Daily Life Monitoring System with Behavior Pattern Recognition Using Ambient Sensors

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***Abstract*—This paper presents a novel life monitoring system using a home agent and ambient sensors as invisible sensors that fit living circumstances with consideration of privacy and Quality of Life (QoL) for achieving autonomous monitoring in daily life. The home agent has a key tag sensor, a human detection sensor, and a remote control sensor for detecting the states of a subject, such as going out (Out) or being at home (Home). The ambient sensors consist of a pad sensor installed in a bed sheet, a triaxial accelerometer inserted in a pillow, a human detection sensor installed near an entrance door, and a piezoelectric sensor installed near a refrigerator. The state of Home or sleeping on a bed (Sleep) is detected using ambient sensors that measure living behavior patterns in real time. As a preliminary experiment aimed at monitoring various life patterns of elderly people, we conducted a monitoring experiment during two months for four university students subjects in their 20s. For this system, sensor signals were stored in a server via a wireless router for visualization on a monitoring computer terminal in real time. We developed a method of recognizing three major life patterns (Out, Home, and Sleep) using machine learning which uses eight algorithms. To evaluate of recognition accuracy, we collected handwritten daily records from the respective subjects used for correct behavior datasets as ground truth. Experimentally obtained results revealed that the mean recognition accuracy was 83.61% for the first half of the monitoring experiment during one month with one-minute downsampled signal intervals. In the last half of the monitoring experiment, data acquisition was interrupted because of a failure of the home agent. We continued the evaluation experiment of life patterns with two delimited periods, which indicated recognition accuracies of 92.53% for 18 days and 93.85% for 27 days.**

Keywords–ambient sensors; home agent; life monitoring; quality of life; machine learning; random forest.

I. INTRODUCTION

Because of the rapid progress of aging societies and increased longevity worldwide, mutual support among generations has already reached its limit, as reflected in distortion of the population pyramids of many nations. The problems of increased numbers of single elderly people, nursing care among care receivers, rarefaction of regional ties, isolation, and marginalization are manifested not only in regional cities and country sides with high aging rates, but also in metropolitan areas with higher population concentrations. For monitoring elderly people from remote areas, the development of information and communication systems, supporting devices, and sensor systems is underway [1]. In particular, security measures to prevent elderly people from a solitary death is urgent in our current society [2].

Particularly, life-support and service robot platforms with communication and interactive functions, along with sensing and monitoring using unconstrained and invisible sensors have been unveiled, offering advanced functionality and performance [3]. These systems are able to monitor several subjects as care receivers in parallel; subjects are assumed to be in nursing facilities focusing on monitoring functions. Moreover, these systems can be used for 24 hours continuously if malfunction is avoided. The advantage of these systems is to send notifications containing information simultaneously and instantly to nurses, caregivers, and family members. These autonomous systems do not require so much as the push of a button or raising one's voice to collect active information.

For specialized sleep monitoring, sensor systems that send notifications with information related to bed leaving behaviors to care takers or nurses are already in practical use [4]. Moreover, robotic nursing care devices with a monitoring function used for elderly people who have Mild Cognitive Impairment (MCI) [5] have been developed. Evaluation methods and criteria have already been established [6]. Various criteria and specifications exist for monitoring sensor systems according to use cases and situations of use. The most important function is automatic and immediate notification of abnormal or unusual information related to care. Contingent circumstances occur if automatic notification is delayed.

As a novel approach to overcome these problems, monitoring systems that specifically examine life pattern rhythms in our daily life have been studied [7]. Actually, humans have individual life rhythms related to health, mind, and mentality. Particularly for elderly people, unsteady or confusing life rhythms cause bad effects of sleep deprivation related to health. Therefore, we infer that monitoring systems can detect the health conditions of elderly people immediately if life rhythms can be extracted using monitoring support systems.

This paper presents a novel life-pattern monitoring system using multiple hidden sensors for adaption to daily life with respect to privacy and Quality of Life (QoL). Our proposed system comprises a home agent and ambient sensors. The home agent has a key tag detection sensor, a motion sensor, and a remote controller detection sensor for recognition of a monitored person as home or out. The ambient sensor

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comprises pad-shape sensors installed in a bed sheet, a triaxial accelerometer installed in a pillow, a motion sensor installed near a door, and piezoelectric film sensor installed in a refrigerator. The ambient sensor measures life behavior patterns at home to determine normal home behavior or sleeping in a bed. Monitored signals are saved on a server using network storage via a wireless router with a visualizing function of signal outputs in real time from respective sensors. As a preliminary experiment before monitoring diverse life patterns of elderly people, we conducted a monitoring experiment for two months to observe four university students subjects. Moreover, we attempted to recognize life patterns from collected datasets using machine learning algorithms. This report presents details of related studies, our proposed system, and recognition results.

The rest of the paper is structured as follows. In Section II, related studies are presented, especially for smart sensors and daily life monitoring systems. Sections III and IV present our proposed method and experimental results obtained using our original datasets, respectively. Finally, Section V concludes and highlights future work.

II. Related Studies

Various methods and experimentally obtained results of daily life monitoring have been reported in earlier studies. From results of a recent study report, Morishita et al. [8] described a monitoring system that detected opening or closing of a door using a magnet sensor with a function to report the safety of a resident and an application to display sensor detection results. Although they conducted a practical test at a residence for low-income elderly people, monitoring results reflected merely movements between rooms through doors. Jiang et al. [9] proposed a monitoring system for use in nursing care facilities. They obtained original datasets related to daily habits in terms of eating and exercise using a dual-band Radio Frequency IDentifier (RFID) and virtual routing locational algorithms. They revealed that their proposed system, which included hush functions and certification protocols, provided high security with real-time processing. Although they revealed that the total burden of waiting data calculation and communication was low, this result merely reflected results from a computer simulation.

Park et al. [10] proposed a framework of a healthcare monitoring system for elderly people using wearable sensors. Their knowledge-based method with self-learning algorithms collected sensor signals in real time while maintaining network security. Nevertheless, they only proposed a framework without conducting evaluation experiments or system implementation. Sumalan et al. [11] proposed a vital sign monitoring system in terms of heart rates, respiratory rates, and blood pressure for elderly people using wireless sensor networks. Although their design concept was set as cost effective for actualizing an application, their proposal remained a system structure without experimentally obtained results.

Ghayvat et al. [12] proposed a daily life monitoring system using electric current sensors, load sensors, and contact sensors. They developed an original model to discriminate between normal or abnormal status. Furthermore, they conducted an evaluation experiment at an elderly home and a nursing care facility. However, the results remained a single tendency of time-series visualization because their study was geared towards the development of communication circumstances for smart homes based on wireless networks and Internet of Things (IoT).

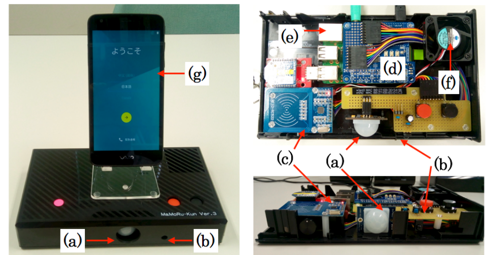

Figure 1. Home agent: (a) motion sensor, (b) remote controller sensor, (c) key sensor, (d) micro-controller board, (e) optional sensor board, (f) air cooling fan, and (g) smartphone

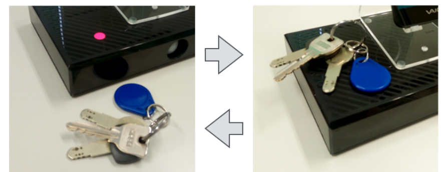

Figure 2. Key sensor. Card key type IC card is inserted into the blue key holder. The home agent detects the key using an RFID module.

Although they described details of the experimental setups, especially related to use at nursing care facilities, the experimentally obtained results were insufficient for a practical use.

As an example of research related to MCI, Mighali et al. [13] proposed a system of monitoring elderly behavior patterns. It incorporated wearable sensors and motion sensors installed in a home. The experimentally obtained results revealed that the mean recognition accuracy achieved 97% for 10 healthy subjects at a living circumstance in a general house. Nevertheless, the recognition targets were merely two patterns of static or dynamic states. Furthermore, the consideration of QoL was insufficient because the system used wearable sensors. Riboni et al. [14] proposed an ambient sensor system that was composed of wearable sensors and home sensors installed inside of electrical appliances. They conducted a practical test for the target of elderly people with MCI. However, the experimentally obtained results remained extraction of abnormal values without extracting patterns related to life rhythms. They merely reported discussion of a plan for the practical test without addressing details of experimentally obtained results.

Moreover, numerous international projects consisting of sensor networks and mobile robot prototypes have been conducted in terms of DOREMI (Decrease of cOgnitive decline, malnutRition and sedEntariness by elderly empowerment in lifestyle Management and social Inclusion) [15], RUBICON (for Robotic UBIquitous COgnitive Network) [16], and OPPORTUNITY (Activity and Context Recognition with Opportunistic Sensor Configurations) [17].

III. Proposed Method

A. Proposed system structure

Figure 1 depicts the home agent, named MaMoRu-kun [18]. The home agent is equipped with a key sensor, a motion

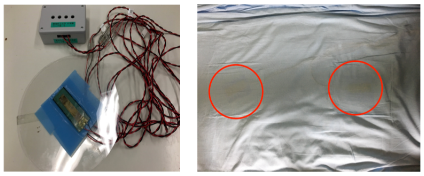

Figure 3. Bed sensor installed to the hip part with a sheet pocket. Piezoelectric films are used for this sensor.

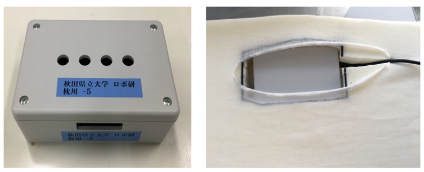

Figure 4. Pillow sensor. A built-in triaxial accelerometer is installed in a pillow with a wireless communication board.

sensor, and a remote control sensor. Figure 2 shows that the key sensor using a RFID-based wireless frequency Integrated Circuit (IC) card induction sensor (MFRC-522 RC522) detects the key status that was placed on the home agent. The motion sensor using a collecting electron type InfRared (IR) sensor module (SB612A) was installed to the front panel of the home agent. The remote control sensor using an IR module (SPS-440) was installed beside the motion sensor.

1) Home agent: We used a micro-controller board with Raspberry Pi 3 model B (BCM2837) as the main processing unit of the home agent. We implemented software to send the collected sensor signals to a router in a fixed interval using a wireless Local Area Network (LAN) of 802.11 b/g/n on a processing board. The board is equipped with an optional board (BME280) used for ambient sensors in terms of a temperature sensor, a humidity sensor, an atmospheric air sensor, and an illumination sensor. For this study, we did not use these sensors.

The sensor case is 120 mm wide, 199 mm long, and 35 mm high. Herein, the smartphone on the case top is used for a demonstration. Using a tethering function of the smartphone, the obtained sensor signals, which are collected with the home agent, can be sent to network storage. For this study, we sent sensor signals using a mobile wireless router.

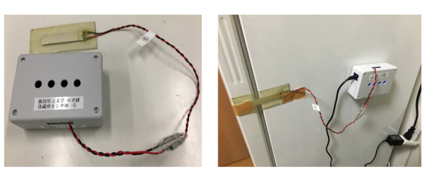

Figure 5. Refrigerator sensor. This is our originally developed sensor using a piezoelectric films bound with a urethane sheet.

Figure 6. Motion sensor used near the entrance to detect a subject's arrival and departure.

2) Ambient sensors: Our proposed ambient sensor system comprises pad-shape sensors installed on a bed, a triaxial accelerometer installed in a pillow, a motion sensor installed near a door, and a piezoelectric sensor installed in the door of a refrigerator. Figure 3 depicts the bed sensor proposed in a report of our earlier study [19]. It was manufactured using a piezoelectric film based on our prototype sensor aimed at detecting bed leaving behavior. We used up to six sensors because the use is intended solely for detecting bed-leaving behaviors. For this study, we optimized the minimum structure for detecting the subject's status on a bed to recognize sleeping behavior patterns. As an optimized result, we used two channels after removing the detection of the body rolling over.

As hidden sensors, we installed bed sensors to the backside of the bed sheet. The sensor can be used not only with a bed, but also with a futon, a Japanese style bed, because of the installation on a sheet, which differs from existing sensors installed on the bed frame [20]. For this implementation, we sewed the sensor pads to a bed sheet near the hip part with a pocket for avoiding drift of the sensor position.

For a pillow sensor, we directly implemented a triaxial accelerometer (LIS3DSHTR) on a sensor board. Figure 4 depicts the pillow sensor and its implementation inside of a pillow after digging a hole from the backside. This sensor works as a transmitter to notify the system of urgent information of unusual body condition triggered by pillow movement. We proposed the basic design of the pillow sensor in our earlier study [19]. This is a revised model obtained after changing the size and wireless communication method from ZigBee to WI-FI. For the current implementation, an electric power cable is extended from the pillow to electric power supply. For dissemination, we will change it to a wireless power supply method.

Figure 5 depicts a refrigerator sensor: our originally developed sensor prototype was created by attaching a piezoelectric film to a door of the refrigerator. In our daily life, a refrigerator is frequently used as a home electrical appliance. Numerous models of refrigerators exist with diverse structures in terms of a freezer, a cold room, and a vegetable room. For this study, our measurement target is the door of a cold room, which has the highest frequency of opening or closing.

Figure 6 depicts a motion sensor: a similar sensor installed in the home agent, near an entrance door. For all sensor boards, we used a WI-FI module (ESP-WROOM-02) for a wireless connection as the assumption of IoT applications. Moreover, we installed them into a plastic case to avoid attachment on the bared board for purposes of durability because we used the sensor system for monitoring subjects at a home or other residence.

B. Method of recognizing life patterns

For this study, we attempted to recognize life patterns based on machine learning methods for monitoring signals obtained from sensors. Actually, deep learning, for which a framework was proposed by Hinton et al. [21], constructed a recognizer automatically based on unsupervised learning of repeated iterations using a huge dataset without annotation. Because of high generalization capability for unlearned datasets, deep learning has been applied widely to various fields, especially in computer vision problems. By contrast, plenty of calculation resources are necessary, especially for learning of large-scale neural networks with multiple layers, even more than ten layers.

As an enhanced combination, transfer learning [25] is used to reduce the burden of learning if recognition targets are generic objects [22], outdoor or indoor scenes [23], or text mining [24]. In contrast, it is a challenging task to obtain weights learned in advance as transfer learning because of the use of original sensors for this study. Therefore, we compared traditional machine learning algorithms used for a recognizer; such algorithms are used widely before the dissemination of deep learning.

Comparison algorithms are of eight types: Gaussian Naive Bayes (GNB) [26], AdaBoost (AB) [27], k-Nearest Neighbor (kNN) [28], Stochastic Gradient Descent (SGD) [29], Support Vector Machines (SVMs) [30], Logistic Regression (LR) [31], Gradient Boosting Decision Tree (GBDT) [32], and Random Forest (RF) [33]. We selected the best performance algorithm from the criteria of recognition accuracy and calculation speed with cross validation [34] using a similar dataset.

IV. Evaluation experiment

A. Datasets

The aim of this study is to realize a smart sensor system for monitoring elderly people for providing relief and safety combined with privacy and QoL using invisible sensors. As a benchmark dataset for evaluating the performance of our proposed system, sensor signals and Ground Truth (GT) labels are necessary for constructing a recognition model. Based on the main user for this system for this preliminary experiment, elderly people, we obtained monitoring datasets and their GT based on life records obtained from healthy university students who live in an apartment. The number of subjects was four persons in their 20s.

Before obtaining monitoring datasets, we underwent an ethics approval review by our university to obtain human data. After receiving approval, we orally explained the purpose and agreement of this research to subjects using a handout that contains the same contents. We prepared an installation manual for setting up the home agent and ambient sensors. After installation, we verified the respective systems in their residence using photographs taken using the camera of a smartphone. No particular difficulty was encountered related to installation or assignment.

All subjects wrote their life records used for GT with obtaining monitoring signals from respective sensors. The recording contents comprise event times of seven patterns: getting up, sleeping, going out, coming home, emergency calls, opening or closing of a refrigerator, and the use of a TV remote control. They used a format to write them with the resolution of minutes from a radio-controlled clock.

Herein, the consistency of life records depended on the respective subjects because for reasons of privacy, we did not use a camera at their residence. The subjects, rather than volunteering, joined this experiment as a part-time job to verify its correct function. If some readily apparent error was identified in terms of not getting up after sleeping, we modified the life record after confirming that fact with subjects.

We conducted a monitoring experiment divided into 2 periods of one month each. The first and second experimental periods were, respectively, from October 27 through November 25 and from November 29 through December 28, 2017. The respectively obtained datasets were defined as Datasets 1 and 2. Herein, Dataset 2 contains data loss because of malfunctions of the home agent and the server. Therefore, the data lengths of one subject and other three subjects were, respectively, 18 days through December 16 and 27 days through December 25. For learning, we used datasets stored in the server with offline signal processing without using the monitoring signals obtained directly from the home agents and the ambient sensors.

The recognition target patterns comprise three states: going out (Out), staying at home (Home), and sleeping on the bed (Sleep). In addition to these three patterns, our system can recognize the opening or closing of a refrigerator door and turning on or off a TV using a remote control from the life records used for GT. By contrast, to maintain the privacy of monitoring subjects, we set target patterns as the minimum necessary for recognition.

The reports [35]-[37] addressed that it is useful to confirm survival at home using an electric kettle, a TV, a microwave oven, and a refrigerator. We consider that unexpected accidents are preventable if a state change between Home and Sleep could be detected. Therefore, we set three states as the basic life patterns, which were the minimum necessary combination for the recognition of this monitoring experiment.

The time resolution was set to one minute intervals based on the figure reported by Mori et al. [38] for the number of sensor responses and the frequency of switching behavior statuses. For this experiment, 43,200 sensor signals were obtained as evaluation targets from each dataset of one month.

The model numbers of the four home agents, which transmit monitoring signals to the server through a mobile router, were M2001, M2002, M2003, and M2004. The discretized sensor signals were displayed each day on a web page as color bars. With consideration of privacy, the visualization range is set to 15 hours from 6:00AM to 21:00PM. By contrast, we used the whole 24 hours of signals for the evaluation of identified life patterns with 10-fold cross validation. For instance, signals of 27 days and 3 days in 30 days were, respectively, divided into training and validation sets with exchange 10 times.

B. Comparison of learning algorithms

Using Dataset 1, we conducted a comparison experiment with learning algorithms. Table I presents comparison results of mean accuracies of ten trials with cross validation. Recognition accuracies except for those GNB and AB were approximately 80%. In the remaining eight learning algorithms, the recognition accuracy of GBDT was 83.72% as the highest accuracy.

Table II depicts results of the processing time for the respective algorithms. As computer hardware, this study used a 2.6 GHz Intel Core i 5 CPU with 8 GB of 1600 MHz DDR

TABLE I. COMPARISON RESULTS OF MACHINE-LEARNING ALGORITHMS [%]

Algorithms	M2001	M2002	M2003	M2004	Average
GNB	72.82	59.90	49.09	48.79	57.65
AB	59.55	71.79	72.26	57.43	65.26
kNN	80.28	84.11	68.43	83.87	79.17
SGD	81.90	87.18	72.35	78.35	79.95
SVM	80.28	86.01	**76.03**	80.00	80.58
LR	83.04	87.91	73.48	80.30	81.18
GBDT	85.28	**92.23**	72.16	**85.20**	**83.72**
RF	**85.94**	91.95	72.50	84.06	83.61

TABLE II. COMPARISON RESULTS OF PROCESSING TIME IN EACH ALGORITHMS [SEC]

Algorithms	M2001	M2002	M2003	M2004	Total
GNB	**0.66**	**0.62**	**0.64**	0.75	2.68
AB	26.48	29.09	27.03	26.41	109.01
kNN	2.80	3.07	2.76	4.69	13.31
SGD	0.67	0.63	0.70	0.68	2.67
SVM	23.95	24.35	26.87	29.93	105.11
LR	2.20	2.27	2.47	2.37	9.32
GBDT	52.45	51.08	48.73	41.94	194.20
RF	0.67	0.66	0.70	**0.60**	**2.62**

3 main memory. The operating system was macOS Sierra version 10.12.6. We used Python's open-source machine-learning library scykit-learn [39] from a command line without using graphics. The processing time was measured as software time using a standard function on Python.

As depicted in Table II, the minimum execution time was 2.62 s for RF. The comparison result denotes that NG and SGD have similar processing speeds. Herein, the processing time of GBDT was 194.20 s, which was 86.93 times longer than that of RF. By contrast, the difference of mean recognition accuracies was merely 0.11%. We selected RF as an algorithm for life pattern recognition for this study.

C. Recognition results of life patterns

For this evaluation experiment, we used all sensors because the amount of data traffic is small compared with image or sound data. Herein, the difference in recognition accuracies was evaluated as the combination of sensors used in preliminary experiments.

TABLE III. RECOGNITION ACCURACY FOR DATASET 1 [%]

No.	M2001	M2002	M2003	M2004	Average
1	76.84	91.53	84.81	91.87	–
2	97.34	88.82	92.78	96.10	–
3	98.74	99.43	83.01	96.60	–
4	99.35	99.05	99.35	93.30	–
5	85.39	99.05	60.97	87.01	–
6	89.08	97.57	82.31	86.36	–
7	95.24	98.72	67.27	82.41	–
8	91.64	92.91	66.98	79.60	–
9	59.85	98.29	82.58	85.99	–
10	65.90	54.12	4.91	41.34	–
Average	85.94	91.95	72.50	84.06	83.61

TABLE IV. RECOGNITION ACCURACY FOR DATASET 2 [%]

Term	M2001	M2002	M2003	M2004	Average
18 days	95.72	92.49	86.11	95.80	92.53
27 days	98.10	94.77	88.69	–	93.85

Table III presents recognition accuracies for Dataset 1. The recognition accuracies for 10 sets of the cross verification are shown as detailed results. The mean recognition accuracy of the four subjects was 83.61%. Details reveal that the highest and lowest recognition accuracies were, respectively, 91.95% for M2001 and 72.50% for M2002. Herein, the recognition accuracies of some subjects were extremely low, as revealed in the details of cross validation results. For this experiment, we evaluated the result as mean accuracy, not merely obtained highest accuracy in the combination of the cross validation. Herein, the low recognition accuracy of M2003 was cased from GT as handwritten life records because the subject sometime forgot to record it.

Table IV presents recognition accuracies for Dataset 2. For this dataset, data deficits were found from malfunctions related to the home agent and the server. Because of the malfunction of the home agent, the mean recognition accuracy for the 18-day monitoring period was 92.53%. Compared with the result on Dataset 1, the mean recognition accuracy improved 8.92% with the effect of the shortened period. To alleviate trouble, we changed M2004 to M2005, which was an alternative home agent. However, the problem of sensor signal monitoring continued. After terminating the receipt of data related to this subject, we continued monitoring for three subjects from the 19th day. The mean recognition accuracy for the partial dataset collected up to 27 days until the server trouble was 93.85%. Although monitoring terms and subjects were insufficient, the former and latter results were, respectively, 8.92% and 10.24% higher than that of Dataset 1.

V. CONCLUSION

This paper presented a novel life monitoring system consisting of a home agent and ambient sensors. As a preliminary experiment aimed at monitoring various life patterns of elderly people, we conducted a monitoring experiment during two months for four university students subjects in their 20s. We developed a recognition method for three life patterns using machine-learning algorithms. Experimentally obtained results revealed that the mean recognition accuracy was 83.61% for Dataset 1, which was obtained from the first half of the monitoring experiment during one month with one-minute downsampled signal intervals. For the last half of the monitoring experiment, data acquisition was interrupted because of a malfunction of the home agent. We continued the evaluation experiment of life patterns with delimiting two periods. The recognition accuracies were 92.53% for 18 days and 93.85% for 27 days in Dataset 2.

For our future work, we expect to consider stable operation of the whole system and prompt responses to malfunctions, if they should occur. Moreover, we would like to increase the number of recognition targets for daily behavior patterns while protecting privacy. Particularly, we would like to realize a new emergency notification function using a pillow sensor. Furthermore, after the cooperation with single elderly people for extending systemization and practical application, we hope to conduct demonstration experiments.

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