Anomaly Detection for an Elderly Person Watching System using Multiple Power Consumption Models

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Abstract: We propose an anomaly detection method for watching elderly people using only the power data acquired by a smart meter. In a conventional system that uses only power data, a warning is issued if the power consumption does not increase after the wake-up time or when the amount of power does not change for a long time. These methods need to set the wake-up time and power threshold for each user. Furthermore, wrong warnings are issued while residents are out of the home. In our method, multiple common power consumption models are created for each household for each short time zone, and a watching system is constructed by regarding the gaps between these models and newly observed data as anomaly values. This can be automatically applied to various situations such as "during sleep," "during home activity" and "time zone for frequently going out in the daytime."

1 INTRODUCTION

According to a survey by the Cabinet Office, Government of Japan (Cabinet Office, Government of Japan, 2016), the total population of Japan is 127.1 million as of October 2015. The population of elderly people aged 65 and over is 33.92 million, which accounts for 26.7% of the total population. It is estimated that the aging rate will continue to rise, reaching 39.9% in 2060, and at which time approximately 1 in 2.5 people will be aged 65 or over. Given this background, the development of a watching system that can recognize an emergency situation involving the elderly is desired from families living apart from the elderly, operators of nursing care services, and so on. Various watching systems have been proposed and most of them can notify the warning using a personal computer, a smartphone or by e-mail.

Various methods have been proposed to detect an anomaly in residents. Many systems monitor the lives of elderly people by way of the installation of various sensors in houses and the performance of sensing in real time (Doi et al., 2006) (Ota et al., 2011). Camera and infrared sensors are representative examples, and it is possible to monitor the behavior of residents with high accuracy using these methods (Doi et al., 2006). However, these methods have privacy problems, and it cannot be said that the mental burden of residents is small. Some systems monitor residents' behavior using sensors installed on electrical household appliances and doors frequently used in everyday life, such as toilet doors and electric pots (kondo, 2011) (Nakano and Ueno, 2014). Residents can use watching services while living their daily life. However, there is a possibility that detection may be delayed or misrecognition may occur when services are not used for a long time. Nakano et al. (Nakano and Ueno, 2016) created a watching system by estimating whether residents directly operated electrical equipment using the full-load current of households measured every minute. This method took into account the living conditions of residents by estimating the operating condition of equipment deeply related to the daily living behavior of residents. However, information on the characteristics of electric appliances used in the home is needed in advance. Because the aforementioned methods require the installation of new sensors, they are difficult to use immediately in various households at present.

Therefore, in this research, we propose an anomaly detection method for watching the elderly that uses only power consumption data obtained every 30 minutes from a smart meter installed in each household. A smart meter is a device that can measure the

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amount of electricity used and it has the communication functionality to allow remote meter reading. In Japan, along with liberalization of electricity retail sales, the installation of smart meters in each household is progressing, and it is planned that the installation in all households will be completed by the end of fiscal year 2024 (Ministry of Economy, Trade and Industry,). Our proposed method does not require the installation of new sensors and it can be applied to all households where smart meters are installed. Furthermore, because only electric power data is used, the mental burden of residents is small.

In a conventional system that uses only power data, a warning is issued if the power consumption does not increase after the wake-up time or when the amount of power does not change for a long time. These methods need to set the wake-up time and power threshold for each user. Furthermore, wrong warnings are issued while residents are out of the home. Additionally, because of the characteristics of the method, it takes time to detect an anomaly.

There are many conventional methods for detecting an anomaly with respect to measurement data. A *k*-nearest neighbor (*k*-NN) algorithm (Dasarathy, 1990) is one of the anomaly detection methods that detects an outlier value. Its advantage is that supervised data is not necessary for anomaly detection. By applying these to power data, it is possible to detect the time of power usage that is different from daily life as an anomaly; however, this will not work as a watching system.

In our method, the problems are overcome by defining features specialized for watching. The routine of residents' activities is learned automatically without setting parameters on the lifestyles for each resident by constructing different power consumption models for each time zone. Furthermore, when newly observed data deviates from the generated model, a warning of an anomaly is issued so that it is possible to quickly detect an emergency situation.

2 ANOMALY DETECTION FOR AN ELDERLY PERSON USING MULTIPLE POWER CONSUMPTION MODELS

In this study, we detect an anomaly for the watching system when the fluctuation of the power consumption is small and different from usual. As a result, unlike a conventional method, even when the power consumption is large, when the fluctuation of power is small and it differs from usual consumption, it is detected as an anomaly. Furthermore, during sleep or a time zone that the resident often goes out, even when the fluctuation of power is small, it is not detected as an anomaly.

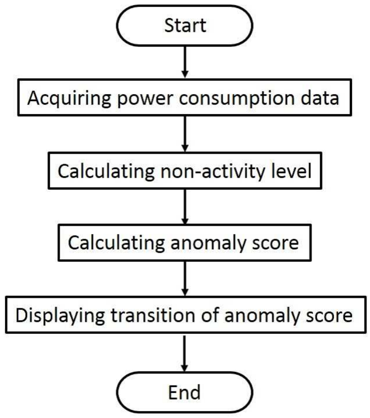


Figure 1: Flow of the proposed method.

Figure 1 shows the flow of the proposed method. First, power consumption data obtained from the smart meter every 30 minutes is used for input. Next, feature vectors are generated using an index called a non-activity level. By accumulating this feature vector, a common distribution model is created, and the gaps in the model are calculated for use as an anomaly score. Finally, the transition of the anomaly score is displayed for the elderly person watching system. Details of each feature are described below.

2.1 Features for Anomaly Detection

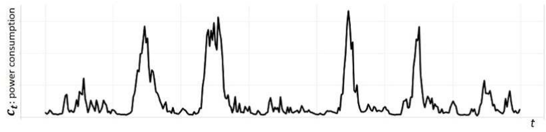
To detect an anomaly in the elderly, an index that increases as the fluctuation of power decreases is necessary. As an index that increases as the fluctuation of power decreases, the reciprocal of the absolute value of the power change can be considered:

$$v_t = \frac{1}{|c_t - c_{t-1}|}, \tag{1}$$

where c_t represents the power consumption observed at time t. When there is no power change, the value of v_t diverges to infinity. Therefore, when v_t is used as an index for watching, it can be detected only when the power change is close to zero. Even if it is an anomaly, however, a minute change occurs in the electrical power. Additionally, in this case, it is necessary to perform anomaly detection appropriately.

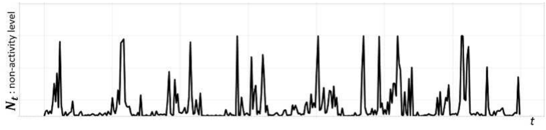
Therefore, in this study, we define the non-activity level N_t as

$$N_t = \frac{1}{1 + \exp(-a v_t)}, \tag{2}$$



(a) Time series data with respect to the power consumption of a household for a week.

(b) v_t calculated by Equation (1) with respect to the time series data of (a).



(c) Non-activity level calculated by Equation (2) with respect to v_t of (b).

Figure 2: Relationship between power consumption data and the non-activity level.

Even if v_t diverges to infinity, that is, when there is no power change, N_t converges to one. Furthermore, by adjusting the coefficient a, it is possible to approximate the value when there is no power change, even when the electric power slightly changes. As a result, it is possible to detect an anomaly even when a minute change occurs in electrical power when an elderly person is in an emergency situation. Note that it is possible to detect an anomaly in a short time by calculating N_t at the same frequency as data acquisition.

Figure 2 shows an example of the relationship between actually observed power consumption data and the non-activity level. Figure 2 (a) shows time series data with respect to the power consumption of a household for a week. It can be observed that the power consumption is large during the day. Figure 2 (b) shows v_t calculated by Equation (1) with respect to the time series data of (a). As shown in this example, v_t has a large value when the change in the power consumption in (a) is close to zero. However, even if this value is used for anomaly detection, it can be detected only when the change in the power consumption is close to zero. As a result, an anomaly cannot be detected when a minute change occurs in the power consumption. By contrast, (c) in Figure 2 is an example of plotting the non-activity level shown in the expression (2). Particularly for the example of $a = 10$, we observe that N_t has a relatively large value, even if there is a small change in the power consumption. Common power consumption models for each time zone are constructed using the non-activity level

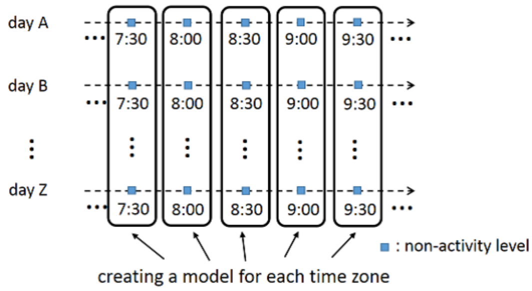


Figure 3: Creation of multiple power consumption models.

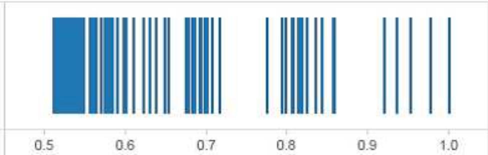
calculated in this manner, and anomaly detection is performed by the k-NN algorithm.

2.2 Creation of Multiple Common Power Consumption Models

In our method, common power consumption models are created and anomaly detection is performed simultaneously with power measurement by regarding the gaps between these models and newly observed data as anomaly scores. The power consumption models are created for each household to respond to the diversity of residents' behavior. If only one activity model is generated by treating the non-activity levels in all time zones, an anomaly cannot be detected because many phenomena with a small power fluctuation are observed during sleep. It is conceivable to construct a model that assumes specific behaviors, such as "during sleep," "during home activity" and "time zone for frequently going out in the daytime." However, it is difficult to assume all types of behaviors because behaviors have diversity, and it is difficult to address temporal deviations in customary behavior.

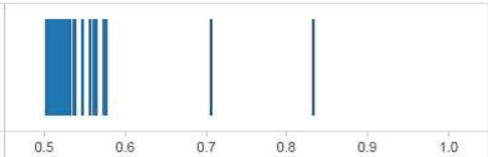
Therefore, in this research, as shown in Figure 3, multiple models are built for the same time zone on different days. Because power consumption data is acquired every 30 minutes, 48 models are generated for each household. The models described here are not defined by mathematical expressions; they are merely distributions of the non-activity levels. Models that depend on the activity of a resident are created for each time zone.

Figure 4 shows an example of the difference of the distributions of the non-activity levels among different time zones. This is a visualization of the data accumulated for three months for the non-activity levels acquired by a particular household. In this figure, the higher the density, the higher the observation frequency of the value, and conversely, a sparser density indicates more unusual phenomena. Figure 4 (a) shows the distribution of the non-activity levels at



(a) Distribution of non-activity levels at 2:30 am.

(b) Distribution of non-activity levels at 7:30 am.



(c) Distribution of non-activity levels at 12:30 pm.

Figure 4: Difference of the distributions of the non-activity levels among different time zones.

2:30 am. We know that the resident of this household goes to bed at this time on a daily basis. It is found that the frequency at which the non-activity level shows a high value is high. Figure 4 (b) shows the distribution of the non-activity levels at 7:30 am. We know that the resident of this household has already woken up at this time. It is understood that the frequency at which the non-activity level shows a high value is not as high compared with case (a). Figure 4 (c) shows the distribution of the non-activity levels at 12:30 pm. It is known that the resident of this household does not go out on a daily basis during this time. It is found that there is almost no frequency for which the non-activity level shows a high value. In this method, for example, when a high value of the non-activity level is newly observed during this time zone, it is detected as an anomaly. As a result, it is possible to respond flexibly to various activities without explicitly defining the behavior of the resident, such as "during sleep," "during home activity" and "time zone for frequently going out in the daytime."

In the above examples, N_t (scalar) was used as an index for the distribution models; however, in our method, instead of N_t, multidimensional vectors $\{N_t, N_{t-1}, N_{t-2} \cdots\}$ can be used. This makes it possible to detect anomalies on a long-term basis.

By configuring only the data at the time of the normal pattern as the accumulated past data, the advantage is that there is no need to manually prepare the supervised data as observed in general machine learning. Additionally, because of the characteristics of the proposed method regarding setting the gaps from

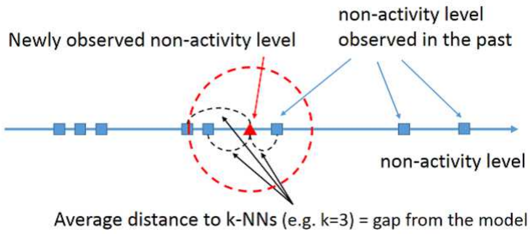


Figure 5: An example of anomaly detection based on k-NN. the non-activity level N_t is used as an index of distribution and this example shows an example when $k = 3$.

accumulated past data as anomalies, it is theoretically possible to perform a calculation even if there are few accumulated data. Furthermore, by automatically deleting past old data when constructing models, even if the resident's life routine changes, it is possible to adapt flexibly.

2.3 Anomaly Detection Based on the *k*-NN algorithm

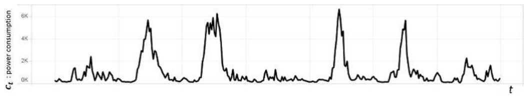
In our method, multiple common power consumption models are created for each household for each short time zone, and a watching system is constructed by regarding the gaps between these models and newly observed data as anomaly values. In the *k*-NN based method, for the newly observed data, k nearest neighbor data is selected from the accumulated past data. Next, we calculate the average distance from those k data and use this as the anomaly score.

Figure 5 shows an example when $k = 3$. If the newly observed data is anomaly data, the average distance increases, and if it is normal data, it decreases. Parameter k is determined experimentally, but if you set k to be small in general, it becomes sensitive to anomaly data, and conversely, it becomes insensitive if it is set large.

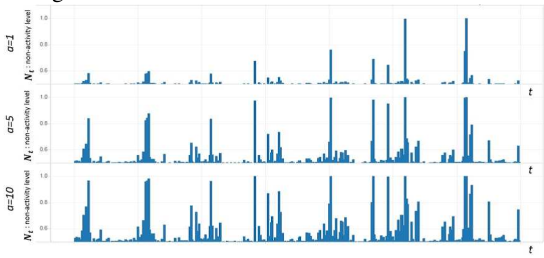
In the above examples, the non-activity level N_t (scalar) is used as an index for distribution models, but if, instead of N_t, multidimensional vectors, $\{N_t, N_{t-1}, N_{t-2} \cdots\}$, are used, the distributions become multidimention.

3 EXPERIMENTS

In this experiment, to show the effectiveness of the proposed method, we verified whether anomaly detection was properly performed by using actual power consumption data. The target was the power consumption data of an elderly single-person household for three months from July 1 to September 30. The

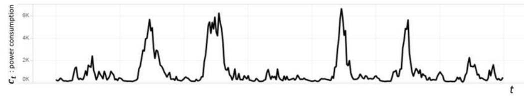


(a) Example of power consumption data for one week for the target household.

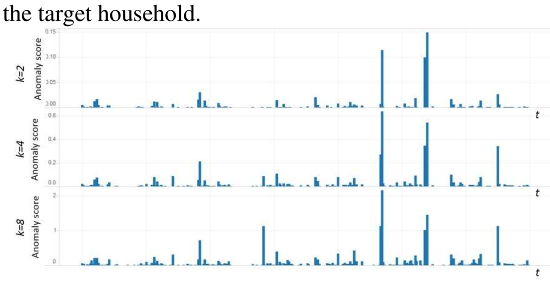


(b) Comparison result of the non-activity levels. The upper row of the figure shows the result of $a = 1$, the middle row shows the result of $a = 5$ and the lower row shows the result of $a = 10$.

Figure 6: Comparison result when a in Equation (2) is changed.



(a) Example of power consumption data for one week for the target household.



(b) Comparison result of the anomaly scores. The upper row of the figure shows the result of $k = 2$, the middle row shows the result of $k = 4$ and the lower row shows the result of $k = 8$.

Figure 7: Comparison result when k of the k-NN algorithm is changed.

power consumption data was acquired by a smart meter every 30 minutes.

First, as a preliminary experiment, the comparison result when a in Equation (2) is changed is shown. Figure 6 shows data for one week for the target household.

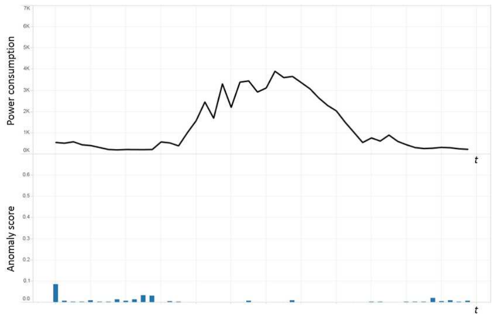
Figure 6 (a) shows an example of power consumption data for one week for the target household. Figure 6 (b) shows the comparison result of the non-activity levels when a in Equation (2) is changed. The upper row of the figure shows the result of $a = 1$, the middle row shows the result of $a = 5$ and the lower row shows the result of $a = 10$. It can be observed that the non-activity level is large as a increases, even if there is a minute power change. When $a = 1$, the non-activity level is small when there is a minute power change. For anomaly detection, a was found to require a somewhat larger value because a minute change occurs in electrical power when an elderly person is in an emergency situation. Therefore, for all subsequent experiments, we used $a = 10$.

Next, as a preliminary experiment, the comparison result when k of the k-NN algorithm changed is shown. Figure 7 shows one week's data for the household of the same subject as the previous preliminary experiment. Figure 7 (a) shows an example of power consumption data for one week for the target household. Figure 7 (b) shows the comparison result of the anomaly scores when k of the k-NN algorithm is changed. The upper row of the figure shows the result of $k = 2$, the middle row shows the result of $k = 4$ and the lower row shows the result of $k = 8$. In this experiment, the total number of data of the accumulated non-activity levels is 91. If $k = 1$, the data is sensitive to an anomaly, and conversely if $k = 8$, the data becomes insensitive to an anomaly. For all subsequent experiments, we used $k = 4$.

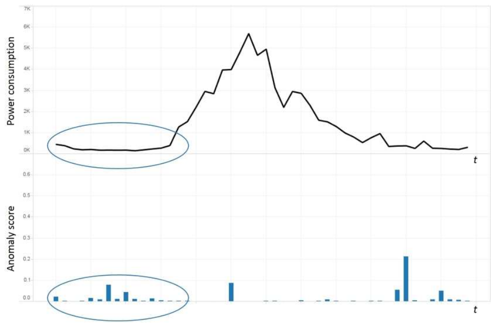
Figure 8 shows the results of the anomaly scores on a particular day.

Figure 8 (a) shows an example of a small anomaly score. This is a pattern that is common in everyday life. Figure 8 (b) shows an example of a small anomaly score. In this case, although the fluctuation of power is small, similar patterns were observed for the same time zone. This should not be detected as an anomaly because this is a typical pattern that occurred during sleep. Figure 8 (c) shows an example of a small anomaly score. In this case, although the power consumption is less than usual, the fluctuation of power is large. This case may be incurred when not using equipment that consumes large amounts of electrical power, such as cooling and heating equipment. Figure 8 (d) and (e) show examples of large anomaly scores. In these cases, the fluctuation of power is small even though it is different from usual. This case may be incurred when the elderly person does not get up in the morning. Figure 8 (f) shows an example of a large anomaly score. In this case, the power consumption is large; however, the fluctuation of power is small. For the elderly watching system, it is important to jedge as an anomaly in this case.

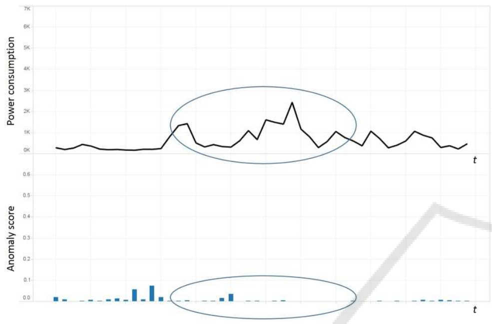
The above results are visualized in real time and shown to the families living apart from the elderly people, operators of nursing care services, and so on. Figure 9 shows the transition of the anomaly score over three months. It is understood that a high anomaly score is observed approximately 30 times in three months. Vigilance is necessary, especially when the



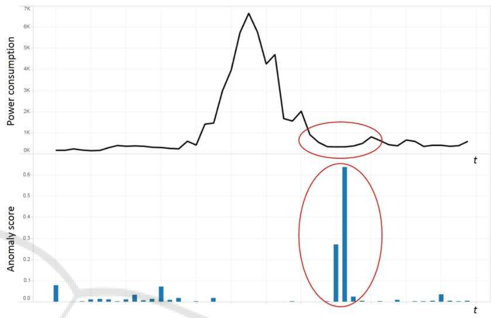
(a) Example of a small anomaly score. This is a pattern that is common in everyday life.



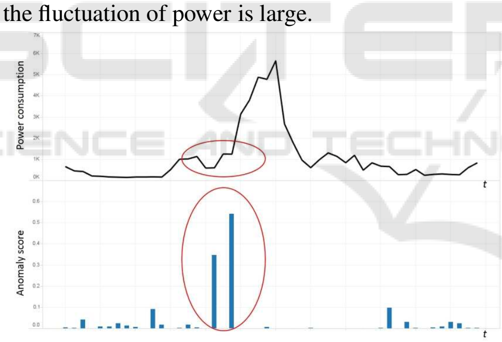
(b) Example of a small anomaly score. In this case, although the fluctuation of power is small, similar patterns have been observed at the same time zone.



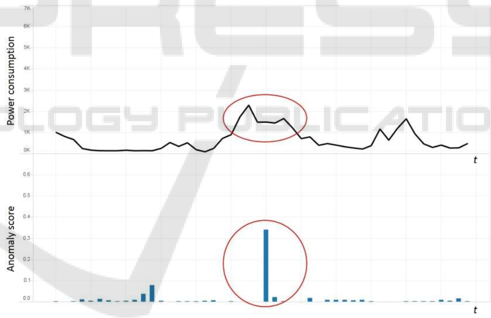
(c) Example of a small anomaly score. In this case, although the power consumption is less than usual, the fluctuation of power is large.



(d) Example of a large anomaly score. In this case, the fluctuation of power is small even though it is different from usual.



(e) Example of a large anomaly score. In this case, the fluctuation of power is small even though it is different from usual.



(f) Example of a large anomaly score. In this case, the power consumption is large, but the fluctuation of power is small.

Figure 8: Examples of anomaly scores estimated by the proposed method. Each upper row shows the power consumption data of one day and each lower row shows the result of anomaly score.

anomaly score is high continuously.

4 DISCUSSION

As shown in Figure 8, it is possible to automatically detect anomalies for various patterns by constructing multiple common power consumption models for each time zone and using the k-NN method to regard the gaps between these models and newly observed data as anomaly scores. Detecting a specific pattern is possible with the conventional method; however, not only it is necessary to set parameters for each household, but also only some typical patterns can be detected. Although our method has two variable parameters, a in Equation (2) and k of the k-NN algorithm, it is not necessary to change these in particular, and the parameters determined during the preliminary experiment can also be applied to other households.

A limitation of the proposed method is that an

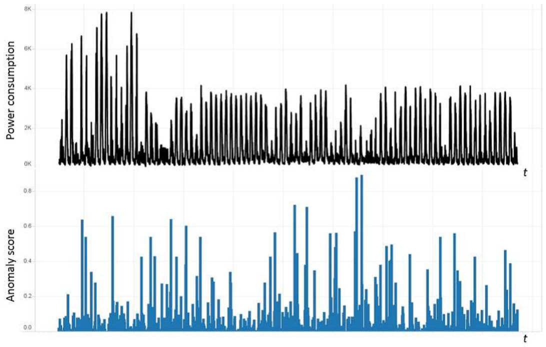


Figure 9: Transition of the anomaly score.

anomaly is barely detected when various power consumption patterns are observed. This is one of the limitations of the *k*-NN algorithm, which makes the gaps from the normal pattern anomalous. To overcome this limitation, it is necessary to arrange the data when constructing a normal pattern model. Because there are four seasons in one year in Japan, and a person's life pattern gradually changes in each season. We believe that it is possible to respond to these changes using data from approximately three months in the near future, that is, not using all past data, when generating the distribution model. Hence, in the experiment, we used data for three months from July 1 to September 30. Thus, it is possible to respond automatically when a life pattern changes for reasons other than the influence of the season.

5 CONCLUSIONS

We proposed an anomaly detection method for watching elderly people using only the power data acquired by a smart meter. Multiple common power consumption models were constructed for each time zone and anomaly detection for watching the elderly was conducted using the *k*-NN algorithm to regard the gaps between these models and newly observed data as anomaly scores. As a result, it was possible to respond flexibly to various activities without explicitly defining the behavior of the resident, such as "during sleep," "during home activity" and "time zone for frequently going out in the daytime."

A future task is to conduct demonstration experiments on elderly people and implement social experiments in cooperation with local governments. To operate in the real world, we will need to properly set the timing to notify us of an anomaly by considering the opinions of families living apart from the elderly and operators of nursing care services.

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