1.1-1

Life Pattern Sensor with Non-intrusive Appliance Monitoring

Makoto Katsukura, Masanori Nakata, Yoshiaki Itou, Noriyuki Kushiro
Living and Environment System Laboratory, MITSUBISHI ELECTRIC CORP.

***Abstract*--** This paper presents a life pattern sensor with a new residents' behavior monitoring method for a health care system. The life pattern sensor detects operations of appliances from electrical current generated by their operating, and identifies patterns of daily residents' behavior based on the correlation of operating appliances. The sensor reduces the system cost by avoiding installation of massive sensor nodes and keeps residents' privacy without intrusion of the house, in comparison with legacy systems like the video-based health care system. The sensor is implemented by utilizing an algorithm with the wavelet transform method and installed in five real houses for a couple of weeks. Accuracy of the identifying appliance detection and the result of the life pattern estimation were evaluated through the field test.

I. INTRODUCTION

Life pattern sensing in the house has a variety of important applications, including energy monitoring, home automation, and health care. The existing systems use the video systems, the occupancy sensors, or the other sensors to detect the life pattern of the residents [1]. However, the privacy is violated by the intrusive video system, and the cost is increased by the installation and the maintenance of the many sensors.

To address these concerns, the method of the appliances detection with a single sensor for the life pattern sensing is proposed in this paper.

II. THE SENSOR

First, the sensor detects whether appliances are running or not, from pattern matching of electrical current (Fig. 1). Next, the sensor estimates what the residents do, from the operation pattern of the appliances.

A. Appliance detection

One research approach uses odd-order harmonic currents of a power line to detect the appliances running [2]. The harmonic currents are depended on the power circuit of the appliance. That approach works well, but it should learn exponential number of sets corresponding to the combinations of the appliances, because the odd-order harmonic currents are combined if the multiple appliances run at the same time.

The proposed life pattern sensor uses small thorn-like peaks of the current as the feature of the appliances. This feature is unchangeable even if the multiple appliances run. Figure 2 illustrates the thorn-like peaks of the electrical current waveform. The thorn-like peaks a1, a2, b1 and b2 of the waveform A and B keep their positions on the time axis even if they are accumulated into the waveform A+B. These thorn-like peaks appear sparsely on the time axis.

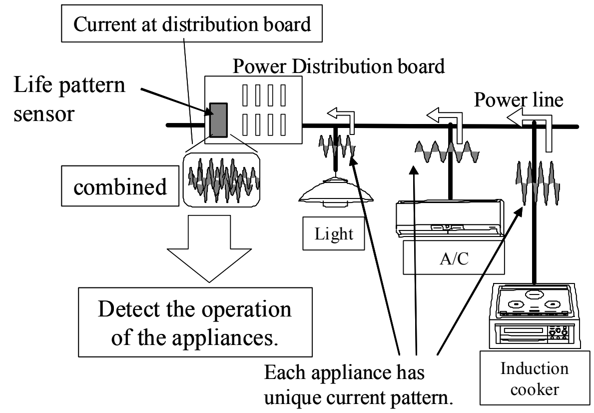

Fig.1. The life pattern sensor with non-intrusive appliance monitoring.

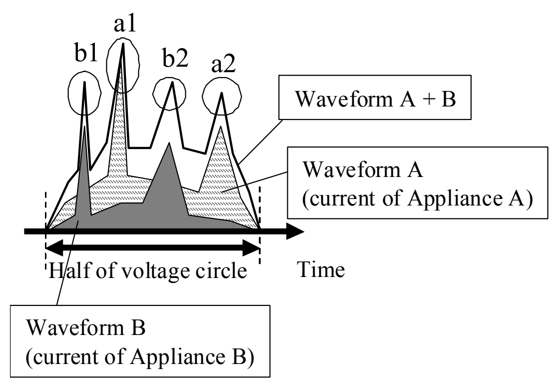

Fig.2. The thorn-like peak of the waveform.

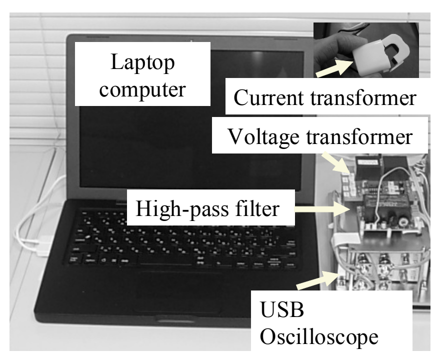

Fig.3. The prototype of the sensor

To calculate levels and positions of the thorn-like peak, the sensor uses the wavelet transform [3] [4]. The wavelet transform resolves the wave into the multi-resolution levels values, wavelet coefficients and scaling coefficients, and the wavelet coefficients express the width and the height of the peaks effectively. Therefore, the sensor uses wavelet coefficients as feature values of the appliances for pattern matching in order to detect the appliances.

Figure 3 shows the prototype of the sensor. The sensor has

978-1-4244-2559-4/09/$25.00 ©2009 IEEE

two current transformers and voltage transformers. The algorithm is installed in the laptop computer. The high-pass filter extracts the small thorn-like peaks (from about 0.5 kHz to 10kHz) and eliminates the fundamental wave of the alternating current (50Hz). The cut off frequency of the filter is 500Hz and the sampling rate of the sensor is 20 kHz.

B. Life pattern estimation

The sensor estimates the resident's life pattern after detecting the operations of the appliance. The sensor focuses on the correlation of the appliances and the residents' life pattern. We assume the residents' life pattern to be being connected with specific appliances' operations. For example, the residents usually use an induction cooker or a microwave oven when they prepare a meal.

III. FIELD EVALUATION

We have evaluated the sensor for a couple of weeks in five practical fields. The sensor learned feature values of four appliances (a vacuum cleaner, an induction cooker, a microwave oven, and an air conditioner (A/C)). The sensor did not learn the combinations. The details of the evaluations are as follows:

TABLE I
THE RESULTS OF THE EVALUATIONS.

	Accuracy rate	
	Unit	**Combination**
Vacuum cleaner	100.0%	99.4%
Induction cooker	100.0%	99.1%
Microwave oven	100.0%	99.4%
A/C	100.0%	95.4%

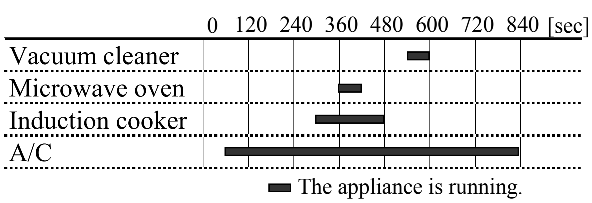

Fig.4. The scenario of the combination test.

Weekday

Hour	A/C	Microwave oven	Induction cooker	Cleaner
22	ON	OFF	OFF	OFF
23	ON	ON	ON	OFF
0	ON	[illegible]	OFF	OFF
1	OFF	OFF	OFF	OFF
2	OFF	OFF	OFF	OFF
3	OFF	[illegible]	OFF	OFF
4	OFF	OFF	OFF	OFF
5	OFF	OFF	OFF	OFF
6	ON	ON	ON	OFF
7	ON	OFF	OFF	OFF
8	ON	[illegible]	OFF	OFF
9	OFF	OFF	OFF	OFF
10	OFF	OFF	OFF	OFF
11	OFF	OFF	OFF	OFF
12	OFF	OFF	OFF	OFF

Dinner
Sleep
Breakfast

Weekend

Hour	A/C	Microwave oven	Induction cooker	Cleaner
22	OFF	OFF	OFF	OFF
23	ON	ON	ON	OFF
24	ON	ON	ON	OFF
1	ON	[illegible]	OFF	OFF
2	ON	OFF	OFF	OFF
3	OFF	OFF	OFF	OFF
4	OFF	OFF	OFF	OFF
5	OFF	OFF	OFF	OFF
6	OFF	[illegible]	OFF	OFF
7	OFF	OFF	OFF	OFF
8	OFF	OFF	OFF	OFF
9	ON	OFF	OFF	OFF
10	ON	ON	ON	OFF
11	ON	[illegible]	OFF	OFF
12	ON	OFF	OFF	OFF

Dinner
Sleep
Breakfast

ON	Detectiong the appliance
OFF	None

Fig.5. The operation records of the appliances.

A. Unit evaluation

The sensor was attached to the distribution board in the actual house, where the target appliances were placed in the each room. There were also the other appliances (e.g. the lightings and the refrigerator). We turned on and off the each appliance 25 times, and evaluate whether the sensor detected the correct appliances or not.

As a result, the sensor answered correctly 100% (Table.1).

B. Combination evaluation

In this case, we turned on and off the appliances along the use case scenarios to evaluate the case of multiple appliances running (Fig.4). As a result, the sensor answered correctly 95% to 99% (Table.1). The results show that our algorithm of the appliance detection is effective for combination cases.

C. Life pattern monitoring evaluation

The sensor had monitored the practical house for five days. The sensor detected operations by the resident.

Figure 5 shows the results of the life pattern monitoring evaluation, the records of the appliance operations in one day of weekdays and one day of weekends. Important events such as sleeping time and mealtime are estimated from the results. The results are confirmed by the interview from the resident. Furthermore, the difference of the life pattern between the weekday and the weekend are obvious in the result, every event in the weekend are later than the weekday.

IV. CONCLUSION

The life pattern sensor with the new resident's behavior monitoring method is described in this paper. The evaluation results of the sensor are as follows:

(a) The accuracy rate of the sensor is 100% at the unit evaluation and higher than 95% at the combination evaluation. The sensor detected appliances correctly including the case of multiple appliances running.

(b) The life pattern of the resident is estimated, and the results are confirmed by the resident.

For the next step, we will improve the algorithm of the life pattern estimation in the automatic detection of resident's life pattern. We expected that our sensor is used to detect unconscious changes of the residents' life pattern, like sickness or dementia.

REFERENCES

[1] K. Matsuoka, "Aware home understanding life activities", Proceedings of 2nd International Conference On Smart Homes and Health Telematic, ICOST'04, IOS press., 2004, pp.186-193.

[2] T. Onoda, H. Murata, G. Ratsch, K-R. Muller, "Experimental analysis of support vector machines with different kernels based on non-intrusive monitoring data Neural Networks", 2002. IJCNN '02., Vol.3, 2002, pp. 2186-2191

[3] I. Daubechies, *Ten Lectures on Wavelets*, Society for Industrial Mathematics, 1992

[4] DB. Percival, AT. Walden, *Wavelet Methods for Time Series Analysis*, Cambridge University Press, 2000