Evaluation

- Impact of temperature
  - Experiment device:

    13 portable devices

  - Temperature:

    Simulate the temperature of the indoor scene



Thank You

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