A life pattern estimation method and its application to anomaly detection of a single elderly are proposed. Our observation system deploys some pyroelectric sensors in an elderly’s house and monitors and measures activities 24 hours a day to grasp residents’ life patterns. Activity data is successively forwarded to the nurse operation center and displayed to nurses at the center. The system reports status related to anomalies together with the basic activities of elderly residents to the nurses, who decide whether recent accumulated data expresses an anomaly or not based on suggestions from the system. In the system, residents whose lifestyle features resemble each other are categorized into the same group. Anomalies that occurred in the past are shared in the group and utilized in an anomaly detection algorithm. This algorithm is based on an “anomaly score.” The score is figured out by utilizing the activeness of the house’s elderly resident. This activeness is approximately proportional to the frequency of sensor response within one minute. The anomaly score is calculated from the difference between activeness in the present and in the past averaged over the long term. The score is thus positive if activeness in the present is greater than the average in the past, and the score is negative if the value in the present is less than average. If the score exceeds a certain threshold, it means that an anomaly event has occurred. An activity estimation algorithm is also developed that estimates the basic activities of residents such as getting up in the morning, or going out. The estimation is also shown to nurses with the anomaly score of residents. Nurses can understand the condition of elderly residents’ health by combining the information and planning the most appropriate way to respond.

Keywords: MIMAMORI, intelligent environments, pyroelectric sensor, behavior model, single life

Fig. 1. Installation of pyroelectric sensor modules in an elderly’s house.

1. Introduction

The number of elderly persons living alone in Japan is increasing because of the aging of the population. Systems that monitor the lives of elderly residents and detect anomaly events have therefore become an active research area [1, 2]. Recently the Mimamo-Link of Tateyama System Laboratory Co. Ltd. was launched on to market, and the US firm General Electric (GE) is planning to start a learning-based monitoring system, Quiet Care, for example. Many such systems are based on technology related to Intelligent Environments [3–6]. In these environments, the observation of human activity or behavior is a key in supporting residents, and there have been many trials that uses accelerometers, vibration sensors, magnetic switches, electric current sensors, or infrared detectors [7–11]. In our research, we assume a system using some pyroelectric sensors that detect an elderly resident’s motion (Fig. 1). In the system (Fig. 2), we deploy a few pyroelectric sensors. Sensor data is successively obtained continuously all the time to estimate life patterns and detect anomaly situations. The activity sensor data obtained is forwarded continuously to the nurse operation center and displayed to nurses there. When an event or trend related to an anomaly occurrence is detected, the calculation system reports the status with basic activity such as getting up or going out event by elderly residents to
nurses, and the nurse in charge decides whether recent data expresses true anomaly or not based on suggestions and records from the system.

The anomalies that nurses want to detect are depression, dementia, illness, and so on. Concretely, data from sensors is gathered wirelessly by a data transmitter and sent to the call center over the Internet or telephone lines. When anomaly candidate data is discovered by the calculation system, it is reported to nurses with the reason why data is regarded as an anomaly. A nurse determining that the candidate is truly anomaly data, recommends that an elderly resident be hospitalized, for example.

Research on anomaly detection methods has conducted to detect rare unusual behavior or a change in life patterns among residents for the system. Ohta et al. proposed an algorithm by finding unusual independent movement that is isolated from movement pattern clusters and tried unusual day extraction simulation [12]. We also have conducted pattern classification and anomaly detection research based on dynamic time warping, hidden Markov models, or Gaussian mixture models [13–15]. Our method in this research extends some of their probabilistic concepts. The method we propose accumulates sensor data for a long span, analyzes data, and categorizes elderly residents whose features in the data resemble each other into the same group. An anomaly occurring in the past is shared in the same group and utilized in the anomaly detection algorithm. This is because anomalies rarely occur and are usually rather difficult to detect in one person’s data, although it is desirable that the system adapt to each person’s unique life pattern. In addition, we estimate activities that intuitively describe life patterns of people such as getting up, going out, and going to bed. This estimation is displayed together with the result of anomaly detection, which provides nurses with a precise understanding of the change in the life patterns of elderly residents.

Algorithms that cluster and visualize patterns in human life by applying HMMs or GMM to massive daily sensor log analysis [16] are one type of the most important basis among our related research. That tried to interpret human behavior modeling result intuitively, and the research resembles our research in this way. The research extracted human behavioral patterns by data-driven approaches based on statistical methods. However, in the actual operation of the health monitoring system, the use of common knowledge about general human lifestyles and especially learning based on long-term observation and examination are also an effective approach. In data on human daily life, for example, we can easily anticipate that there are some regularities attributable to factors such as the seasons or week. Concretely, life on weekdays and life on the weekends should be different in most people. In our research, we utilize these kinds of intuitive knowledge.

Figure 3 shows the overall configuration of the system.

2. Categorization of Resembling Life Patterns

It is important to categorize their life patterns with some kind of criteria. Ideally, the system should adapt each of the criteria individually, because lifestyle varies depending on the person and family. It is difficult when the system is actually in operation, however, as previously mentioned. This is why we adopt the method of grouping similar life patterns. We hereinafter discuss feature values as criteria useful for grouping residents.

Generally, human lives display some particular regularity, influenced by the season, week, custom, and so on. A person who takes a lesson every Tuesday afternoon is usually not at home on Tuesday afternoon, for example. We assume, based on common sense and pre-analysis of long-term elderly data that persons who are similar in their regularities are likely to live similar lives. In this research, we propose using four feature values, namely mean total response per day, week regularity, season cycle regularity, and room use pattern, which are thought to illustrate residents’ life pattern, and categorize each of them respectively (Fig. 4).

The pyroelectric sensor responds when heat sources such as a human being pass through their field of view. The count increases each time the heat source passes through. The sensors in this research are designed to save
energy by returning an integer value from 0 to 15 each minute. The sensor returns the value that represents the number of detected motions inside the detection scope. If more than 15 motions occur, the number output may be rounded to 15. This design was based on the observation that it is quite rare for elderly residents to cause more than 10 detections within one minute by the sensor. We analyzed such data from a few pyroelectric sensors per one house. There are, for example, three sensors in one house, located in the bedroom, in the living room and at the entrance.

Residents with the same result for each categorization are regarded as members of the same group whose life patterns resemble each other. Mean total response per day, week regularity and season cycle regularity are categorized into two patterns, and room-use patterns into three. These categorizations are guided by nursing staffs working in monitoring operation centers and the supporting
technical staff of the monitoring system. After discussion with the leading staffs, we decided upon the 4 categorizations criteria above. To determine the number of categories for each criterion, we conducted pre-experiments. For the ground truth, we first used two young persons’ activity data. Each examinee lived for several months alone with several pyroelectric sensors in the house and wrote a daily activity memo. The memo described typical event such as uprising, taking a bath, having meals, going out and so on. Temporary parameters are first determined in pre-experiments with the young persons, then the parameters are checked with the activity data from several elderly persons. Since it is difficult to get detailed activity memos from elderly residents, validation was done by matching days for going out and count for going out of each day based on interview records taken by nurses when they made periodic phone calls to elderly residents, usually twice a month. For mean total response per day, week regularity, and season cycle regularity, we conducted several $k$-means clustering on pre-accumulated long-term data, and found that $k = 2$ was the best. For the room-use pattern, we decided the number of category as 3 based on the observation that there were three very large groups. They use a single room almost all day, use major two rooms alternately during the day and use major two rooms for a certain amount of time. From discussions with several different nursing / technical staff groups, these categorization numbers were found to be the same and unchanged. As a result, we determined that each resident belongs to one of $24 (= 2^3 \times 3)$ life patterns.

Mean total response per day represents the general briskness of the resident. To obtain this value, we summed the total number of responses of sensors in one house and averaged it in long days.

Week regularity is dependence on a weekly activity calculated from the variability in sensor response among the days of the week. This concept is based on the presumption that residents with similar lifestyles display similar characteristics of sensor response like as shown in Fig. 5. The figure shows an elderly person’s activity data for three weeks. The response of all sensors as shown on the vertical axis represents the sum of sensor responses (usually 3 sensors per house). Concretely, this feature value is the standard deviation of the average number of sensor responses on the same day of week. This value is normalized by the mean total response per day of each resident. According to the assumption above, the smaller this value, the more regular life the resident’s lifestyle.

Among most of the residents we examined, there was a trend for the number of sensor responses per a day to indicate a minimal value in summer and a maximal value in winter, as depicted in Fig. 6. Season cycle regularity measures this characteristic by calculating the standard deviation of the average number of sensor responses for each month. This value is normalized by mean total response per day of each resident.

The room-use pattern is a pattern that is associated with the room layout of each house. This classification is based on the ratio of the sensor response for each sensor attached in a house, and room-use is divided in three patterns according to this ratio. As mentioned before, the three patterns are defined as follows based on observational find-
ings:

- Pattern 1: The total sensor responses in a day are accounted for by one particular sensor.
- Pattern 2: There are two dominant sensors that respond alternately depending on the hours of the day.
- Pattern 3: Two dominant sensors respond similarly during most of the day.

Residents with the same categorization for each feature value are grouped in the same life pattern. Based on this method, we conducted an experiment to categorize several residents into 24 patterns. For evaluation experiment, we used data on 15 houses other than pre-examination data, in which there are three sensors – one each in the bedroom, and living room and one at the entrance. Residents of all houses are elder people living alone. Fig. 7 displays the sensor responses of 6 residents from among all 15 residents. This figure displays the number of sensor response per minute for each sensor averaged for 365 days. Six residents are randomly selected from among all residents. Before the experiment, we manually categorized residents’ patterns by looking at the shape of graphs such as figures based on discussions with the leading staffs of the nursing staffs and the technical staff of the monitoring site. We then applied the categorization algorithm to data and compared results with the label we had manually used to categorize all data precisely and on the basis of discussions. The experiment was conducted with four different learning (averaging data) spans, – 3 months, 6 months, 9 months, and one year. The algorithm was originally designed for averaging annual data, especially in season cycle regularity. We experienced the data of shorter spans because we thought that the feature value may represent the difference even in such short spans. Shortening the learning span also shortened the computation time.

Fig. 6. Regularity of season cycle.

Fig. 7. Sensor response examples.
As a result, if residents are categorized in the same group, there are similar characteristics in the shapes of their graphs. Residents D and F, for example, are categorized in the same group. In addition, the result when the span is set to one year was the most valid categorization compared with our intuitive categorization. The reason for this is that, among the four feature values, mean total response per day and season cycle regularity may be values varying in the annual cycle, and the independence of these two features is high when the learning span is 365 days. We propose these categorization algorithms as one type of possible criteria for describing residents’ life patterns, and decided to use the algorithms in the anomaly detection algorithms in the following.

3. Activity Estimation

This system was developed to enable nurses to understand more intuitively the results of abnormality detection by indicating the combination of simple activity estimation results to anomaly detection results described by the anomaly score. Fig. 8 displays the concept of detection.

We first calculated the time each day for getting up, outing, and coming home from sensor responses at the house of examined residents. These calculations were performed by an algorithm that distinguishes between going out and staying inactive at home, which represent no-response of the sensor at the same time. We then estimated getting up time and going out habits. For the uprising time, we averaged all of the Tuesday data if we wanted to detect the getting up time on Tuesdays. The result was decided as the estimated uprising time on the examined day. For the outing time, we use a detection algorithm to detect habitual going out, which always occurred at a regular time and day of the week. This kind of going out is labeled habitual outing. We then detect briskness on the examined day from calculated mean uprising time and habitual going out. In this system, we explained the residents’ life styles using three states called active, inactive at home, and going out. For going out, the system compares data and habitual outing data that the system learned and then, if the start of the going out time is recognized to agree with the time of habitual going out, going out is estimated as habitual outing. The system explains estimated coming home time. For getting up time, the system defines the time at which residents’ states change from inactive to active as getting up.

In all residents’ data, there is behavior that is estimated by a simple method in high detection rate observing accumulated record data. These were uprising and going out. In uprising, the part where the response of the sensor changed from almost nothing to frequently occurring is considered getting up, with the exception of cases such as the resident sleeping all day and staying up all night. When residents go out, they usually pass through the entrance. We can detect outing by considering the part where no-response duration continued after the sensor responded frequently is as going out. We expect some effectiveness when this information is combined with anomaly detection results. If an “active” resident indicates “plus anomaly,” which means the response of the sensor increases much more than usual, we specifically estimate the reason is that the resident is at home at a time when the resident usually goes habitual outing. We also provide useful information for efficient service management like this: “We are going to call for the certainty of the resident’s safety after 7:00 PM because the resident usually...
goes habitual outing today.”

We first explain the no-response detection algorithm, which is the core of this getting up and outing detection system. This core algorithm checks the response of each sensor deployed to the house and categorizes the activity state of the resident into three states: active, inactive at home, and going out. The algorithm first makes a judgment whether the resident is active at home or not. The condition for this purpose is defined as no-response situation in which any response detected from all sensors in the house continues for ten minutes. We then decide this no-responding situation from whether an inactive state at home or going out is the case. We decided the condition as: 1) total responses of the entrance sensor are more than 10 during the last 10 minutes before the start of the no-response state. 2) Total responses of the entrance sensor are more than 5 during the last 2 minutes before the start of the no-response state. Parameter settings are the result that parameter was adjusted to represent a high detection rate compared to actual data in estimation experiments for getting up and going out. Since nurses discuss and demand not to miss or overlook events, parameters are set mainly regarding detection sensitivity. When the state was defined as outing or inactive at home, each state branches to an algorithm that detects coming home or recovery from no-response state. When we detected coming home, a very small response, which is noise from the sensor during outing, may be detected because a change in the sunlight through a window or a flickering of shadow from a visitor in front of the lighted entrance may affect the sensor. Avoiding misdetection in coming home, we decided a condition compared with actual data to detect only coming home so as not to mistake noise from the sensor during going out. We set the condition so that after any sensor response more than 2 times per 1 minute, all sensor responses more than 10 times in total during the next 5 minutes including the time. These parameters are decided also by observing collected activity data with the nursing and technical staffs.

We then explain a method that detects recovery from no-response state. There is a characteristic that the number of responses per day of sensors changes in a season cycle. Generally the number of sensor responses per day tends to have a peak in the winter and to be at a minimum in the summer. When we observed actual response data, it was considered that almost all of the responses in a resident’s life increase or decrease according to the number of sensor responses per day in the season. Fig. 9 plots the mean number of responses per minute from a certain resident’s data in August 2008 and January 2009. It is observed that the response for the winter exceeds that for the summer remaining almost the same shape of graph in each hour. According to these findings and hypothesis if we do not determine appropriate parameters with seasons for detection, misdetection from noise will increase in winter when the total response increases and mistaken detection will occur in summer when the number of responses is down to a very low level. We then defined the threshold for detection of recovery from the no-response state as follows:

\[
\text{Threshold}(m) = O + k \times \left( T_M(m) - T_Y \right) / T_Y
\]

where",

\[ T_Y = \text{averaged “total sensor responses in a day” with a year} \]

\[ T_M(m) = \text{mean of the “total sensor responses in a day” in month } m \]

Threshold(m) : “threshold of recovery from no-response state” in month m

It is known from common knowledge and also from some long-term observations that total sensor responses in a day have a minimum in summer and a maximum in winter. If we average this number for each month as in the calculation of season cycle regularity and compare the result with the annual mean according to this equation, in summer when the response decrease the second numerator becomes negative and, conversely, in winter, when the response increase it becomes positive. Using this method we automatically change the threshold according to the level of difference in the annual mean and monthly mean. Based on this method, if the number of response of any sensor per minute exceeds a threshold value, we defined the state that recovers from inactive at home as active. The detection of this change by this threshold is used for the uprising detection. We decide, for example, that a resident is inactive at home sleeping every 4:00 AM. We then recognize the time when the first change of inactive at home to active occurs as uprising where 0 is an offset that means the general threshold for the resident and k is a gain that appropriately regulates the value of the season cycle regularity. In future studies, we will obtain the threshold of the recovery from no-response, which we can apply to all of the people to decide this parameter appropriately for each resident. In this study, we first explain that this method of deciding the threshold can certainly detect much better the recovery from the no-response state than a method in which a fixed threshold is used. We conducted detection rate estimation experiments for detection of uprising in a certain resident. Parameters that resulted in the most accurate detection are \( O = 9, k = 12 \). Small experiments are performed to determine these parameters. The
true event occurrence time was judged from the ground truth, and if error was less than 15 minutes then the system’s detection is regarded as correct. For $O_i$, $8$, $9$ and $11.5$, $12$, $12.5$ were tried for $k$. Among the pairs, pair $9$ with $11.5$, $9$ with $12$, $9$ with $12.5$ had over 90 percent accuracy for about 3 month data. The parameter set may be different if target elderly living area characteristics change greatly from the data we have. For our data from several different area, the parameter set was unchanged. And even with a large difference, it may not be difficult to catch the feature of the area from sensor data for a few week data for several houses.

When we calculate mean uprising time, we average the time on the same day of the week. We thought that changes in lifestyle over long days influence the getting up time, therefore we decided to use the value of the past 15 weeks for the calculation of the mean. For estimation of habitual outing, two types of information are useful in this research when we estimate and categorize the typical behavior pattern of a resident. These are the time of the activity happened and the duration of the activity. Fig. 10 is the result of plotting the annual outing time and outing duration of the Tuesday data from a resident on a two-dimensional plane. Note from this graph that there are some going out times that occur at almost the same time and continue for the same duration. We then estimate habitual outing as follows:

1. Divide a two-dimensional plane consisting of outing time and outing duration per day into $m$ for the vector of outing time and into $n$ for the vector of outing duration, and then make a grid of $m \times n$.

2. Find the cell in which the outing per day applies from a grid of $m \times n$.

3. If there is more than one outing that is categorized into the same cell, outing is recognized as habitual outing when we processed data from examination day to past $k$ weeks.

For $m$ and $n$, we decided settings of parameters that enabled us to detect habitual outing easily from preparatory experiments. A day is 1440 minutes, so we therefore decided as follows:

- Outing time: $0$, $220$, …, $1440$ ($m = 21$)
- Outing duration: $0$, $30$, $60$, $120$, $240$, $360$, $600$, $840$, $1440$ ($n = 8$)

We decided $k = 10$ and $l = 5$ from preparatory experiments in the same way for detection rate estimation that detects habitual going out.

### 4. Anomaly Detection

We define an anomaly as a situation in which the number of sensor responses greatly increases or decreases compared with normal time. To determine whether a situation is an anomaly or not, we calculate the increase and decrease in the number of responses from the usual time for each time of the day. Therefore, if the increase or decrease exceeds a certain threshold, an anomaly occurred at the time. The threshold is calculated from the increase or decrease on the day some kind of anomaly occurred in the past. The days on which the anomaly occurred are registered in the anomaly database in advance based on records. Fig. 11 displays the concept of anomaly detection. As the figure illustrates, an anomaly for which the response increases is defined as a “plus anomaly,” and that for which the response decreases is defined as a “minus anomaly.” The example of the plus anomaly is a case in which the response during the night is active, though the resident is usually in bed at this hour. On the other hand, the example of the minus anomaly is, in contrast, sudden going out.

The concrete explanation of this method is as follows:

1. For the day of examination, calculate the value 30-minute difference in response, the number of sensor responses for the last 30 minutes from the present time for each minute.

2. Calculate the same value for the past 15 weeks (approximately 3 or 4 months) and average the value for each day of the week.

3. Figure out “one-minute anomaly score” by comparing the two values above by using the equation below:

$$e := (D - D_M)/(\alpha - D_M)$$
Where $D$ is a 30-minute difference in response of each minute and $D_M$ is a 30-minute difference in response averaged for each day of the week for last 15 weeks. $\alpha$ is a constant number and set to $1.0$ to prevent $e$ from diverging to infinity. In addition, one-minute scores are accumulated for the last 10 minutes into an “anomaly score.”

4. Calculate the anomaly criterion as the criterion for whether the “anomaly score” is an anomaly or not. The criterion is derived from the “anomaly score” on the day an actual anomaly occurred, based on anomaly data pre-registered in the anomaly database.

5. Calculate the proportion of the anomaly score for each anomaly criterion. The proportion is called the anomaly ratio. If the ratio exceeds a certain threshold, we determine that an anomaly of some type corresponds to the anomaly criterion. The parameter for calculating $D_M$ was set to 15 weeks (approximately 3 months) because the span is close to the length of a season. The rest of the parameters in this algorithm were determined empirically by inspecting a large amount of data.

We conducted an experiment for this algorithm. We used a certain resident’s data for the experiment. The data includes that for more than a year. The last 71 days are used for the anomaly detection and the rest are used for learning. In data, there is one drastic increase in the response on the 11th day and there is a long absence of response between the 45th day and the 69th day. The two data items are regarded as the plus anomaly and the minus anomaly. We examine whether these two anomalies were detected as anomalies or not. **Fig. 12** is the result of applying our anomaly detection algorithm to the living data of a resident. **Figs. 12(a) and 12(b)** represent the plus anomaly and the minus anomaly of the same span, respectively, and the threshold to each anomaly ratio is 0.75 for the plus anomaly and 0.98 for minus anomaly. As the anomaly ratio, we used the summed ratio of the two sensors that mainly responded in the house. In **Fig. 12(a)**, an anomaly is accurately detected on the 11th day, when the number of sensor responses drastically increased. Similarly, in **Fig. 12(b)**, anomalies are detected mainly between the 45th day and the 69th day, when there was no response because the resident was not at home during the span. In the detection of minus anomaly, however, many other anomalies are detected if we lower the threshold from 0.98 to 0.95, for example. This means that adjustment of the threshold of a minus anomaly should be done carefully. In this experiment, contents of anomalies are restricted to cases when the number of response dramatically increased or decreased. This means that no concrete reason or the anomaly can be figured out simply from sequential sensor data records, and nurses should use such information as an important opportunity to start looking into the target elderly person’s activity data precisely. Of course, the reasons for the detected anomalies should be informed concretely, ideally. In the future, for example, “the resident seems so feeble that she/he needs to be hospitalized” should be displayed.

**5. Conclusion**

We have proposed an anomaly detection and behavior pattern estimation method to monitor elderly persons living alone based on long-term data and nursing staffs’ experience. Examined residents have been categorized according to sensor data. Records of anomalies that happened to residents are then shared in the same group. The categorization result is referred in the anomaly detection algorithm that detects drastic increases and decreases in
the sensor response. In addition, we have detected basic activities in life, such as going out by using an activity estimation algorithm. This estimation and the result of the anomaly detection algorithm are displayed together to nurses in the elderly resident observation system. The combination of information enables nurses to understand elder residents’ lives precisely. The experiment has demonstrated that sensor-monitoring systems can be utilized not only for activity estimation but also for anomaly detection. Continuous monitoring of resident’s daily lives is therefore very important in the sensor monitoring system. Our future work will focus on the study of the life pattern categorizing method. The criteria manually decided in the current research should be determined automatically, based on the properties of the data accumulated.

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