Non-intrusive Human Behavior Monitoring Sensor for Health Care System

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Abstract. This paper presents a non-intrusive human behavior-monitoring sensor for health care system, especially for elderly person. The sensor detects operation of appliances with thorn like peak of electrical current generated by their working, 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 sensors and keeps residents' privacy without intrusion of their private space. The human behavior-monitoring sensor is implemented by utilizing an algorithm with a wavelet transform method and is installed in five real residences for a couple of weeks. Accuracy of detecting operations of appliances and identifying life patterns are estimated through the field test.

1 Introduction

The ratio of over 65 years people of the population in Japan will increase 31.8% in 2030 and reach 40.5% in 2055 [1]. About 80% of elderly persons are in a good health and about 20% of households are living in an old couple or alone independent from their family [2]. Reflecting these social conditions, there is a growing interest to introduce a health care system into a residence, especially for elderly persons.

A human-behavior monitoring sensor, which detects anomaly of behavior of residents and identifies abnormal conditions of their health, is an indispensable technology for the system.

Some systems have already succeeded in detecting illness or symptom of dementia of the resident with sensing data [3]. Most of existing systems [3-4] use video systems and/or a lot of occupancy sensors. However, the privacy is invaded by video systems and the cost is increased by installation of massive sensors. Both privacy invasion and system cost hinder penetration of the system into the market. To address these issues, a non-intrusive human behavior-monitoring sensor is proposed in this paper.

2 Basic Approach

To avoid the cost and privacy invasion issues, the human behavior-monitoring sensor identifies anomaly of behavior of the residence through the following two procedures:

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Step1: The sensor, attached to a distribution board in each house without intruding private space, detects particular appliances by pattern matching of thorn like peak of electrical current generated by appliances' working (Fig. 1).
Step2: The sensor identifies residents' behavior from a correlation of appliances' operations without installing massive sensors.

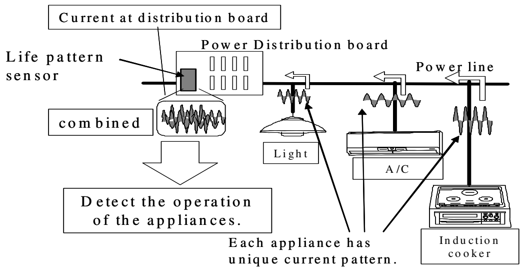

Fig. 1. Non-intrusive human-behavior monitoring sensor

Few attempts have so far been made at detecting electrical events with pattern matching of electrical current of appliance using. Hart [9] studied the algorithm to detect appliances from changes of power consumption. Patel [10-11] advanced the algorithm to detect electrical events by high frequency electrical noise. The method utilizes high frequency noise appeared on the power line as features for pattern matching. Those two approaches are focusing on to catch electrical events, such as turning on or off of appliances. The issue is that these methods are hard to detect appliances running anytime like a refrigerator.

Onoda's method [5] detects appliances with odd-order harmonic currents with fast Fourier-transform (FFT) and support vector machine [8]. The method solves the above-mentioned issue, however, the method should learn exponential number of sets corresponding to the combinations of appliances, because the harmonic currents are combined if the multiple appliances run at the same time (Fig.1). It requires much time for learning the sets. We propose a new method to reduce "time for learning" by addressing "thorn like peaks", which are generated by each appliance.

3 Appliance Detection Method

The human behavior-monitoring sensor uses small thorn-like peaks of the current as a feature for pattern matching. The feature is stable even though multiple appliances are running. 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 like A+B (Fig.2). Therefore, the sensor reduces learning process for exponential number of sets corresponding to the combinations of appliances.

The sensor uses the wavelet transform [6-7] method for extracting features (frequency and position) from the thorn like peaks. The wavelet transform is available for resolving the frequency and position of the peak into the multi-resolution levels values as wavelet coefficients and scaling coefficients. The wavelet transform method is suitable for implementing in an embedded hardware because it requires little computational complexity and memory for calculation.

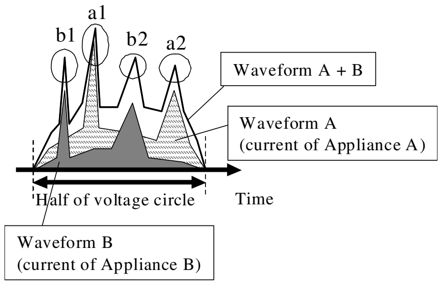

Fig. 2. Basic principle for appliances detection

The sensor identifies operation of appliances based on the three features: frequency, level and position of the peaks. The prototype of the sensor consists of a laptop computer, an oscilloscope (20kHz sampling rate), current transformers and a voltage transformer. The high-pass filter selectively extracts thorn-like peaks from about 0.5 kHz to 10kHz from domestic power line.

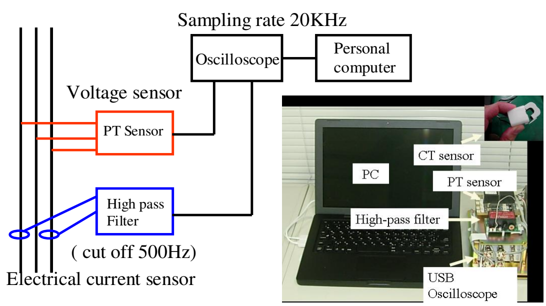

Fig. 3. Prototype of the human behavior-monitoring sensor

3.1 Algorism for Appliances Detection

Appliances detection is performed through the following three processes:

Process1: Measurement of thorn like peak
Process2: Calculation of the features of the peaks
Process3: Identification of appliance from the features with pattern matching

Process1: Measurement of Thon Like Peaks. Fig. 4 shows waveform of an induction cooker and an air conditioner (A/C).

The high-pass filter extracts feeble features (thorn like peaks) of higher harmonics by removing the strong ingredient of the supply frequency.

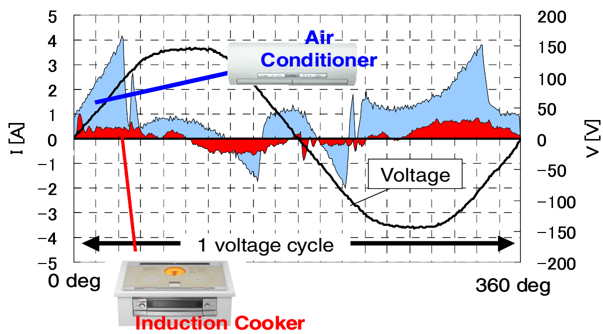

Fig. 4. Example of waveform for induction cocker and air conditioner (Cut off frequency 500Hz high pass filter are inserted)

Process2: Calculation of the Features of the Peaks. The wavelet transform method [6] is applied for calculating features (frequency, level and position). MODWT (Maximal Overlap Discrete Wavelet Transform) [7] is utilized as a method for calculation because of the requirement to handle discrete value elicited by the prototype of the sensor. The wavelet transform resolves the frequency and position of the peak into the multi-resolution levels values as wavelet coefficients and scaling coefficients (Fig.5).

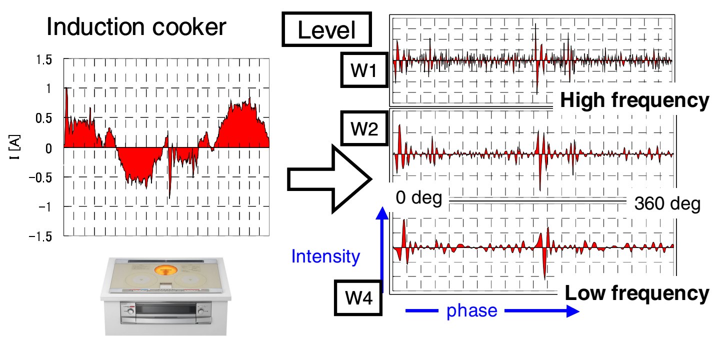

Fig. 5. Results of MODWT for induction cocker

For the moment, let us look closely that how the wavelet transform separates the peaks into features. The left side of Fig. 5 shows the electrical current of the induction cooker. The wavelet transform separates the peaks into the different frequency, shown at the right in Fig. 5. The above right shows high frequency of the peaks and the lower shows low frequency of the peaks. A sharp peak appears in the higher frequency portion and blunt peak appears in the lower frequency portion. The peaks are separated into the different dimensions, called "level L".

Wavelet coefficient X in level L is described in $X[t,L]=W(x[t],L)$, where x[t] is current in time t. Then, binarized X[t,L] by the threshold value σ for identifying the position of the peak.

$$\overline{X}[t,L,\sigma] = f(X[t,L],\sigma)$$

$$f(X[t,L],\sigma) = \begin{cases} 1 & (X[t,L] \geq \sigma) \wedge (\sigma \geq 0) \\ 0 & (X[t,L] < \sigma) \wedge (\sigma \geq 0) \\ 1 & (X[t,L] \leq \sigma) \wedge (\sigma < 0) \\ 0 & (X[t,L] > \sigma) \wedge (\sigma < 0) \end{cases}$$

σ is varied in the range [–4.0, -2.0, -1.0, -0.5, -0.2, 0.2, 0.5, 1.0, 2.0. 4.0]. The range of threshold value σ is determined empirically from the prior experiment. An example of the results for the induction cocker is shown in Fig.6.

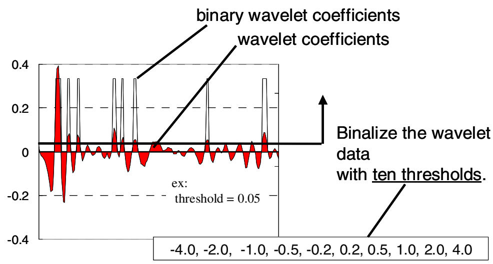

Fig. 6. Results of wavelet coefficients for induction cocker

Process3: Identification of Appliance by Pattern Matching of the Features. The sensor performs the pattern matching after the calculation of the features of the peaks. The features for targeted appliances are stored at a prioritized leaning step.

Appliances are identified by pattern matching between learnt feature $T_m[t,L,\sigma]$ and measured features $\overline{X}[t,L,\sigma]$ (Fig.7).

$$M(\overline{X}[t,L,\sigma],T_m[t,L,\sigma]) = \begin{cases} 1 & \textit{if} \quad (T_m[t,L,\sigma]=1) \wedge (\overline{X}[t,L,\sigma] = T_m[t,L,\sigma]) \\ 0 & \textit{other} \end{cases}$$

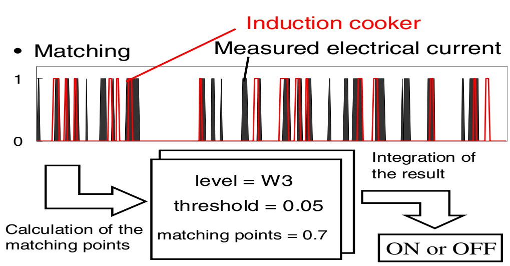

Fig. 7. Pattern matching

The above-mentioned matching calculation is repeated for all “t” and all threshold value “σ”. The number h_m (the number of coincidence) is shown as:

$$h_m(L) = \sum_{\sigma}\left(\sum_{t}\left(M(\overline{X}[t,L,\sigma],T_m[t,L,\sigma])\right)\right) \tag{1}$$

The total number used for the judgment S_m is calculated as:

$$s_m(L) = \sum_{\sigma}\left(\sum_{t}\left(T_m[t,L,\sigma]\right)\right) \tag{2}$$

P_m (the rate of coincidence) is calculated for every level L of Wavelet.
P_m is calculated as:

$$p_m(L) = \frac{h(L)}{s(L)} \tag{3}$$

If P_m is over or equal to the threshold λ_m for all the level L, then the appliance is regarded as "ON". *If* P_m is under threshold λ_m, the appliance is regarded as "OFF".
The status S_m (the status of appliance "m") is shown as:

$$S_m = g(p_m[L],\lambda_m[L]) = \begin{cases} ON & if \quad {}^{\forall}L, \quad p_m[L] \geq \lambda_m[L] \\ OFF & Other \end{cases} \tag{4}$$

The value of λ_m is determined empirically from the prior experiment.

4 Life Pattern Identification

The sensor identifies residents' behavior with correlation and/or sequence of residents' usage of appliances. It is assumed that the residents' behavior is related to specific appliances. For example, the residents frequently use an induction cooker or a microwave oven when they prepare their meal and use a vacuum cleaner when they clean up their room.

4.1 Relation between Appliances and Human Behavior

Appliances, which are used in each life event, are surveyed with questionnaires for 26 peoples, who were selected randomly from teenage to 70 years old persons. In the questionnaire, typical events occurred in their daily life, and appliances they ordinarily use, when they execute each event, are questioned.

As the results, about 40 events and 30 appliances are elicited from the inquiries. 40 events are classified into 6 categories shown in Table 1. Table 1 shows the strength of relation between life events and use of appliances.

From the view points of detecting particular life event from others, appliances, like lighting are not significant, but appliances, like oven range, IH cocker, vacuum cleaner and washing machine etc., are significant. Lightings are used at all kinds of life events, so that it cannot be connect to a particular life event.

We select four kinds of appliances: air conditioner, oven range, IH cocker and vacuum cleaner, to identify the following significant events: sleep, meal and cleaning in this paper. These events are significant for detecting anomaly of behavior of residents and identifies abnormal conditions of health.

Table 1. Ratio of appliances using for each life pattern

Category	Event	Light	Air cond.	Television	Oven Range	IH Cocker	Rice cocker	Vac. Cleaner	Washing Mach	Dryer	Venchlator
1	Sleep	85.4	56.3	40	4.2	2.1	0	0	2.1	0	2.1
2	Meal	60.6	28.9	31.5	52.6	60.5	44.7	0	0	0	23.4
3	Bath/Wash	78.9	6.1	6.1	0	0	0	0	0	36.4	24.2
4	Washing	28.6	0	0	0	0	0	0	92.9	0	0
5	Cleaning	41.7	0	0	0	0	0	100	0	0	0
6	Others	71.2	37.3	25.4	1.7	0	0	0	1.7	0	1.7

5 Evaluation of the Sensor

We have evaluated the sensor for a couple of weeks in five residents (F1-F5 in Fig.8). The sensor learned the current peaks for four target appliances: vacuum cleaner, induction cooker, microwave oven and air conditioner (A/C).

Accuracies for detecting appliances were evaluated in the following two cases: single operation of each appliance (Unit test) and multiple operations of appliances (Combination test) in F1-F5 residents. In Fig.8, the left upper graph shows the schedule of the field test for five residents.

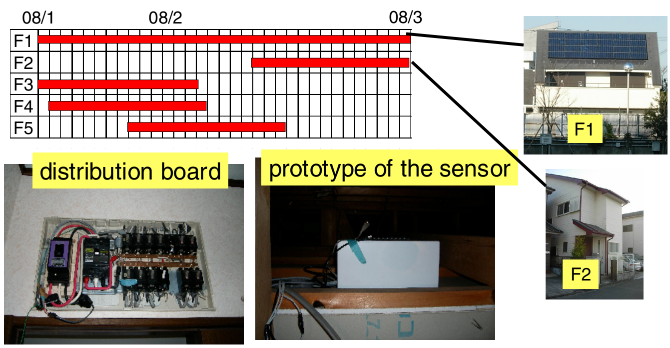

Fig. 8. Field test for the non-intrusive human behavior-monitoring sensor

5.1 Unit Test

The sensor was attached to the distribution board in five houses (Fig.8). The four appliances were installed dispersedly in each house. There were some other appliances (e.g. lightings and refrigerator, television) besides the four target appliances in each house.

Each appliance was turned on and off 25 times for the unit test, and evaluate whether the sensor detected correct appliances or not.

As a result, the sensor shows 100% accuracy (Table.2).

Table 2. Results of the unit and combination tests

	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%

5.2 Combination Test

The appliances were turned on and off on scenarios shown in Fig.9 to evaluate the case of multiple appliances working in five houses. As a result, the sensor shows 95-99% accuracies in five fields (Table 2).

We confirmed that the sensor has enough capability for detecting appliance both for a single operation and multiple operations of appliances.

Fig.9 shows example of the results in field 1 and field 2. There are few errors to detect appliances in the combination evaluation test. The reason for these errors is confirmed in detail as the followings.

One error happened in the air conditioner (A/C). A/C requires a few minutes for stand-by before starting. Electrical current of A/C in stand-by mode is too small to detect A/C by the sensor.

The other error happened in detecting the induction cooker. A/C generates strong and wide spectrum noise when it starts after stand-by mode, then the sensor miss-detected the induction cooker during A/C starting up. But the error of detection was recovered in a short time after the A/C runs at stable mode. The redundancy is an advantage of our proposed algorithm.

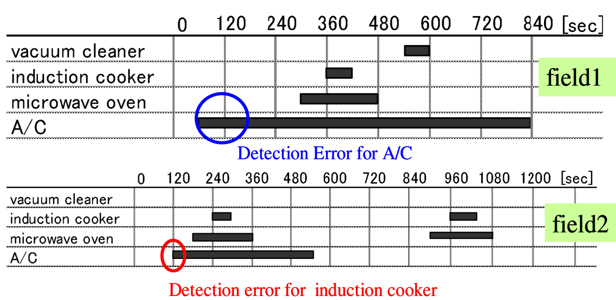

Fig. 9. Scenario of the combination test

5.3 Life Pattern Monitoring

The sensor monitored life pattern for a week in each residence. Interviews were executed for residents during the field test to grasp their life pattern concurrently.

Fig.10 shows examples of the results of life pattern monitoring both for a weekday and a weekend in field 2 and field 3. Significant events, which identify the life

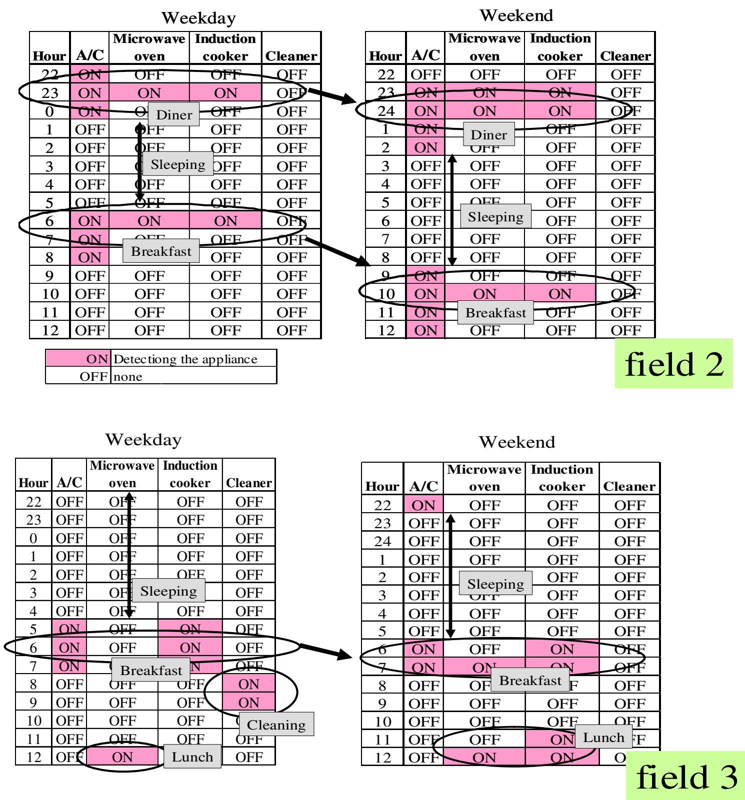

Fig. 10. Results of the field test

patterns, such as sleep and meal, are identified from the results. The differences of the life pattern between weekday and weekend are obvious, both events in the weekend are later than the weekday.

These results were checked against the results of the interview for each resident. Thus, we confirmed that the sensor succeeded in identifying the life patterns, sleep, meal and cleaning, by utilizing history data of four kinds of appliances using.

6 Conclusion

This paper describes a non-intrusive human-behavior monitoring sensor for a health care system. The sensor detects operations of appliances from electrical current generated by their operating, and identifies life patterns of daily residents' behavior based on the correlation and/or sequence of operating appliances.

The sensor reduces system cost by avoiding installation of massive sensors and keeps residents' privacy without intrusion of the house. We focused on the thorn-like peaks of the electrical current for detecting electrical appliances. The sensor is implemented by the algorism based on the wavelet transform method and installed in five real houses for a week. Accuracy of the identifying appliance detection and the life pattern were evaluated through the field test.

As the results, the followings are confirmed:

(1) The sensor result 100% accuracy at the unit test and higher than 95% accuracy at the combination test.
(2) The life pattern of the resident is identified from the log of the appliances.

There is room for further investigation for the study. For example, we should increase target appliances for identifying the life pattern in detail and should install the sensor in various homes for a long time.

Concurrently, we are starting to implement the sensor on the low-cost embedded hardware for accelerating penetration of practical use of the system (Fig.11). In near feature, we will install the sensor into the residence for elderly people and try to identify anomaly of their life pattern.

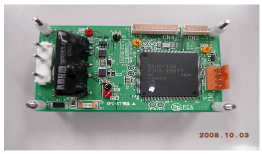

Fig. 11. The human behavior-monitoring sensor on the embedded hardware

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