Yet Another Approach for Food Recognition: Monitoring Power Leakage from Microwave Oven

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Abstract
In this paper, we demonstrate a food recognition method by monitoring power leakage from a domestic microwave oven. Universal Software Radio Peripheral (USRP) is applied as a low-cost spectrum analyzer to measure the microwave oven leakage as received signal strength indication (RSSI). We aim to recognize 18 categories of food that are commonly cooked with a microwave oven. By analyzing 184 features designed after analyzing the features of measured RSSI, we attain an average recognition accuracy of 82.3% with various distances between the microwave oven and the USRP and different data downsampling frequencies for raw data processing.

Author Keywords
Food Recognition; Power Leakage; Microwave Oven; USRP

ACM Classification Keywords
B.m [Hardware]: Miscellaneous.

General Terms
Human Factors, Design, Measurement

Introduction
Food recognition has been an important topic that researchers in related fields focus on. Methods have been

No.	Feature Name	Detail	No.	Feature Name	Detail
1	average	$\frac{x_1+x_2+x_3+\ldots+x_n}{n}$	2	max most frequent value	max value among the most frequent values
3	range	Max($x_1 \ldots x_n$)-Min($x_1 \ldots x_n$)	4	min most frequent value	min value among the most frequent values
5	skewness	skewness of $x_1, x_2 \ldots x_n$	6	kurtosis	kurtosis of $x_1, x_2 \ldots x_n$
7	mean deviation	mean deviation of $x_1, x_2 \ldots x_n$	8	standard deviation	standard deviation of $x_1, x_2 \ldots x_n$
9	maximum	Max value among $x_1, x_2 \ldots x_n$	10	minimum	Min value among $x_1, x_2 \ldots x_n$
11	median	Median value among $x_1, x_2 \ldots x_n$	12	root mean square	$\sqrt{\frac{\sum x^2}{n}}$ $(x{:}x_1, x_2 \ldots x_n)$
13	coefficient of variation	coefficient of variation of $x_1, x_2 \ldots x_n$	14-18	auto-covariance	0.05s,0.1s,0.5s,1.0s,2.0s shift auto-covariance
19-23	auto-correlation	0.05s,0.1s,0.5s,1.0s,2.0s shift auto-correlation	24-46	all 1-23 features for step difference	change x_n to $y_n (=x_n - x_{n-1})$ in all calculation

Table 1: 46 features for recognition.

proposed for food recognition by other researchers, such as recognizing food images and monitoring the chewing sound. These methods call for users to submit a picture of the food or wear a device when having meals. The extra efforts asked from users might introduce usage burden or complexity though we should admit the ubiquity of previous methods. We propose to exploit the features of food-cooking facilities to recognize the food automatically as a complementary method co-operating with previous methods. The solution we propose in this paper is to monitor the feature changing of the power leakage from the microwave oven when different categories of food are cooked. The conceptual block diagram is illustrated in Figure 1.

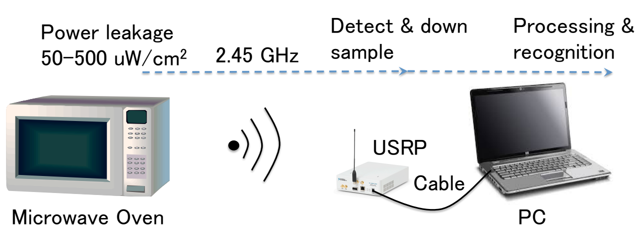

Figure 1: The conceptual block diagram of proposed food recognition system.

Related Works

The food recognition for dietary logging and monitoring has been focused on by researchers and two main categories of recognition methods have been proposed. Solving recognition problems as image categorization or classification problems is the most popular method. The "Foodlog" system based on cell phone camera function was proposed by Kitamura et al., and according to [1], the system extracts the features of food color, circle edge and SIFT feature from food images taken by user via cell phone and uploaded to an online system, attaining the accuracy of 91.8% for food-non-food recognition and the accuracy of 38.2% of food balance estimator of 5 food categories. The other food recognition methods using wearable devices to recognize and record the food intake have also been proposed. P. Sebastian et al. proposed a food intake recognition method via investigating acoustics of chewing different kinds of food [2]. Actually, the research on the power leakage of the microwave oven has been conducted on energy harvesting [3] and WLAN

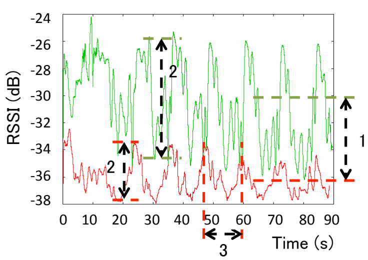

Figure 3: Raw data measured with the recognition distance of 0.3 m and the downsampling frequency of 2 kHz. Red: pizza. Green: French fries.

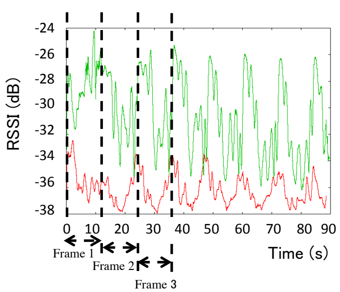

Figure 4: First three frames of raw data with the recognition distance of 0.3 m and the downsampling frequency of 2 kHz. Red: pizza. Green: French fries.

network communication quality [4].

Recognition Scheme

In this section, we illustrate the recognition scheme of proposed method.

System Configuration

In order to investigate how the distance between the microwave oven and the USRP (which we call "recognition distance") affects the recognition result, we take the recognition distance into consideration as one of the parameters. Three recognition distances are investigated which are 0.3 m, 5 m and 10 m respectively. We set up three measurement points at all the three recognition distances simultaneously as shown in Figure 2. In each measurement set, the USRP is connected to the laptop via an ethernet cable.

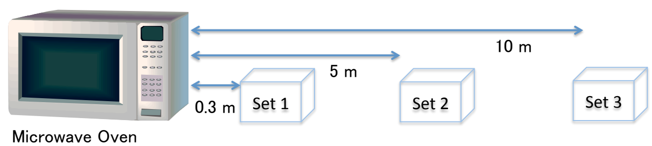

Figure 2: System deployment of the three measurement sets at different recognition distances.

In our recognizing system, the microwave oven we utilize is the NE-EZ2 manufactured by National, a turning-plate microwave oven that is ordinarily available in the market. When the NE-EZ2 microwave oven is heating different kinds of food, the center frequency of leakage signal will slightly shift.

Food Category

We select 18 categories of food that is usually sold at grocery stores. The detail information about the 18 categories of food is listed in Table 2. The "Time" column in Table 2 stands for the heating-time of each kind of food. We should note that all food categories we select are off-the-shelf products from food manufacturers, which are normally heated in packet as they are, resulting different heating-time lengths as shown in Table 2. For each category of food, we heat ten packages with the same weight and manufacturer.

Data downsampling

After measuring raw data (signal) via the USRP, we proceed data downsampling before extracting features because the original raw data size is too large to be processed directly by PC. In order to investigate how downsampling frequency affects recognition accuracy, we adopt four downsampling frequencies, 500 Hz, 1 kHz, 2 kHz and 5 kHz respectively. We show the raw data with the recognition distance of 0.3 m and the downsampling frequency of 2 kHz in Figure 3. Three main feature aspects are marked with number in Figure 3: 1. Average RSSI level; 2. Fluctuation; 3. 12-second turning cycle.

Feature Extraction

In order to make use of the first two feature aspects, we select 46 features as we demonstrate in Table 1. The x_1, x_2 ... x_n stands for the value of raw data at each sampling point. And the y_2, y_3 ... y_n stands for the step difference of the x array ($y_2 = x_2$ - x_1). Furthermore, for the third feature aspect, we extract features in Table 1 from the all-time-length data, the first three frames (1s-12s, 13s-24s, 25s-36s) as shown in Figure 4 (thus totally 184 features) and conduct recognition.

Recognition Accuracy

We utilize all features in Table 1 to the raw data under all recognition conditions (recognition distances and downsampling frequencies). Machine learning software

WEKA (Waikato Environment for Knowledge Analysis) is applied to conduct recognition. We present the recognition accuracy result using the feature extraction above (184 features) in Table 3. The average recognition accuracy under all conditions in Table 3 is 82.3%. We show the confusion matrix with 5-meter recognition distance and 2-kHz downsampling frequency (recognition accuracy of 84.4%) in Table 4. The letters a-r are correspondent to the food categories in Table 2.

Food	Brand	Weight (g)	Time (s)
Corn dog (a)	LAWSON	60	40
Cream stew (b)	LAWSON	250	100
Curry sauce (c)	LAWSON	250	100
Dumpling (d)	LAWSON	80	80
French fries (e)	Orelda	100	90
Fried rice (f)	LAWSON	230	200
Gratin (g)	Meji	200	270
Fried chicken (h)	AjiNoMoto	100	80
Okonomiyaki (i)	TableMark	294	240
Spaghetti (j)	Nissin	300	310
Pizza (k)	AQLI	100	90
Porridge (l)	Home-made	250	80
Rice (m)	LAWSON	250	170
Rice ball (n)	Nissui	80	110
Siumai (o)	Nissui	85	90
Taiyaki (p)	LAWSON	92	90
Octopus dumplings (q)	TableMark	100	140
Water (r)	Home-made	100	120

Table 2: Detail information of 18 categories of food.

Distance vs Frequency	500 Hz	1 kHz	2 kHz	5 kHz
0.3 m	80.6%	81.7%	80.0%	83.9%
5 m	80.6%	80.6%	84.4%	84.4%
10 m	79.4%	81.7%	85.6%	84.4%

Table 3: Recognition accuracy of 18 categories of food using totally 184 features with different recognition distances and downsampling frequencies.

Conclusion

In this paper, we demonstrate a food recognition approach by monitoring the power leakage from a microwave oven as a complementary method for food recognition. With extracting 184 features from the raw measured data of totally 18 categories of food while they are heated by the microwave oven, we acquired an average recognition accuracy of 82.3%.

%	a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	p	q	r
a	100	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
b	0	60	30	0	0	0	0	0	0	0	0	0	0	0	0	0	10	0
c	0	30	60	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0
d	0	0	0	80	10	0	0	10	0	0	0	0	0	0	0	0	0	0
e	0	0	0	0	80	0	0	0	0	0	0	0	0	0	10	10	0	0
f	0	0	0	0	0	90	0	0	0	0	0	0	10	0	0	0	0	0
g	0	0	0	0	0	0	100	0	0	0	0	0	0	0	0	0	0	0
h	0	0	0	10	0	0	0	50	0	0	0	30	0	0	0	10	0	0
i	0	0	0	0	0	0	0	0	100	0	0	0	0	0	0	0	0	0
j	0	0	0	0	0	0	0	0	0	100	0	0	0	0	0	0	0	0
k	0	0	0	0	0	0	0	0	0	0	100	0	0	0	0	0	0	0
l	0	0	0	0	0	0	0	20	0	0	0	80	0	0	0	0	0	0
m	0	0	0	0	0	10	0	0	0	0	0	0	90	0	0	0	0	0
n	0	0	0	0	0	0	0	0	0	0	0	0	0	90	0	0	10	0
o	0	0	0	0	10	0	0	10	0	0	0	0	0	0	80	0	0	0
p	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0	90	0	0
q	0	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	90	0
r	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0	10	80

Table 4: Confusion matrix with all 184 features, 5-meter recognition distance and 2-kHz downsampling frequency.

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